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Margin Boost Clustering based Multivariate Dolphin Swarm Optimization for Routing and Reliable Data Dissemination in VANET

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Abstract: ***VANET is the Vehicular Ad hoc NETworks where the vehicle nodes communicate to others without any fixed infrastructure. Due to frequent topology changes, VANET suffers from challenges like routing and data dissemination between the vehicles. This research work develops an efficient technique called Mean shift Margin Boost Clustering Based Multivariate Dolphin Swarm Optimized Routing (MMBC-MDSOR) technique for improving the routing and reliable data dissemination in VANET. A mean-shift margin boost clustering is an ensemble clustering technique to divide the total network into a number of groups. Each group comprises the number of vehicle nodes by the ensemble method uses the iterative Gaussian kernelized mean shifted clustering technique to assign each vehicle towards the closest cluster centroid based on the different stability parameters such as vehicles density, direction, distance and velocity to form a cluster head. By using cluster head, the data communication is controlled between vehicle nodes as well as the end to end delay is reduced. Multivariate Dolphin Swarm Optimized Routing (MDSOR) is the cluster based optimization to select the optimal cluster head based on fitness function in terms of distance, signal strength and bandwidth. Then the optimal route path between source to destination is identified to disseminate the messages. The designed MDSOR in MMBC-MDSOR increases the reliability, throughput and minimizes packet drop ratio. The above technique can be applied wherever there is high congestion on the road due to the failure of optimal link discovery and data distribution between the vehicles in emergency condition. The simulation result shows that the MMBC-MDSOR Technique can enhance the reliability, throughput and also minimizes the end to end delay and packet drop ratio in VANET as compared to state-of-the-art works.***

Index Terms: ***Meanshift Margin Boost Clustering, Multivariate Dolphin Swarm Optimization, VANET***

I. INTRODUCTION

A VANET is a type of wireless network, in which vehicle acts as a node to communicate one to another. The geographic routing is the process of finding the route path for Data dissemination based on vehicle location. In Geographic routing, the source node transmits the data packets through a neighboring node. Data dissemination is difficult in VANETs because of network disconnections and the mobility.

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Therefore the clustering based data dissemination avoids this problem by grouping the geographically adjacent vehicle nodes into a cluster resulting significantly improves the scalability of the network. The communication between the links is more stable for effective communication in a dynamic environment. A new cluster-based reliable routing method known as CEG-RAODV was developed in [1] to find the most reliable path from the source to destination. But the method failed to use optimization technique for selecting the optimal cluster head to improve the reliable data dissemination and minimizes packet drop.A multi-valued Discrete Particle Swarm Optimization (DPSO) technique was developed in [2] to detect the optimal path for effective data dissemination. The designed technique increased the packet delivery ratio and average throughput but the end to end delay was not minimized. A Clustering and Probabilistic Broadcasting (CPB) was introduced in [3] for data dissemination. Though the methods increase the packet delivery ratio and minimize the average message delay, the method was not implemented in the high dynamic networks. A bio-inspired cognitive agent-based vehicle routing optimization was developed in [4] to discover the shortest path between the pair of nodes. But the reliable data dissemination was not performed. An Intelligent clustering using moth flame optimization technique was introduced in [5] for increasing the communication and reliable data delivery between the vehicles. But the optimization technique failed to use multiple objective functions for finding the optimal route path. A Vehicular Genetic Bee Clustering (VGBC) based on honey bee algorithm was designed in [6]. The designed algorithm minimizes the computational overhead but the reliable data dissemination was not performed.A new clustering algorithm based on agent technology was introduced in [7] to increase routing performance with high packet delivery and minimum delay. But the clustering algorithm failed to minimize the packet drop. A Lion optimization algorithm was designed in [8] to select the optimal route path with minimum cost. But the performance of reliable data delivery along the selected route path remained unaddressed.A hybrid opportunistic and position-based routing protocol was developed in [9] for finding the optimal neighboring nodes to transmit the data with minimum delay. But the routing stability was not achieved. An Artificial Spider Geographic Routing (ASGR) was introduced in [10] to select the efficient paths to the destination for increasing the packet delivery and minimize transmission delay.

The routing algorithm failed to provide stable communication while maintaining higher delivery ratio and less delay.

The major issues are identified from the above-said existing methods such as failure to improve the reliable data dissemination, high packets drop, lack of improving the routing stability and so on. In order to overcome such kind of issues, an efficient technique called MMBC-MDSOR is developed in VANET.

The major contribution of the proposed MMBC-MDSOR technique are summarized as follows,

- To improve reliable data dissemination and optimized routing, MMBC-MDSOR is introduced. This contribution is achieved by the ensemble clustering and optimization technique. The Meanshift Margin Boost Clustering is applied to partition the network into different groups based on the different stability parameters. The cluster head is chosen for controlling the data communication between the vehicle nodes. Then the source node sends the data to a destination through the optimal cluster head. This helps to minimize the end to end delay.
- To improve the reliability and minimize the packet drop, MDSOR is designed to select the optimal cluster head based on fitness function in terms of distance, signal strength and bandwidth. As a result, the optimal route path from source to destination is established and forwards the data packets. This process increases the throughput.

The rest of the paper is organized into five different sections. In Section 2, the related works are reviewed. Section 3 provides a brief description of MMBC-MDSOR technique in VANET. In section 4, the simulation scenarios are presented with certain parameters. The simulation results of proposed with the conventional schemes are discussed in Section 5. Section 6 concludes the research works.

II. RELATED WORKS

A Link Reliability-based Clustering Algorithm (LRCA) was designed in [11] to offer effective and reliable data transmission and also achieve higher stability. The designed algorithm failed to minimize the end-to-end delay for improving the routing strategy. A Chain-Branch-Leaf (CBL) clustering approach was presented in [12] for improving vehicle communication. But the reliable data delivery was not achieved since it failed to select the optimal route path between source to destination.An Artificial Bee Colony (ABC) algorithm was developed in [13] to select the best route with minimum cost for transmitting the data packets. But the clustering based data transmission was not performed to provide a stable connection between the vehicles in the network.A Clustering algorithm based on Ant Colony Optimization (ACO) technique was introduced in [14] to choose the near optimal node for data transmission. The designed technique failed to consider the more objective functions for optimal route path findings for data transmission.In [15] an Analytical Network Process (ANP) was employed as a multicriteria decision tool to choose the optimal next forward vehicle for data dissemination. The method minimizes the latency but the reliable data dissemination was not performed. An Effective and Efficient Adaptive Probability Data Dissemination protocol (EEAPD) was introduced in [16] for increasing the delivery ratio and minimizing the packet drop as well as delay. The protocol failed to solve a vehicle connectivity problem.

Simple and Efficient Adaptive data Dissemination (SEAD) protocol was designed in [17] to improve the packet delivery and minimize the delay. But the SEAD failed to analysis the connectivity problem between communicating vehicles.An Efficient and Reliable Broadcast Protocol based on the Quality of Forwarding (ERBPQF) technique was introduced in [18] to improve the message dissemination. The designed technique failed to optimize the overhead in dense traffic condition.An Improved Genetic Algorithm-based Route Optimization Technique (IGAROT) was developed in [19] to discover optimal routes for efficient communication between the vehicles. The performance of routing parameters remained unaddressed. A cluster-based life-time routing protocol was introduced in [20] to achieve better route stability and throughput, and minimize the end-to-end delay. But the reliable data delivery was not achieved with minimum packet drops.

The major problems in the existing routing and data dissemination techniques are overcome by introducing a novel technique called MMBC-MDSOR. The detailed process of MMBC-MDSOR technique is presented in the next section.

III. METHODOLOGY

A Meanshift Margin Boost Clustering Based Multivariate Dolphin Swarm Optimized Routing (MMBC-MDSOR) technique is developed for improving the reliable data dissemination in VANET. The major issue in VANET is to detect the optimal route path since the vehicle nodes moved dynamically with different velocity and it directs to broken the link between the nodes. Therefore, the frequent link failure does not provide reliable communication between the vehicles. This problem is overcome by MMBC-MDSOR technique using clustering the vehicle nodes based on the different stability parameters and identifying the optimal route path with multivariate functions such as distance, signal strength and bandwidth. The Multivariate optimization is used to find the optimal neighbouring node with better link quality for disseminating the data packets.

The vehicle network is arranged in a graph ‘G(v,e)’ model where v denotes a number of vehicle nodes $vn_1, vn_2..v_n$ over a square area of m * m, e denotes a links between the two vehicle nodes in the network. Initially, the vehicle nodes are divided into a number of clusters $c_1, c_2...c_n$. For each cluster, cluster head ch is selected for disseminating the data packets $dp_1, dp_2..dp_n$. The MMBC-MDSOR technique performs the routing and reliable data dissemination with the above said system model. Before the routing process, optimal neighboring nodes are selected in VANET.

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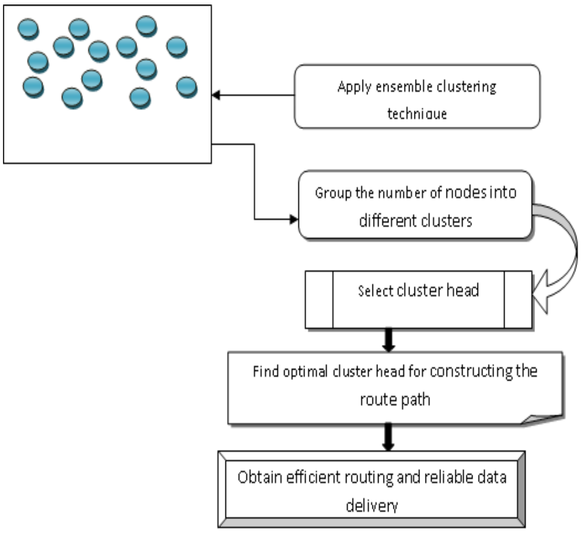

Fig. 1 Framework Diagram of the MMBC-MDSOR Technique

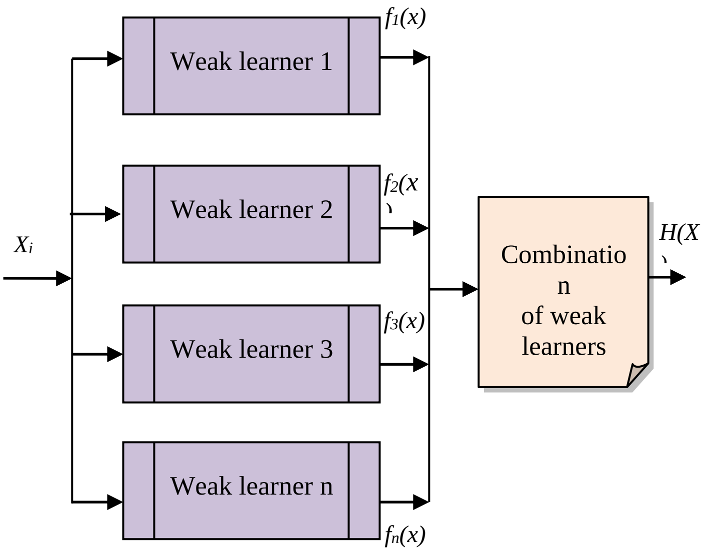

Fig. 2 Structure Of Ensembled Mean Shift Margin Boost Clustering

Fig.1 depicts the framework diagram of the proposed MMBC-MDSOR technique to obtain efficient routing and reliable data dissemination. Initially, the vehicle nodes are distributed randomly in the network. The clustering and optimization of MMBC-MDSOR is explained in the following subsections.

A. Ensembled Mean Shift Margin Boost Clustering

The first process in the proposed MMBC-MDSOR technique is to divide the total network into a number of clusters. In VANET, moving vehicles is represented as nodes to create a mobile network and exchange the data among them. Due to the dynamic changing topology, the communication links are broken between the vehicles. It may increase the routing overhead and reduces the lifetime of the network. Therefore, the total network is divided into a number of groups using a clustering scheme to perform effective data dissemination among the road vehicles in a dynamic environment. The clustering method achieves high scalability in the large number of networks and high mobility. Clustering is the process of grouping the vehicles into subsets based on some conditions, rules or characteristics to achieve scalability. The proposed MMBC-MDSOR technique uses the ensembled mean shift margin boost clustering for grouping the vehicles into different clusters. The ensembled mean shift margin boost clustering is a machine learning algorithm that converts the clustering output of weak learners into strong. A weak learner is a base cluster that slightly provides accurate clustering results. On the contrary, a strong learner is also a cluster that provides accurate clustering results. Therefore, the proposed technique uses the ensemble technique to improve clustering performance. The structure of the ensemble clustering technique is shown in figure 2.

Fig. 2 depicts a flow process of ensembled mean shift margin boost clustering to group the vehicle nodes into different clusters. The boosting algorithm considers the training sets $\{x_i, y_i\}$ where x_i represents a number of vehicle nodes $vn_1, vn_2, vn_3, \ldots .vn_n$ and $, y_i$ represents clustering results i.e.$H(X)$. The boosting algorithm constructs the 'n' weak learners for grouping the vehicle nodes. The weak learner is an iterative Gaussian kernalized mean shifted clustering technique which is a centroid-based clustering algorithm iteratively assigns each vehicle towards the closest cluster centroid. For each iteration, the nodes moves closer to the cluster center. When the algorithm stops, all the nodes are assigned to clusters. It's a simple and flexible clustering technique than the other technique. In order to attain the stable clusters, an iterative Gaussian kernalized mean shifted clustering technique considers the different stability parameters such as vehicle density, direction, distance, and velocity. Based on these parameters, the total network is divided into different clusters.

- **Vehicle density**

The vehicular communications make the vehicle density estimation for more accurate data disseminating capabilities on the existence of nearby vehicle nodes. The vehicle density is the measure of the number of vehicles per unit length of the roadway. It is mathematically computed as follows,

$$v_d = \frac{n}{L} \quad (1)$$

In (1),v_d represents the vehicle density, n denotes a number of vehicles, L represents the unit length of road occupied by the vehicles (meter). Higher the vehicle density improves the communication among the vehicles.

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- **Direction**

The second stability parameter is the moving directions of vehicles from one place to another. Let us consider the vehicles in a two-dimensional space. The current coordinate of the vehicle is (x_2, y_2) and previous coordinate of the vehicle is (x_1, y_1). Then the direction of the node is computed as follows,

$$\tan\theta = (y2 - y1 / x2 - x1) \quad (2)$$

In (2), $\tan\theta$ denotes a tangent function used to find the direction of the node. The angle (θ) is the radian from the x-axis which is used as a direction of the vehicle.

- **Distance**

The third stability parameter is the distance between the vehicle nodes. Let us consider the coordinate of the vehicle 1 is (x_1, y_1) and the coordinate of the vehicle 2 is (x_2, y_2) in the two dimensional space. Then the distance between the nodes is computed using Euclidean distance .

$$D = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad (3)$$

In (3), D represents the distance between the vehicle nodes.

- **Velocity**

The link duration between the nodes depends on the relative velocity of the vehicle nodes because it increases the link distance between nodes. The vehicles moved in the higher velocity, it goes in and out from the transmission range which causes a link breakage in the network. The node velocity is a measure of the movement of the vehicle nodes in the given period of time. The velocity is mathematically computed as follows,

$$V = \frac{D_{vn}}{t} \qquad (4)$$

In (4), V denotes a velocity of the node, D_{vn} denotes a distance travelled by the vehicle node (vn), t denotes a time. The velocity is measured in terms of a meter per seconds (m/sec).

The iterative Gaussian kernelized mean shifted clustering acts as a weak learner to partitions the entire nodes into different clusters based on above said parameters such as vehicle density, direction, distance, and velocity.

Compared to an existing clustering algorithm, the iterative Gaussian kernelized mean shifted clustering not specifying the number of clusters in advance. The number of clusters is determined based on the number of vehicle nodes. The numbers of nodes are partitioned to form a number of clusters. For each cluster, the mean is calculated as follows,

$$\mu = \frac{\sum_{i=1}^{n} \alpha_i \, vn_i}{\sum_{i=1}^{n} \alpha_i} \qquad (5)$$

In (5), μ denotes a mean of the cluster, α_i denotes a weight, vn_i represents the vehicle nodes. Therefore, the mean is calculated as the weighted average of the vehicle nodes. For each mean (i.e. centroid), the nearby nodes are grouped into the cluster based on the Gaussian kernel function.

$$k(\mu, vn_i) = \exp\left(-\frac{\|vn - \mu\|^2}{2\sigma^2}\right) \qquad (6)$$

In (6), k denotes a Gaussian kernel function, $\|vn - \mu\|^2$ denotes a squared distance between the vehicle node and cluster mean (i.e. centroid), σ denotes a deviation from its mean. For each iteration, the vehicle nodes shifts to the nearest cluster mean. This process is iterated until the vehicle nodes are not moved into the clusters.

The weak learner's results are summed into one single learner which is expressed as follows,

$$H(x) = \sum_{i=1}^{n} fi(x) \quad (7)$$

In (7), $H(x)$ represents the output of the strong cluster and $f_i(x)$ represents an output of weak learners. After combining the weak learner, the similar weight is assigned.

$$H(x) = \sum_{i=1}^{n} \vartheta * f_i(x) \quad (8)$$

In (8), ϑ_i represents the initial weight of weak learners $f_i(x)$. Then the boosting algorithm computes the training error for each weak learner results. The training error between the actual and predicted output is measured as follows,

$$\beta_e = (f_0(x) - f_i(x))^2 \quad (9)$$

In (9), β_e denotes a training error of the weak leaner, $f_o(x)$ represents the actual output of the weak leaner, $f_i(x)$ denotes a predicted output. Based on the error value, weak learner weight is adjusted. The initial weight is increased if the weak learner incorrectly grouped the vehicle nodes into the clusters. The weight is decreased if the weak learner correctly grouped the vehicle nodes into the clusters. At each iteration, the proposed Margin Boost uses gradient descent in the function space for selecting the weak learner with minimum training error.

$$F = \arg\min \beta_e (f_i(x)) \quad (10)$$

In (10), F represents the gradient descent function, $\arg\min$ stands for the argument of the minimum, β_e denotes a training error of the weak leaner $f_i(x)$. The final output of the margin boost clustering algorithm is the weighted linear combination of the outputs of the weak learners.

$$H(X) = \sum_{i=1}^{n} \vartheta'' * f_i(x) \quad (11)$$

In (11), ϑ'' represents the updated weight of the weak learner $f_i(x)$. In this way, the clusters are formed by grouping the nearest vehicle nodes based on the geographic position information. After the cluster formation, the cluster head is selected for effective data dissemination in the network by providing the co-ordination between the vehicles. Therefore the cluster head acts as a local coordinator for that particular cluster. Cluster members communicate the network through its cluster head.

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A node with the minimum average distance among cluster members is selected as the cluster head. The algorithmic description of the ensemble clustering is given below.

Input: Number of vehicle nodes $vn_1, vn_2, vn_3 \ldots, vn_n$
Output: clustering the vehicle nodes
Begin
Step 1. Construct 'n' number of weak learners
Step 2. Partition the vn_i to form a number of clusters
Step 3. For each vn_i
Step 4. Compute v_d, θ, D, V
Step 5. **For** each cluster' j'
Step 6. Compute mean μ
Step 7. Calculate the $k\ (\mu, vn_i)$
Step 8. Group vn_i into clusters j based on the distance
Step 9. Combine weak learners into strong

$$H\ (x) = \sum_{i=1}^{n} f_i\ (x)$$

Step 10. End for
Step 11. For each $f_i\ (x))$
Step 12. Initialize the weight 'ϑ'
Step 13. Calculate the training error β_e
Step 14. Update the weight ϑ''
Step 15. End for
Step 16. Find weak learner with minimum error argmin β_e (f_i(x))
Step 17. Obtain strong clustering results

$$H(X) = \sum_{i=1}^{n} \vartheta'' * f_i\ (x)$$

Step 18. Select the cluster head (ch)
Step 19. End for
Step 20. End

Algorithm 1 Ensemble mean shift margin boost clustering

Algorithm 1 describes the ensemble clustering for partitioning the total network into a number of clusters. The number of weak learners is constructed in boosting algorithm for performing clustering process. At first, the vehicle nodes are partitioned into a number of clusters. Then the vehicle nodes are grouped based on the stable parameters such as vehicle density, direction, distance and velocity parameters At first, the numbers of vehicle nodes are clustered based on different stable parameters. The ensemble algorithm groups the weak learners into strong clusters. After that, the weight is assigned to each weak learner. Then the training error is computed for each weak learner. Based on the error value, the initial weight is updated. The boosting classifier selects the weak learner with minimum training error.

For each cluster, the cluster head is chosen for coordinating all the vehicle nodes within the cluster. In this way, the vehicle nodes are grouped based on the geographical positions of neighboring nodes. This helps to minimize the end to end delay while disseminating the more data packets from source to destination.

B. Dolphin Swarm Optimization Based Routing in VANET

After the cluster formation, the source node in the cluster initiates the data packets to be sent to the destination through the cluster head. Therefore, the source node finds the optimal route path for disseminating the data packets to the destination. In the clustering based optimization, the optimal neighboring cluster head is selected for disseminating the data packets from source to destination. The optimal neighboring cluster head is selected using Multivariate Dolphin Swarm Optimization (MDSO) algorithm. The multivariate is an optimization problem considers more than one objective functions. The objective functions are distance, signal strength and bandwidth availability between the nodes. The dolphin swarm optimization algorithm is novel swarm intelligence optimization depending on the behavior of which one detects or attacks the position of its prey. A proposed MDSO algorithm works by having a population (called a swarm). Initialize the population of the Dolphins (i.e. number of cluster heads $ch_1, ch_2, ch_{3,\ldots} ch_n$) and are moved around in the search space (i.e. network). After the initialization, fitness is computed for each dolphin to identify the global optimum solution. The fitness function is an objective function that is used to find the optimal one from the population. The objective function is a distance between the two cluster heads, signal strength and bandwidth availability. The distance between the two cluster heads is computed using time of arrival (ToA). It is the time difference between the beacon message transmitted from the one cluster head and reply message return back from the cluster head. It is measured as follows,

$$d = t_a\left(B_{msg}\right) - t_t\left(B_{msg}\right) \quad (12)$$

In (12),d denotes a distance, $t_a\left(B_{msg}\right)$ represents the arrival time of beacon message from the cluster. $t_t\left(B_{msg}\right)$ denotes a transmitting time of the beacon message from the source cluster head. The cluster head 1 sends the beacon message to all the cluster head. If the ch_1 receives the reply beacon message with minimum time from other node, then the cluster head is chosen the nearest cluster head.

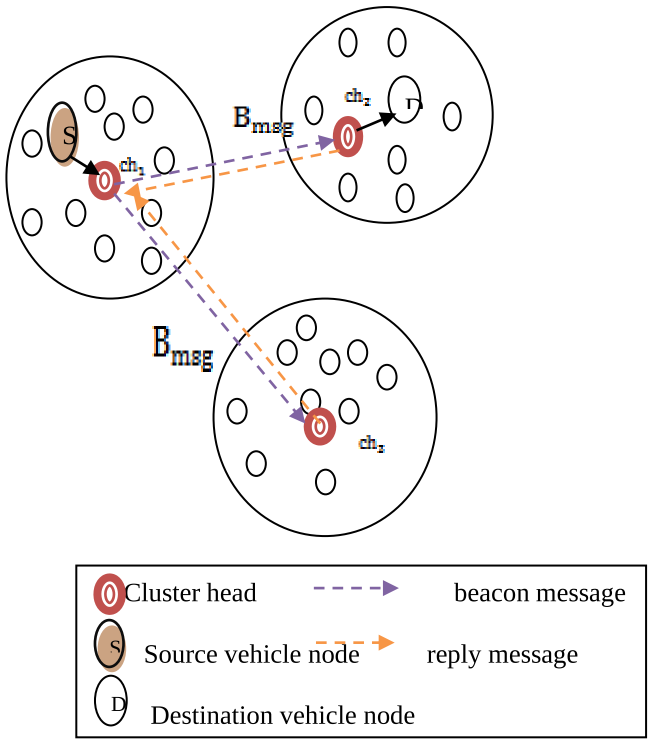

Fig. 3 beacon message distribution between the clusters

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$P_{Rx}=10 \log 10(P_{Tx}/P_{Ref})$ (13)

In (13), P_{Rx} represents the received signal power, P_{Tx} denotes a transmitted signal power, P_{Ref} denotes reference power. The signal strength is measured in decibel (dB).

- The bandwidth availability between the cluster head is computed based on the difference between the total bandwidth and consumed bandwidth.

$$Bw_{avl} = Bw_t - Bw_{cd} \quad (14)$$

In (14), Bw_{avl} denotes a bandwidth availability between the cluster head node, Bw_t represents the total bandwidth, Bw_{cd} denotes an overall consumed bandwidth. Based on the estimation, the fitness is calculated as follows,

$$F = (\min\ d\ \ \&\&\ (P_{Rx} > \delta_{th})\&\&\,(Bw_{avl} > Bw_{th})) \quad (15)$$

In (15), F denotes a fitness, d represents the distance, P_{Rx} denotes a received power, δ_{th} represents the threshold for received signal strength, Bw_{avl} denotes a bandwidth availability, Bw_{th} represents the threshold of bandwidth availability.

Due to the dynamic movement of the vehicle nodes in search space, the optimization technique performs position and velocity update for each iteration. For each time't', the position and the velocity of the dolphin is measured by constructing the square domain in the complex plane. Therefore, the position and velocity is obtained as follows,

$$x_r(t) + i\ x_i(t) \quad (16)$$

$$v_r(t) + i\ v_i(t) \quad (17)$$

In (16), (17), $x_r(t)$ denotes a position of the dolphin in real part, $x_i(t)$ denotes a position of the dolphin in imaginary part, 'i' denotes a imaginary unit. $v_r(t)$ denotes a velocity of the dolphin in the real part. $v_i(t)$ represents velocity of the dolphin in the imaginary part.The position and velocity of the dolphin is updated with the current position and velocity at time step (t+1).

$$x_r(t+1) = x_r(t) + v_r(t+1) \quad (18)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (19)$$

$$v_r(t+1) = \alpha_1.v_r(t) + b_{r1}(t).(p_r(t) - x_r(t)) + b_{r2}(t).(g_r(t) - x_r(t)) + b_{r3}(t)(g_i(t) - g_r(t)) \quad (20)$$

$$v_i(t+1) = \alpha_2.v_i(t) + b_{i1}(t).(p_i(t) - x_i(t)) + b_{i2}(t).(g_i(t) - x_i(t)) + b_{i3}(t)(g_r(t) - g_i(t)) \quad (21)$$

In (18) (19) $x_r(t+1)$, $x_i(t+1)$ represents the updated position of the dolphin in the real and imaginary part at a time 't+1', $v_r(t+1)$ $v_i(t+1)$ represents the updated velocity of the dolphin in the real and imaginary part at time't+1'. In (20), (21) ,α_1, α_2 denotes a inertia wights, $b_{r1}(t)$, $b_{i1}(t)$, $b_{r2}(t)$, $b_{i2}(t)$, b_{r3}, $b_{i3}(t)$ are the acceleration controlling functions. $b_{r3}(t)\ (g_i(t) - g_r(t))$ and $b_{i3}(t)\ (g_r(t) - g_i(t))$ are the error correction terms. The prey found by the dolphin position are $p_i(t), p_r(t)$.

Based on the updated position and velocity, the fitness is evaluated and finds the best vehicle node. Otherwise, each dolphin position is updated based on the swimming mode. Since the most of dolphins dynamically adjusts their swimming modes along with their needs. So the position updating is expressed as follows,

$$y_{dol}=1/2\ \{f(x_r(t)+f(x_i(t))\} \quad (22)$$

In (22), f denotes a optimization problem, y_{dol} denotes a newly updating position of the dolphin. Based on the updates results, the dolphins' individuals are sorted in the ascending order. For each updated position of dolphin, the fitness is computed.

Evaluation of the population according to the newly update positions and obtain the best individual. In this way, the neighboring cluster head is selected for data dissemination. Followed by, optimal route path between the source and destination nodes are constructed and the data are transmitted along the route path. This helps to minimize the packet drop and improve the data transmission. The multivariate dolphin swarm optimized routing algorithm is described as follows.

Input: cluster heads $ch_1, ch_2\, ch_3, \dots ch_n$, data packets $dp_1, dp_2, dp_3, \dots .\, dp_n$

Output: Improve reliable data delivery and minimize the delay

Begin

Step 1. Source node sends dp_i to ch_1
Step 2. Initialize the number of cluster heads $ch_1, ch_2\, ch_3, \dots ch_n$
Step 3. **For each** ch_i
Step 4. Compute distance d, signal strength P_{Rx} , bandwidth availability Bw_{avl}
Step 5. Calculate fitness F
Step 6. T=t+1
Step 7. While (t < Max iteration) **do**
Step 8. **If** (t$\leq$ ω)
Step 9. Update the position and velocity of the dolphin $x_r(t+1), x_i(t+1), v_r(t+1), v_i(t+1)$
Step 10. Evaluate the fitness according to the newly update positions
Step 11. Obtain the best solution
Step 12. Else
Step 13. For each ch_i
Step 14. Calculate y_{dol} and update the position
Step 15. End for
Step 16. Sort all dolphins in an ascending order
Step 17. End if
Step 18. Evaluate the fitness according to the newly update positions
Step 19. T = t+1
Step 20. End while
Step 21. Obtain the best solution
Step 22. Select optimal ch and construct route path
Step 23. Disseminate dp_i to optimal CH
Step 24. End for
Step 25. End

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Algorithm 2 multivariate dolphin swarm optimized routing algorithm

Algorithm 2 describes the multivariate dolphin swarm optimized routing in VANET. At first, populations (i.e. number of) of dolphins (i.e. cluster head) are initialized randomly in search space (i.e. network). Then the fitness function for each initialized cluster head is computed based on the distance, signal strength and bandwidth availability between the nodes. After that, the cluster head finds the optimal neighboring clustering nodes. Subsequently, the positions and velocity of the vehicle nodes are updated due to dynamic movement of vehicle. After changing the position, the fitness is computed based on the newly update positions for selecting the optimal cluster head to disseminate the data packets to the destination. The optimal route path between the nodes is established and improves the data delivery and minimizes the delay.

IV. SIMULATION SETTINGS

The simulation of proposed MMBC-MDSOR technique and existing methods CEG-RAOD and Multi-valued DPSO are implemented using NS2.34 network simulator. Totally 500 vehicle nodes are used for the simulation in a square area of A^2 (1100 m * 1100 m). The Random Waypoint mobility model is used in the simulation environment. The simulation time is set as 300 sec. The DSR protocol is used to perform routing and reliable data dissemination in VANET. The simulation parameters and the values are shown in Tab I.

Tab I Simulation parameters settings

Simulation Parameters	Values
Network Simulator	NS2.34
Square area	1100 m * 1100 m
Number of vehicle nodes	50,100,150,200,250,300,350,400,450,500
Number of data packets	25,50,75,100,125,150,175,200,225,250
Mobility model	Random Waypoint model
Speed of sensor nodes	0 – 20 m/s
Simulation time	300sec
Protocol	DSR
Number of runs	10

V. RESULTS AND DISCUSSION

The simulation results of MMBC-MDSOR technique and existing methods CEG-RAOD and Multi-valued DPSO are discussed in this section with different parameters such as scalability, packet drop ratio, end to end delay and transmission overhead with respect to a number of data packets. The simulation results are described with the help of table and graph. For each subsection, the sample mathematical calculation is provided to show the performance of the proposed MMBC-MDSOR technique and existing methods.

A. *Performance analysis of reliability*

Reliability is the ability of an algorithm to disseminate the data packets in a large network between the vehicle nodes. The reliability is measured in terms of the packet delivery ratio. Packet delivery ratio is measured as the ratio of a number of data packets received to the total number of packets sent from the source node.

PDR=Number of packets received / n *100 (23)

In (23), PDR represents the packet delivery ratio, n denotes a number of a packet sent. Reliability is measured in terms of percentage (%). Similarly, eight different cases are performed with various vehicle density and number of data packets. The results are reported in Tab II.

Tab II Reliability versus vehicle density

Vehicle density	Reliability (%)		
	MMBC-MDSOR	CEG-RAOD	Multi-valued DPSO
50	88	84	80
100	90	86	82
150	92	88	84
200	93	89	85
250	94	88	84
300	95	90	85
350	94	91	86
400	93	90	85
450	95	91	86
500	94	89	85

Tab II describes the simulation evaluation results of reliability based on the number of vehicle density. for the simulation purposes, a number of vehicle density is taken from 50 to 500 and the numbers of data packets are varied from 25 to 250. the reported ten different results show that the MMBC-MDSOR technique improves the packet delivery ratio than the existing techniques. the graphical results of the reliability are shown in fig 4.

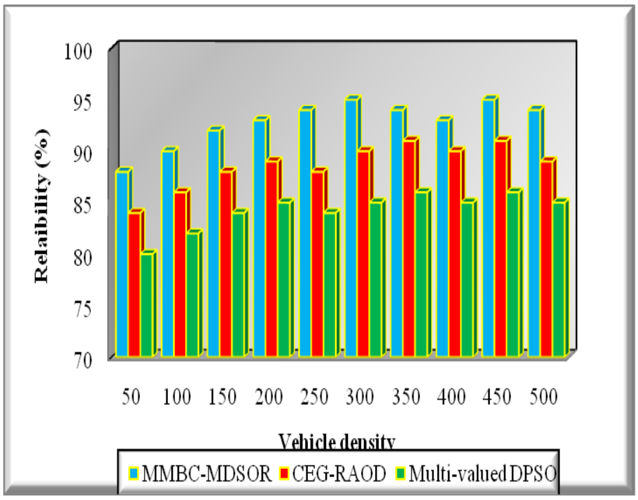

Fig. 4 performance results of reliability

Fig. 4 depicts the performance results of reliability using three different techniques namely MMBC-MDSOR, CEG-RAOD and Multi-valued DPSO versus vehicle density. The reliability of three different techniques is represented in three different colors.

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From the figure, it is clearly observed that the reliability of the data packet dissemination is considerably increased using MMBC-MDSOR technique when compared to existing techniques.This significant improvement is achieved by performing the cluster based optimized routing in VANET.

The links between the vehicle nodes are established and construct the optimal route path from source to the destination node. Then the source node sends the data packets to the destination through the optimal cluster head. This helps to improve the reliability in the data packet delivery.

The ten different results of MMBC-MDSOR technique is compared with existing CEG-RAOD and Multi-valued DPSO. The comparison results show that the MMBC-MDSOR technique increases the reliable data delivery by 5% and 10% when compared to existing CEG-RAOD and Multi-valued DPSO respectively.

B. *Performance analysis of packet drop Rate*

Packet drop ratio is defined as the ratio of a number of data packets dropped at the destination to the total number of packets sent from the source node. The mathematical formula for calculating the packet drop ratio is expressed as follows,

PDR=number of packets dropped / n * 100 (24)

In (24),PDR represents the packet drop rate, n denotes a number of packet sent. Packet drop ratio is measured in terms of percentage (%).

Tab III Packet drop ratio versus vehicle density

Vehicle density	Packet drop ratio (%)		
	MMBC-MDSOR	CEG-RAOD	Multi-valued DPSO
50	12	16	20
100	10	14	18
150	8	12	16
200	7	11	15
250	6	12	16
300	5	10	15
350	6	9	14
400	7	11	16
450	5	9	14
500	6	11	15

Tab III illustrates a packet drop ratio with respect to vehicles density. The table values show that the packet drop ratio is significantly reduced using the proposed MMBC-MDSOR technique than the existing techniques. The observed results are plotted in the two-dimensional graph.

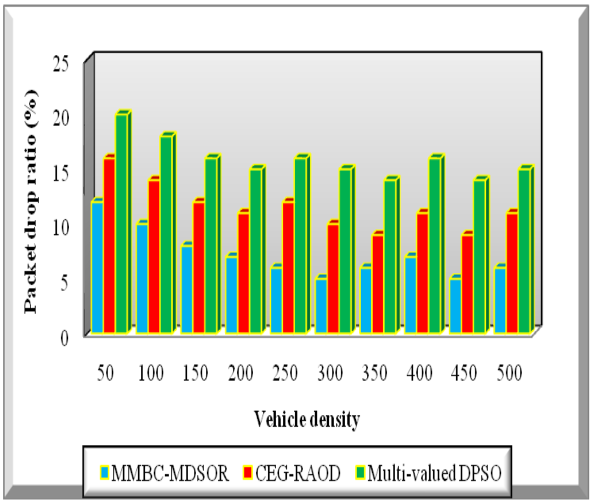

Fig. 5 performance results of packet drop ratio

In fig. 5, the performance results of the packet drop ratio of the three different techniques are illustrated with different colors. The results confirm that the MMBC-MDSOR technique increases the packet delivery and minimizes the packet drop ratio. This improvement is achieved by identifying the better link quality between the cluster head.

The link quality of the node is measured based on the received signal strength, and distance between the nodes and bandwidth availability. The node which has higher signal strength and minimum distance as well as the maximum bandwidth availability is selected as an optimal cluster head for efficient data delivery. Therefore, the neighboring cluster head with better link quality is chosen for increasing the delivery and minimizing the packet drop.

C. *Performance analysis of end to end delay*

End-to-End Delay is an amount of time taken for disseminating the data packets from source node to destination in VANET. End to end delay is mathematically estimated as the time difference between the data packet arrival time and data packet sending time from the source node. The end to end delay is mathematically calculated using the below formula,

$$EED = T\ (dp_a) - T\ (dp_s) \quad (25)$$

In (25), EED denotes an end to end delay, $T\ (dp_a)$ represents the data packet arrival time, $T\ (dp_s)$ denotes a data packet sending time. The end to end delay is measured in the unit of milliseconds (ms).

These results are obtained using the above said mathematical calculation. Similarity, ten various results of end to end delay is reported in tab IV.

Tab IV end to end delay versus vehicle density

Vehicle density	End to End delay (ms)		
	MMBC-MDSOR	CEG-RAOD	Multi-valued DPSO
50	12	14	17

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100	14	16	19
150	15	18	21
200	18	22	25
250	21	23	27
300	22	25	29
350	24	27	30
400	26	30	33
450	27	32	36
500	31	34	38

Tab IV shows the simulation results of end to end delay using three methods MMBC-MDSOR technique, CEG-RAOD and Multi-valued DPSO with respect to vehicle density. The end to end delay is measured based on the data packet arrival time and transmission time. The ten simulation results show that the end to end delay is considerably minimized when compared to existing techniques.

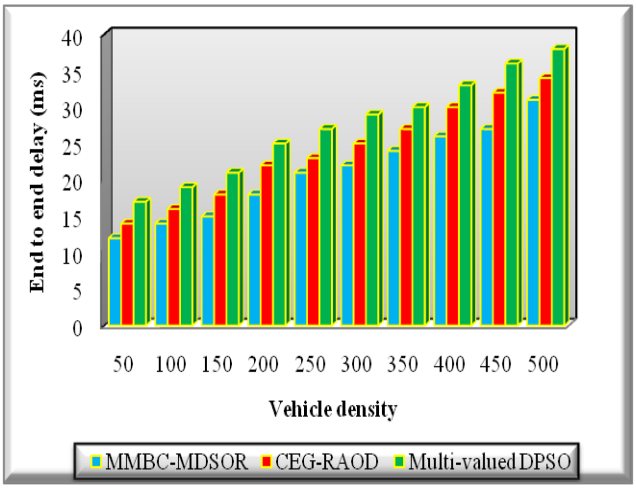

Fig. 6 Performance Results of End to End delay

Fig. 6 shows the simulation results of end to end delay with respect to a number of vehicle nodes. The above graphical results show that the ends to end delay is significantly reduced using MMBC-MDSOR technique than the existing techniques. This improvement is achieved by partitioning the total network into a number of clusters. The clustering based data dissemination minimizes the end to end delay.

While considering the number of hops between the source and destination, the transmission delay gets increased. Instead of sending the data packets to multiple hops, the source node only sends to their optimal cluster head based on the geographic position. Then the cluster head finds the optimal route to the destination using a multivariate optimization technique. The source node sends their cluster head and finds the nearest cluster head to forward the data packets. Then the cluster head sends data packets to their destination node. Therefore, the clustering based optimized routing technique effectively improves the reliable data transmission with minimum end to end delay.

D. *Performance analysis of throughput*

Throughput is defined as an amount of data delivered from one place to another in a given period of time. The throughput is mathematically calculated as follows,

Throughput=dp received at the destination / time (26)

Tab V throughput versus data packet size

Data packet size (KB)	Throughput (bps)		
	MMBC-MDSOR	CEG-RAOD	Multi-valued DPSO
10	130	100	95
20	245	200	179
30	362	315	280
40	485	420	392
50	542	500	452
60	662	623	582
70	742	710	653
80	855	821	783
90	932	910	872
100	1115	1052	986

In (26), dp represents the data packets, throughput is measured in terms of bits per second (bps).

Tab V shows the simulation results of throughput based on the size of the data packet being sent from the source node to the destination. While varying the data packets size, various throughput results are obtained. The above-reported results show that the MMBC-MDSOR technique increases the throughput than the state-of-the-art methods.

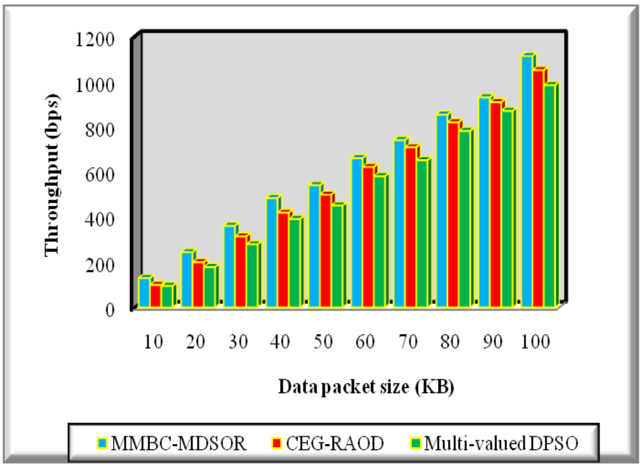

Fig. 7 performance results of throughput

Fig. 7 depicts the simulation results of throughput of various data packet size which is varied from 10KB to 100KB. As shown in the above graphical results, the MMBC-MDSOR technique increases the network throughput while transmitting the data packet from source to destination. This is because of the MMBC-MDSOR technique selects the optimal route between the source node and destination. The source node sends a data packet to the cluster head. This helps to improve the link quality between the nodes and increase the data packet transmission. Higher the network throughput achieves less transmission overhead in the VANET.

The reported results show that the throughput of the MMBC-MDSOR technique is improved by 11% and 20% when compared to existing CEG-RAOD and Multi-valued DPSO respectively.

The simulation results and discussions clearly show that the MMBC-MDSOR technique obtains reliable data dissemination and optimized routing by achieving the higher delivery ratio, throughput and minimum delay as well as packet drop.

VI. CONCLUSION

An efficient MMBC-MDSOR technique is developed with the objective of achieving reliable data dissemination with minimum delay and packet drop in any VANET environment. The above said aim is attained with the contribution of ensemble mean-shift margin boost clustering and multivariate optimization technique. At first, the distributed vehicle nodes are grouped into the different clusters using ensemble algorithm. The cluster head is selected and coordinates all the members within the groups. With this selected cluster head, the data dissemination is carried out to minimize the end to end delay between source and destination node. After that, the multivariate optimization technique is used which is capable of finding the optimal cluster head and route path with better link quality. This process increases the data delivery and network throughput and minimizes the packet drop. Simulation is performed with different performance metrics such as reliability, packet drop rate, end to end delay and throughput. The observed results confirm that MMBC-MDSOR technique is very effective in terms of improving the reliability in packet delivery, throughput and reducing the packet drop as well as end to end delay than the CEG-RAOD and Multi-valued DPSO.

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