Research Article

Deep Learned Ruzicka Similaritive Spectral Clustered Oppositional Dragonfly Optimized Routing In VANET

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Abstract: VANET is an Ad–hoc network where all the vehicles move dynamically within the network coverage area and communicate to other vehicles in a single hop or multi-hop through the road-side unit (RSU). Due to the Ad–hoc nature of vehicles, continuously changing their locations and achieving seamless connectivity between the vehicles and communication efficiency in VANETs are the major challenging problems. A new technique called Deep Learned Ruzicka Spectral Clustering-based Oppositional Dragonfly Optimized Routing (DLRSC-ODOR) is introduced for improving the reliability of data dissemination and minimizing the end to end delay in VANET. The DLRSC-ODOR technique uses the deep learning concept comprises an input layer, two hidden layers, and an output layer. The number of vehicle nodes as given to the input layer. Then the inputs are transformed into the first hidden layer. The Ruzicka similarity-based spectral clustering is applied to group the vehicle nodes based on the different mobility parameters such as the density of vehicles, moving direction, distance, and velocity. Followed by, the cluster head is chosen for efficient data dissemination to minimize the delay. Then the clustering results are transformed into the second hidden layer where the optimal cluster head is chosen for disseminating the data packets from source to destination. The Multiattribute oppositional dragonfly optimization technique is applied for finding the global optimum cluster head. Finally, the optimal route path from the source to the destination is established at the output layer. Then the data dissemination is performed to achieve reliability. Simulation is carried out with different metrics such as reliability, packet drop rate, end to end delay and throughput. The observed results show that the DLRSC-ODOR technique efficiently improves the reliability, throughput and minimizes the end to end delay as well as packet drop rate than the state-of-the-art methods.

Keywords: VANET, deep learning, Ruzicka similarity, spectral clustering, Multiattribute oppositional dragonfly optimization technique

1. Introduction

VANET is the basis for intelligent transportation systems which helps to perform the seamlessconnections between vehicles on the road. The vehicles are equipped with wireless interfaces and provide varies services such as traffic monitoring, vehicle navigation and so on. Therefore, the stable link and communication is the most challenging task due to the mobility of vehicles in VANETs. The clustering technology is a promising solution to enhance the routing reliability and scalability by arranging similar vehicles into several virtual groups, called clusters. Each cluster includes a center vehicle, called a cluster head, which is responsible for communication within the cluster or between the clusters. Therefore, the proposed method uses cluster-based routing for improving data dissemination in VANET. The existing BEXCMWO technique designed to perform cluster-based optimized routing but the link estimation was not considered in the optimization for minimizing the packet drop.

A Cluster-Based routing Model called CEG-RAODV was introduced in [1] to identify the optimal route path for disseminating the data packets. The designed model improves the reliability but it failed to minimize the packet drop rate. A Multi-valued Discrete Particle Swarm Optimization (DPSO) technique was developed in [2] to discover the optimal path for improving the data dissemination. The Multi-valued DPSO failed to minimize the performance of delay. In [3], a Mean shift Margin Boost Clustering Based Multivariate Dolphin Swarm Optimized Routing (MMBC-MDSOR) technique was developed to enhance the routing performance and data dissemination with higher reliability. But it failed to consider the node energy for optimal route path discovery.

A passive data dissemination approach with dynamic clustering was developed in [4]. The designed approach minimizes the overhead and reliability of data dissemination was not improved. A new clustering algorithm based on agent technology was designed in [5] to enhance the routing with higher packet delivery ratio and minimum delay. But the performance of the packet drop rate remained unaddressed.

A hybrid relay nodes selection approach was introduced in [6] for disseminating the message with minimum delay. The designed approach failed to use the optimization technique for relay node selection to further minimizing the delay.

The clustering algorithm based Data Dissemination Protocol was presented in [7] based on path information. Though the algorithm improves the dissemination rate, the performance of delay was not minimized. A recommended intelligent clustering based on the moth flame optimization approach was introduced in [8] for reliable data delivery. The approach failed to consider multi-objective functions. An analytical network process (ANP) was developed in [9] based on a multicriteria decision tool to choose the optimal vehicle for forwarding the data packets. But the reliable data transmission remained unsolved.

A cluster-based life-time routing (CBLTR) protocol was designed in [10] for improving the throughput. However, the protocol failed to select the optimal cluster head. A link reliability-based clustering algorithm (LRCA) was designed in [11] for improving reliability while transmitting the data. The algorithm improves the packet delivery but does not reduce the end-to-end delay.

A genetic algorithm-based route optimization technique (IGAROT) was designed in [12] for routing the data packets. The designed technique failed to effectively find the global optimum solution. A multi-hop clustering algorithm was developed in [13] to select the optimal neighboring nodes for enhancing stability and reliability. The designed algorithm failed to consider the various mobility parameters for clustering the vehicles. A grey wolf optimization based clustering algorithm was developed in [14] for reliable data delivery of information. The algorithm was not considering the multi-objective functions for solving the optimization problem. A micro artificial bee colony (MABC) algorithm was introduced in [15] for effective reliable communication. The clustering of vehicle nodes was not performed to further improve the data transmission. An Ant Colony Optimization (ACO) based algorithm was designed in [16] for improving the end to end packet delivery. But the end to end delay was not minimized. A bio-inspired cognitive agent approach was developed in [17] for autonomous urban vehicle routing optimization. However, the approach failed to perform the cluster-based routing for minimizing the delay.

A clustering algorithm based on ant colony optimization was introduced in [18] using different mobility characteristics such as transmission range, direction, and speed of the nodes. The reliability of data transmission was not improved. A new selective cross-layer design based ant colony optimization was developed in [19] for data transmission. Though the approach minimizes the delay, the packet drop rate was not minimized.

A data dissemination protocol based on complex networks' was introduced in [20] for transmitting the packets with minimum delay. But the optimization technique was not used for achieving reliable data delivery. A new cluster-based data dissemination approach was introduced in [21] for reducing the delay and enhancing the packet delivery ratio. Reliable data distribution was not achieved.

1.1 Proposal Contribution

The major issues reviewed by the above-said literature are overcome by introducing a novel technique called DLRSC-ODOR technique. The major contribution of the proposed DLRSC-ODOR technique is summarized as follows,

- The novel DLRSC-ODOR technique is introduced for improving the reliability in the data dissemination through the clustering and multiattribute optimization technique. The deep learning concept improves the clustering accuracy and optimization process. On the contrary to an existing clustering algorithm, the DLRSC-ODOR technique uses the Ruzicka similarity-based spectral clustering for partitioning the vehicle node into different clusters. Then the multiattribute oppositional optimization finds the global best cluster head for disseminating packets.
- To minimize the packet drop rate, the proposed DLRSC-ODOR technique selects an optimal cluster head with better link stability and bandwidth availability. This helps to improve the data transmission resulting increases the network throughput.
- To minimize the delay, the DLRSC-ODOR technique performs cluster-based optimized routing. The source node transmits the data packets to the destination through the nearest optimal cluster head.

1.2.Organization Of The Paper

The structure of the article is organized as follows. Section 2 briefly describes the proposed methodology DLRSC-ODOR for reliable data dissemination in VANET. Section 3 provides information on the simulation settings with the number of vehicle nodes. In section 4, the simulation outcomes and comparative analysis are presented using various performance metrics. Finally, section 5 concludes the paper

2. Methodology

. The existing BEXCMWO technique was introduced for routing and data dissemination in VANET. The BEXCMWO technique used bagging ensemble X-Means Clustering technique for partitioning the vehicle nodes into the different clusters based on the majority voting scheme for minimizing the overfitting. The BEXCMWO technique also used a whale optimization algorithm for solving the multi-objective (i.e. multicriteria) optimization problem in the cluster head selection based on distance, residual energy, and bandwidth availability. On the contrary to existing technique, a new technique called Deep Learned Ruzicka Spectral Clustering-based Oppositional Dragonfly Optimized Routing (DLRSC-ODOR) is introduced for enhancing the reliability of data dissemination and minimizing the end to end delay in VANET. The architecture diagram of the DLRSC-ODOR technique is presented in Figure 1.

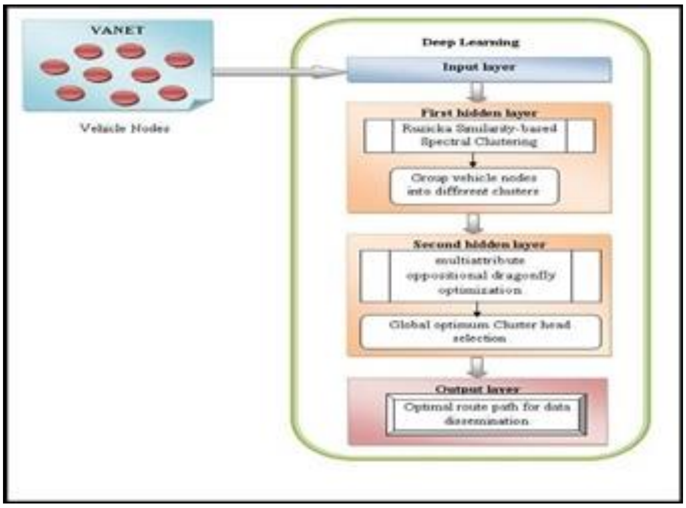

Figure 1 Architecture Diagram of DLRSC-ODOR technique

As shown in the above figure, DLRSC-ODOR technique uses the deep learning concept for providing accurate results. Besides, the DLRSC-ODOR technique uses the Ruzicka similarity-based spectral clustering is applied in the first hidden layer to group the nodes. In the second hidden layer, the multiattribute oppositional dragonfly optimization technique is applied for selecting the optimal cluster head using multi-objective (i.e. multiattribute) functions such as distance, residual energy, and bandwidth availability, signal strength and link stability. The detailed process of the DLRSC-ODOR technique is described in the below subsections.

2.1 Network Model

The VANET is organized in a graphical model $G = (V,E)$ where the number of vehicles is represented by 'V'deployed in a squared area of '$n * n$' in a graph G, 'E' denotes a communication between the vehicles. The vehicle nodes are clustered into 'j' number of groups $C_1, C_2, C_3, \ldots C_j$. The center of the cluster is called as cluster head (N_H) which is responsible for disseminating the data packets from source vehicle (S_v) to destination vehicle (D_v). The proposed DLRSC-ODOR technique uses the network model for routing as well as data dissemination in VANET.

2.2 Deep Learned Ruzicka Spectral Clustering-Based Oppositional Dragonfly Optimized Routing

The DLRSC-ODOR technique uses the deep learning concept for routing as well as data dissemination in VANET. Deep learning is a type of machine learning algorithm which utilizes the several layers to provide accurate results from the raw input. The advantage of deep learning than the other algorithm is to effectively processa large number of inputs with lesser complexity problems. The statement "deep" in "deep learning" represents the number of layers used in the network through which the input is transformed. The deep learning includes one input layer which receives the raw input and more than one hidden layer for processing the input and one output layer where the results are displayed for the given input. The structural design of deep learning is a layer-by-layer method and each layer learns the input from the previous layer and transforms it's as input to the next layer.

Deep learning includes the neuron-like nodes which are connected directly into the next successive layers. The node in the one layer is fully connected to others. The numbers of vehicle nodes are given as input layer at a time 't' is denoted as '$x_i(t)$'. Then the received inputs are transformed into the hidden layers. The adjustable weights between the input and hidden layer represents ω_1, ω_2 as shown in figure 1. The output of the hidden layer is denoted as '$H(t)$'. The hidden layers outputs are transformed into the output layer. The hidden layers and output layers are interconnected through dynamic weights ω_1 and ω_2. The output of input layer of the deep learning is expressed with the input and weight value,

$$X(t) = \sum_{i=1}^{n} \omega_1 * x_i(t) \quad (1)$$

Where, $X(t)$ output of input layer input, ω_1 denotes an adjustable weight between input and hidden layer, $x_i(t)$ represents the input i.e. 'n' number of vehicle nodes. For each input, the different weights are assigned. The weight is a random number which is used for identifying the strength of the connection between the nodes.

2.2.1 Ruzicka Similarity-Based Spectral Clustering For Routing In Vanet

In the first hidden layer, a ruzickasimilarity-based spectral clustering technique is applied for grouping the vehicle nodes based on the mobility characteristics such as distance, velocity, vehicle density, moving direction. The vehicle density is measured as the ratio of a number of vehicles deployed per unit length. It is calculated as follows,

$$den_v = \frac{x_i(t)}{l} \quad (2)$$

Where, $x_i(t)$ represents the vehicle density, the 'l' denotes a unit length of the road in meter (m). Higher the density of vehicle nodes deployed in the road resulting in it improves the data dissemination. The next parameter is the direction of the moving vehicle in VANET. The direction of the vehicle node is mathematically calculated as given below,

$$\theta = \tan^{-1}\left(\frac{s_2 - s_1}{t_2 - t_1}\right) \quad (3)$$

Whereθ denotes an angle uses the tangent function to find the moving direction of the node. The angle θ is the radian from the x-axis which is used as a direction of the vehicle. The coordinate of vehicle nodes in the two dimensional are (s_1,t_1) (s_2,t_2). Subsequently, the distance between the vehicle nodes is measured using a given mathematical formula,

$$d = \left((s_2 - s_1)^2 + (t_2 - t_1)^2\right)^{1/2} \quad (4)$$

Where, d denotes the distance between two vehicle nodes and their coordinates are (s_1,t_1) and (s_2,t_2) which helps to identify the location nodes in the network. Finally, the velocity is measured as a movement of the vehicle nodes in a specific time period. The velocity is calculated as,

$$\vartheta = \frac{Td_N}{time} \quad (5)$$

Where, ϑ denotes a velocity of the node, Td_N represents a distance travelled by the vehicle node in a specific time period '$time$'. The velocity is measured in the unit of a meter per seconds (m/s). The proposed DLRSC-ODOR technique groups the vehicles into different clusters based on the mobility parameters as distance, velocity, vehicle density, moving direction through the similarity measure. The Ruzicka similarity coefficient is used to measure the similarity between the vehicle nodes. The mathematical formula for calculating the similarity between the nodes is shown below,

$$\alpha = \frac{N_1 \cap N_2}{\sum N_1 + \sum N_2 - N_1 \cap N_2} \quad (6)$$

Where, α represents a Ruzicka similarity coefficient, N_1, N_2 are the two vehicle nodes, $\sum N_1$ denotes sum of N_1 score, $\sum N_2$ denotes sum of N_2 score, $\cap$ denotes a mutual dependence between the two vehicle nodes. The Ruzicka similarity coefficient (α) provides the value between 0 and 1. Likewise, similarities of all the vehicle nodes are computed based on the vehicle density, moving direction, distance and velocity of the nodes using the statistic similarity coefficient. Based on the similarity value, the weight matrix is constructed as follows,

$$\beta_{ij} = \alpha \quad (7)$$

Where, β_{ij} represents a weight matrix, α denotes a similarity between the two vehicle nodes. With the weight matrix, the unnormalized Laplacian matrix is constructed as follows,

$$lp_{ij} = \vartheta_{ij} - \beta_{ij} \quad (8)$$

Where, lp_{ij} represents a Laplacian matrix, ϑ_{ij} is the diagonal matrix, β_{ij} denotes a weight matrix. Then the diagonal matrix is constructed with the degrees $v_1, v_2, v_3, \ldots v_n$ on the diagonal as given below,

$$\vartheta_{ij} = \begin{bmatrix} v_1 & & & & \\ & v_2 & & & \\ & & v_3 & & \\ & & & \ddots & \\ & & & & v_n \end{bmatrix} \quad (9)$$

From (9), ϑ_{ij} represent a diagonal matrix with a size of 5x5. Then the normalized Laplacian matrix is constructed with the diagonal matrix as given below,

$$\mathrm{lp_{ij}}\,(n) = \frac{1}{\sqrt{\vartheta_{ij}}}\,\alpha\,\vartheta_{ij}^{\;-1/2} \quad (10)$$

Where, $\mathrm{lp_{ij}}\,(n)$ denotes a normalized Laplacian matrix, ϑ_{ij} is a diagonal matrix, α represents a similarity coefficient. The normalized Laplacian matrix is constructed with the Eigen vectors 'e' and Eigen values 'w'. Let '$\mathrm{R_{ij}}$' is the matrix whose columns are the eigenvectors equivalent to the 'k' smallest Eigen values. Therefore, the new matrix is constructed as follows,

$$Z_{ij} = \frac{\mathrm{R_{ij}}}{\sum \mathrm{R_{ij}}} \quad (11)$$

Where Z_{ij} denotes a new matrix, the rows of the matrix '$\mathrm{R_{ij}}$' as a collection of 'n' vehicle nodes and it grouped into different 'k' number of clusters by using a k-means algorithm. K-means is the centroid based algorithm. The 'k' number of clusters and the cluster centroid is initialized. Then the clustering process is done by satisfying the objective function (i.e. distance). The distance between the vehicle nodes and the cluster centroid is measured as follows,

$$d_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{n} \left\| N_i - C_j \right\|^2 \quad (12)$$

Where, d_{ij} denotes a squared distance between the vehicle node N_i, and cluster centroid C_j. Then the algorithm finds the minimum distance between the cluster centroid and the vehicle node using gradient descent function.

$$F\ (x) = \arg\min d_{ij} \quad (13)$$

$$F\ (x) = \arg\min \sum_{i=1}^{n}\sum_{j=1}^{n} \left\| N_i - C_j \right\|^2 \quad (14)$$

Where, $F\ (x)$ is the gradient descent function, $arg\ min$ abbreviated as argument of the minimum to find the minimum distance between the vehicle node and cluster centroid. Then the vehicle node which is closer to the centroid is grouped to cluster 'j' if and only if a row of the matrix is assigned to cluster j. In this way, all the vehicle nodes are grouped into the particular cluster. After that, the cluster head is selected for each cluster for coordinating the cluster member i.e. vehicle nodes. Then the cluster head is chosen for routing the data packets. The cluster based data transmission minimizes the delay of data dissemination in VANET.

2.2.2 Multiattribute Oppositional Dragonfly Optimization Based Routing In Vanet

After clustering, the optimization is performed at the second hidden layer to find the cluster head for routing the data packets from source to destination vehicle in VANET. The multiattribute oppositional dragonfly optimization is the metaheuristic technique used to find an accurately good solution to an optimization problem in search space. In the optimization technique, multiattribute represents the proposed algorithm solves the multiple objective problems such as distance, signal strength, residual energy, bandwidth availability, link stability. On the contrary to existing dragonfly optimization, the proposed DLRSC-ODOR technique uses oppositional based learning to obtain the global optimum by avoiding the local optimum for the next generation. Therefore, the proposed optimization algorithm improves the convergence speed, flexibility, error tolerance, and higher accuracy. The behavior of the dragonfly is a movement and seeking its food source. Here the dragonfly is related to the number of cluster heads 'N_H' and the food source is related to multiattribute i.e. distance, signal strength, residual energy, bandwidth availability, link stability.

The proposed algorithm worked based on the population (called a swarm). The optimization starts to initialize the population of the dragonfly (i.e. N_H) and are moved around in the search space (i.e. network).

$$P = \{N_{H1}, N_{H2}, N_{H3}, \ldots N_{Hn}\} \quad (15)$$

Where P denotes a current population of the dragonflies. By applying the opposition based learning, the proposed optimization technique generates the opposite dragonfly population in order to obtain a global best solution than a random. Therefore, the opposition based population generation is mathematically expressed as follows,

$$P' = u_i + v_i - P \quad (16)$$

Where, P' represents an opposite solution of the current population, u_i and v_i denotes a minimum and maximum value of the dimensions in the current population 'P'. In this way, the current population and the opposite population are generated in the search space. After the initialization of dragonfly, the fitness is computed for each dragonfly in the current as well as the opposite swarm population. The fitness is calculated based on multiattribute functions such as distance, signal strength, residual energy, bandwidth availability and link stability. Initially, the Euclidian distance is computed using following mathematical equations,

$$d = \left(\left(p_2 - p_1\right)^2 + \left(q_2 - q_1\right)^2 \right)^{-1/2} \quad (17)$$

Where d denotes a distance between the two cluster head and the coordinates are $(p_1,q_1)(p_2,q_2)$. The signal strength of the cluster head is mathematically calculated as follows,

$$s_r = 10\log\left(\frac{t_x}{s_r}\right) \quad (18)$$

Where, s_r denotes a received signal power, t_x is the transmitted signal power, s_r is the reference power. The received signal power of a vehicle node is measured in the unit of decibel (dB). The residual energy of the cluster head is measured as a difference between the total energy and consumed energy of the cluster head.

$$r_e = t_e - c_e \quad (19)$$

Where, r_e denotes a residual energy of cluster head, t_e is the total energy of the cluster head, c_e is the consumed energy. Bandwidth availability is measured as a difference between the total bandwidth and the amount of bandwidth consumed by the cluster head.

$$bw_a = t_{bw} - c_{bw} \quad (20)$$

Where, bw_a denotes an availability of bandwidth, t_{bw} represents the total bandwidth, c_{bw} denotes an overall consumed bandwidth. Link stability between the cluster head is identified for providing the longer connectivity resulting it minimizes the packet drop.

$$L_s = \frac{T_r}{d} \quad (21)$$

Where, L_s represents a link stability, T_r denotes a transmission range of cluster head, d is the distance between the two node. Based on the above-said estimation, the fitness is calculated as follows in equation (22)

$$f = \{\min d \,\&\&(s_r > s_{th})\,\&\&(r_e > th_e)\,\&\&(bw_a > bw_{th})\,\&\&\, better L_S\} \quad (22)$$

Where, f denotes a fitness function, $\min d$ denotes a minimum distance , s_r represents the signal strength , s_{th} is the threshold for signal strength, r_e is the residual energy , th_e is the threshold for residual energy, bw_a is the bandwidth availability, bw_{th} is the threshold for bandwidth availability, $better\ L_s$ is the better link stability. After that, the current population and opposite populations are combined into one and sorting all dragonflies along with their fitness value. Finally, 'n' best dragon flies are selected from the combination for further processing. In order to simulate the swarming behavior of dragonflies in the search space, four processes are used namely separation, alignment, cohesion and attraction towards the food source. These four process of optimization technique helps to find the global optimal solution among the population based on their fitness function. At first, the separation process is used to discover the current position of dragonfly and their neighboring dragonflies.

$$A = -\sum_{j=1}^{n}\left(l(t) - l_j(t)\right) \quad (23)$$

Where, A denotes a separation of the dragonflies, $l(t)$ denotes a current position of a dragonfly, $l_j(t)$ represents a position of the neighboring dragonflies, 'n' is a number of neighboring dragonflies in search space. Then, the alignment process indicates the movement velocity matching of dragonflies to that of the neighborhood.

$$B = \frac{1}{n}\sum_{j=1}^{n}\delta_j(t) \quad (24)$$

Where, B denotes an alignment, $\delta_j(t)$ represents a velocity of 'neighboring dragonflies, 'n' denotes a number of neighboring dragonflies. Thirdly, the cohesion is the tendency of dragonflies towards the middle of the mass of their neighborhood.

$$M = \frac{1}{n}\sum_{j=1}^{n} l_j (t) - l (t) \quad (25)$$

Where, M represents a cohesion of the dragonfly, $l_j (t)$ is the position of the 'neighboring dragonfly, $l (t)$ is a position of a current dragonfly, n is the number of neighborhoods. At last, the attraction towards food source is measured based on the current position of the dragonfly and the position of the food source.

$$K = l_f(t) - l(t) \quad (26)$$

Where, K denotes an attraction towards a food source, $l_f(t)$ is the position of the food source, $l(t)$ current position of a dragonfly. Based on the fitness of the current dragonfly with their neighborhoods, the position gets updated as follows,

$$l(t+1) = l(t) + \nabla\, l(t+1) \quad (27)$$

Where, $l(t+1)$ represents the updated position of the dragonfly, $l(t)$ is the current position of a dragonfly, $\nabla\, l(t+1)$ is the step vector which denotes the movement direction of the dragonfly and it is defined as follows,

$$\nabla\, l(t+1) = \{h_1A + h_2B + h_3M + fK\} + \tau * l(t) \quad (28)$$

Where, h_1 denotes a weight of separation (A), h_2 is the weight of alignment B, h_3 is the weight of cohesion M, f represents a food vector, K is the attraction towards a food source, τ denotes an inertia weight which controls the convergence behavior of dragonfly optimization, $l(t)$ denotes a position of the dragonfly at time 't'. Based on the updated position of the dragonfly, the global best cluster heads are identified between the source and destination vehicles. Then the route path from source to destination is created and then the reliable data dissemination is performed in VANET. The algorithmic process of proposed DLRSC-ODOR technique is described as follows,

Input:Vehicle nodes $N_1, N_2, N_3, \ldots N_n$, Data packets $\mathrm{dp}_1, \mathrm{dp}_2, \mathrm{dp}_3, \ldots . \mathrm{dp}_\mathrm{n}$

Output: improve the data dissemination

Begin

\\Input **layer**

1. Number of $N_1, N_2, N_3, \ldots N_n$ receives at input the layer at time ‘t’
2. Output of input layer $X(t)$
\\ Hidden **layer 1**
3. for each node N_i
4. Measure
5. Measure the similarity between the two-vehicle nodes α
6. Construct unnormalized Laplacian matrix $\mathrm{lp}_{\mathrm{ij}}$ with diagonal matrix ϑ_{ij} and weight matrix β_{ij}
7. Construct normalized Laplacian matrix $\mathrm{lp}_{\mathrm{ij}}\,(\mathrm{n})$
8. Construct a newmatrix with eigenvectors and Eigenvalues
9. Initialize the clusters $\mathrm{C}_1, \mathrm{C}_1, \mathrm{C}_3, \ldots \mathrm{C}_\mathrm{n}$ and centroid

$$F(x) = \arg\min \sum_{i=1}^{n} \sum_{j=1}^{m} \arg\min \left\| N_i - C_j \right\|^2$$

10. Group the node to cluster
11. end for
12. for each cluster $\mathbf{C_j}$
13. select one cluster head $\mathrm{N_H}$
14. end for
\\ Hidden **layer 2**
15. Initialize the population of dragonfly i.e cluster head $\mathrm{N_{H1}}, \mathrm{N_{H2}}, \mathrm{N_{H3}}, \ldots \mathrm{N_{Hn}}$
16. Initialize the opposite population of dragonfly P'
17. for each $\mathrm{N_{Hi}}$, in P and P'
18. Compute fitness f
19. Combine the populations P and P'
20. Sorting the dragonfly based on fitness
21. Select the current best ‘n’ dragonfly
22. Calculate A, B, M, K
23. If ($f > f_j$) **then**
24. Update the position of dragonfly
25.End if
26. If (maximum_ iteration is reached) then
27. Obtain global best cluster head
28. else
29. Go to step 18
30.End if
31. End for
\\ **Output layer**
32. Construct route path from $\mathrm{S_v}$ and $\mathrm{D_v}$ for disseminating the dp_i
end

Algorithm 1 Deep Learned Ruzicka Spectral Clustering-based Oppositional Dragonfly Optimized Routing

Algorithm 1 describes the step by step process of Deep Learned Ruzicka Spectral Clustering-based Oppositional Dragonfly Optimized Routing technique. Initially, the vehicle nodes are given as input to the input layer. Then the input is transformed into the hidden layer 1. In the first hidden layer, the vehicle nodes are grouped into different clusters based on the different mobility characteristics such as density, moving direction, distance, and velocity. The cluster-based routing minimizes the end to end delay. The cluster head selection is done in the second hidden layer. Then the clustering results are transformed into the second hidden layer. At the second hidden layer, the source vehicle finds the optimal cluster head for disseminating the data packets to the destination. The proposed optimization technique initializes the populations of the current and opposite populations of a dragonfly. The fitness of each dragonfly is calculated with a multiattribute function. Then the two populations get combined and sorting the dragonfly according to their fitness value. Finally, ‘n’ best dragonfly is selected for further processing. Then the four various principles of the swarm behaviors of the dragonfly are calculated for finding the global best through the position updates. Then the optimal cluster head is selected at hidden layer 2. Finally, the path from the source to the destination is constructed through the optimal cluster head and disseminating the data packets. As a result, the reliability of the data dissemination gets improved and minimizes the packet drop.

3. Simulation Setup And Parameter Settings

The simulations of the proposed DLRSC-ODOR technique and existing CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3], BEXCMWO are implemented using NS2.34 network simulator. Totally, 500 vehicle nodes are deployed in a square area of 1100 m * 1100 m to conduct the simulation. The DSR protocol is used to perform routing as well as data dissemination in VANET. The Random Waypoint model is used as a mobility model. The various simulation parameters are listed as shown in table 1.

Table 1 Simulation Parameters and values

Simulation Parameters	**Values**
Network Simulator	NS2.34
Simulation 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

4. Comparative Performance Analysis

The simulation results of the proposed DLRSC-ODOR technique and existing methods are CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3], BEXCMWO are discussed in this section with different parameters such as reliability, packet drop rate, end to end delay and throughput based on a number of vehicle nodes. The results are discussed with the help of graphical representation. For each subsection, the sample mathematical calculation is provided to show the performance of the proposed ESRBC-TOD technique and existing CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3], BEXCMWO.

4.1 Result Analysis Of Reliability

Reliability measured as a packet delivery ratio which is the ratio of a number of data packets received to the total number of data packets sent. Based on the definition, the reliability is mathematically calculated as follows,

$$R_{dp} = \left(\frac{No.of\ dp_R}{total\ dp\ sent}\right) * 100 \tag{29}$$

Where, $No.of\ dp_R$ denotes a number of the data packet received at destination and $total\ dp\ sent$ denotes the number of data packets (dp) sent by the source node. The unit of reliability is percentage (%).

The reliability of different methods is calculated and the simulation result of reliability with respect to vehicle densities is given in Table 2.

Table 2 Tabulation of Reliability

Vehicle density	Reliability (%)				
	CEG-RAOD	**Multi-valued DPSO**	**MMBC-MDSOR**	**BEXCMWO**	**DLRSC-ODOR**
50	84	80	88	92	96
100	86	82	90	94	98
150	88	84	92	95	97
200	89	85	93	94	95
250	88	84	94	95	96
300	90	85	95	96	98
350	91	86	94	95	97
400	90	85	93	94	95
450	91	86	95	96	97
500	89	85	94	95	96

The ten different results of reliability with the vehicle density are listed in table 2. As shown in Table 2, when the vehicle density increases followed by link connectivity gets increased hence the proposed DLRSC-ODOR technique gives a better performance of reliability. The simulation result of reliability with respect to various numbers of vehicle density is depicted in below figure 3.

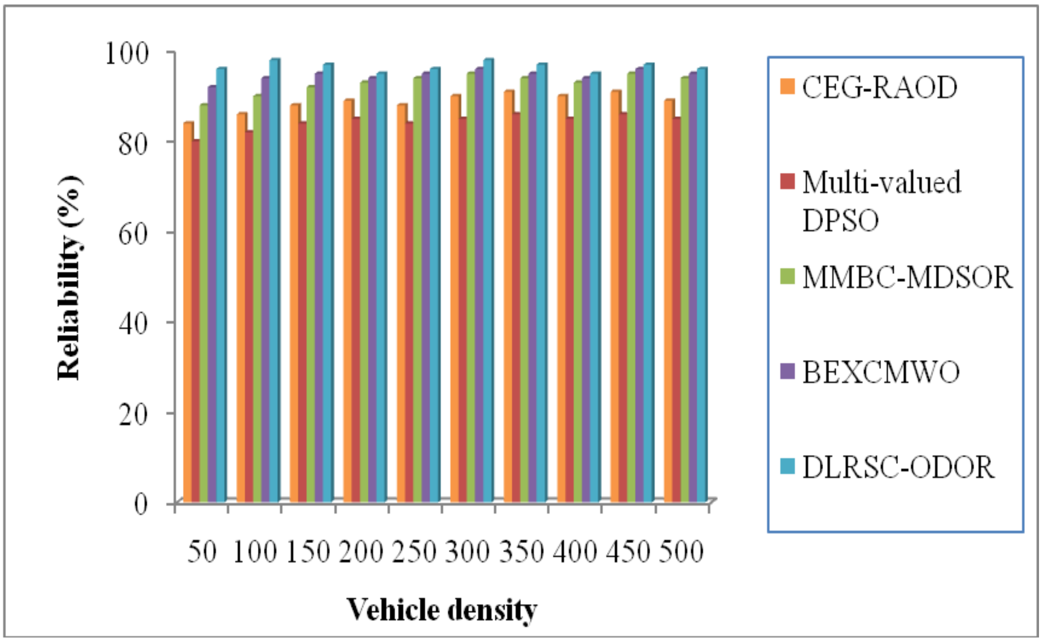

Figure 4 comparative analysis of reliability

Figure 4 shows the comparative analysis of reliability using four different methods namely the DLRSC-ODOR technique and existing CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3], BEXCMWO. As shown in the graph, the 'x' axis represents the vehicle density whereas the 'y' axis represents the reliability. The vehicle density is taken in the range from 50 to 500. The above graphical results evidently prove that the reliability of the DLRSC-ODOR technique is improved than the existing methods.. The optimization technique uses an oppositional based learning concept for finding the global optimum cluster head. Then the data packets are transmitted through the optimal cluster head. This helps to improve the data packet delivery. The average of ten results confirms that the reliability is considerably improved using the DLRSC-ODOR technique by 9%, 15% , 4% and 2% as compared to Multi-valued DPSO [2], MMBC-MDSOR [3], BEXCMWO respectively.

4.2 Result Analysis Of Packet Drop Rate

Packet drop rate is mathematically calculated as a ratio of a number of data packets dropped to the number of packets sent. The formula for calculating the packet drop rate is given below,

$$dp_{rate} = \left(\frac{No.of\ dp_D}{total\ dp\ sent}\right) * 100 \quad (30)$$

Where dp_{rate} represents a packets drop rate, $No.of\ dp_D$ is the number of the data packet dropped at destination and $total\ dp\ sent$ denotes a number of data packets (dp) sent by the source node. The unit of the packet drop rate is a percentage (%).

The packet drop rate of four different methods with respect to vehicle densities is depicted in below Table 3.

Table 3 Tabulation of Packet drop rate

Vehicle density	Packet drop rate (%)				
	CEG-RAOD	Multi-valued DPSO	MMBC-MDSOR	BEXCMWO	DLRSC-ODOR
50	16	20	12	8	4
100	14	18	10	6	2
150	12	16	8	5	3
200	11	15	7	6	5
250	12	16	6	5	4
300	10	15	5	4	2
350	9	14	6	5	3
400	11	16	7	6	5
450	9	14	5	4	3
500	11	15	6	5	4

Table 3 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 DLRSC-ODOR technique than the existing techniques. The simulation result of the packet drop rate with respect to vehicle densities is depicted in figure 5.

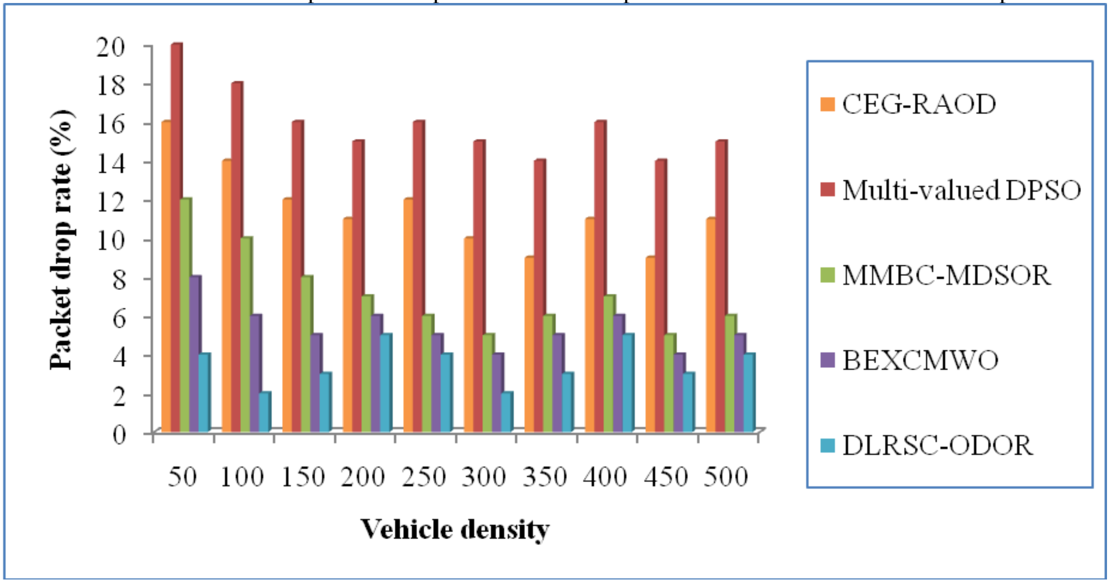

Figure 5 Comparative analysis of packet drop rate

Figure 5 illustrates a comparative analysis of the packet drop rate of different methods DLRSC-ODOR technique and existing CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3], BEXCMWO. The vehicle density is given as input to calculate the drop rate while disseminating the packets from source to destination. While sending 25 data packets, the DLRSC-ODOR technique drops 1 data packets and their dropping percentage is 4% whereas the packet drop rate of other three methods is $16\%, 20\%, 12\%$ *and* 8% using CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3] and BEXCMWO respectively. This improvement of DLRSC-ODOR technique is achieved by the optimization. The proposed optimization technique considers the bandwidth availability, signal strength, residual energy and link stability between the nodes. The average of ten results shows the DLRSC-ODOR technique minimizes the packet drop rate by 69%, 78%, 48% and 35% when compared to existing methods.

4.3 Result Analysis Of End To End Delay

End to end delay is the amount of time between the data packet arrival and data packet sending from the source node. The mathematical formula for calculating the end to end delay is expressed as follows,

$$E_D = \left(Dp_{at} - Dp_{st}\right) \tag{31}$$

Where, E_D represents the end to end delay, Dp_{at} is the time for arriving the data packets, Dp_{st} is the data packets sending time . The unit of end to end delay is milliseconds (ms).

These results are obtained using the above said mathematical calculation. Similarity, ten various results of end to end delay is reported in table 4.

Table 4 Tabulation of End to End delay

Vehicle density	**End to end delay (ms)**				
	CEG-RAOD	**Multi-valued DPSO**	**MMBC-MDSOR**	**BEXCMWO**	**DLRSC-ODOR**
50	14	17	12	10	8
100	16	19	14	12	10
150	18	21	15	13	11
200	22	25	18	16	14
250	23	27	21	19	16

300	25	29	22	21	18
350	27	30	24	23	21
400	30	33	26	24	22
450	32	36	27	26	23
500	34	38	31	29	25

Let us consider the number of 25 data packets, the DLRSC-ODOR technique takes $8ms$ of delay for receiving the data packet at the destination end. The existing techniques take $14ms$, $17\ ms$, $12ms$ and $10ms$ of delay. Then ten various results of delay time are shown in figure 6.

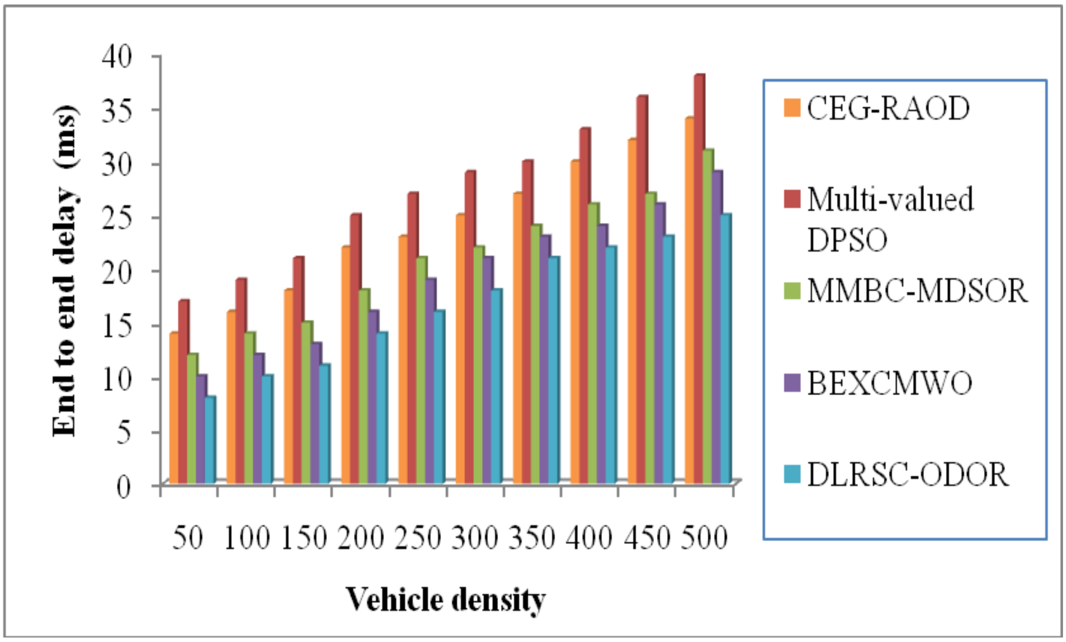

Figure 6 Comparative analysis of end to end delay

Figure 6 depicts the simulation results of end to end delay versus vehicle density taken in the range from 50 to 500. The graphical result proves that the end to end delay of the proposed DLRSC-ODOR technique is minimized than the other three methods. In this way, the data packets are transmitted only to the cluster head than the cluster members. This, in turn, minimizes the data packet receiving time. Besides, the bandwidth availability and link stability between the nodes help to further minimize the end to end delay. The simulation result of the proposed DLRSC-ODOR technique is compared with the results of the existing technique. The comparison results confirm that the end to end delay is considerably minimized by $32\%, 40\%, 21\%\ and\ 14\%$ when compared to existing CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3] and BEXCMWO respectively.

4.4 Result Analysis Of Throughput

Throughput is an amount of data packets (i.e. size) successfully delivered from source to the destination vehicle through the cluster head in a specific time period. Mathematically throughput is calculated as given below,

$$TH_{DP} = \left(\frac{Amount\ of\ DP\ delivered}{t}\right) \tag{32}$$

Where, 'TH_{DP}' denotes an amount of data packets successfully delivered to a destination end, t denotes a specific time period. The throughput is estimated in terms of bits per second (bps).

Table 5 Tabulation of Throughput

Data packet size (KB)	Throughput (bps)				
	CEG-RAOD	Multi-valued DPSO	MMBC-MDSOR	BEXCMWO	DLRSC-ODOR
10	100	95	130	150	170
20	200	179	245	280	320
30	315	280	362	390	410
40	420	392	485	530	550
50	500	452	542	575	615
60	623	582	662	690	720
70	710	653	742	790	810
80	821	783	855	900	940
90	910	872	932	975	1000
100	1052	986	115	1200	1250

Table 5 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 DLRSC-ODOR technique increases the throughput than the state-of-the-art methods.

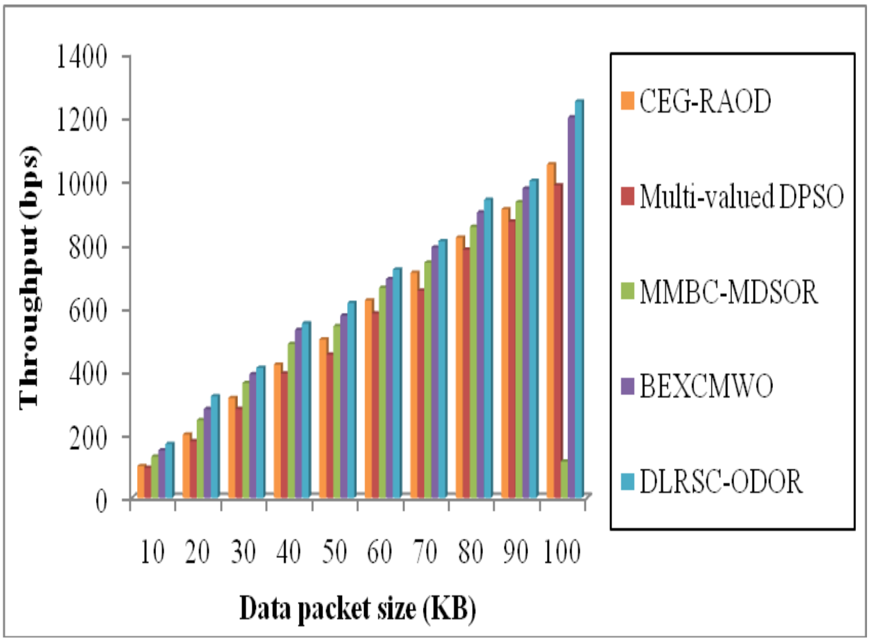

Figure 7 Comparative analysis of throughput

As shown in figure 7, simulation results of throughput are obtained with respect to various packet sizes in the range from 10KB to 100KB. The above graph shows that the simulation result of throughput is found to be improved by using the DLRSC-ODOR technique than the other methods. This is due to the DLRSC-ODOR technique selects the optimal route path between the source and destination using oppositional dragonfly optimization. The optimization technique finds a globally optimum cluster head for routing the data packets. This helps to enhancement in network throughput. Higher the network throughput achieves higher packet delivery in VANET. The comparison of ten different resultsshows that the throughput of the DLRSC-ODOR technique is considerably improved by 29%, 39%, 15% and 6% as compared to existing CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3] and BEXCMWO.

4.5Result Analysis Of Link Stability

Link stability is measured in terms of Energy consumption. Link stability defined as the ratio of number of higher residual energy vehicle node selected to the total number of vehicle nodes. Mathematically link stability is calculated as given below,

L_S=(no of higher residual energy vehicle node selected / total number of vehicle nodes)*100 (33)

Where, 'L_S' represents the link stability which is measured in terms of Percentage (%).

Table 6 Tabulation of Link Stability

Vehicle density	Link Stability (%)				
	CEG-RAOD	Multi-valued DPSO	MMBC-MDSOR	BEXCMWO	DLRSC-ODOR
50	54	50	60	70	76
100	57	53	63	73	79
150	60	56	64	75	80
200	63	58	65	76	83
250	66	59	67	78	84
300	69	62	70	79	87
350	71	66	73	80	89
400	74	68	74	83	90
450	76	71	76	85	91
500	77	73	77	86	92

Table 6 shows the simulation results of link stability based on selection of higher residual energy vehicle nodes. While varying the number of vehicular nodes, various link stability results are obtained. The above-reported results show that the DLRSC-ODOR technique increases the link stability than the state-of-the-art methods.

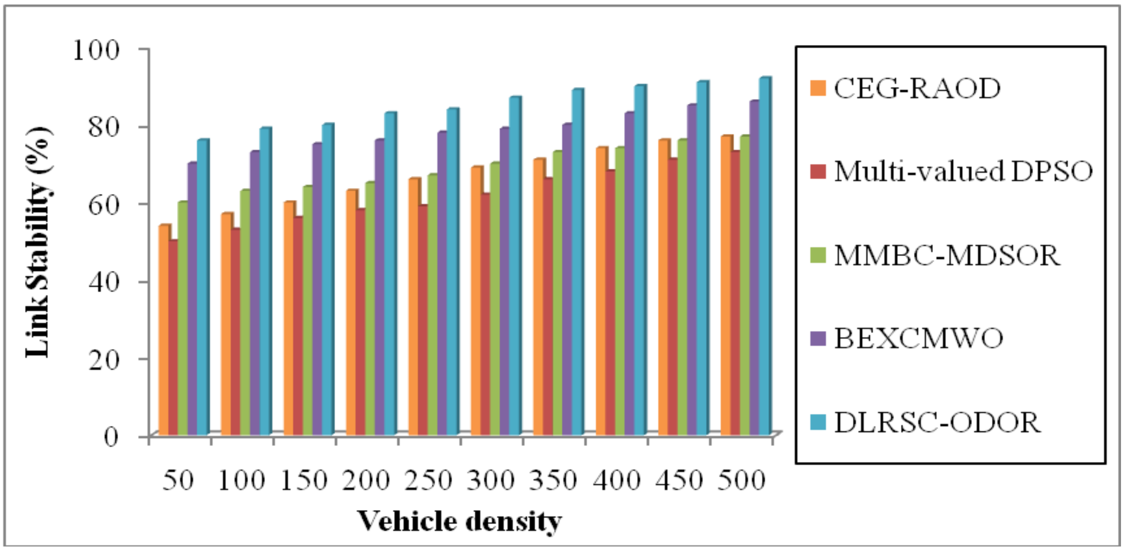

Figure 8 Comparative analysis of Link stability

Figure 8 illustrates simulation results of link stability versus vehicle density taken in the range from 50 to 500. The vehicle density is given as input to calculate the link stability while disseminating the packets from source to destination. The compression result evidently proves that the DLRSC-ODOR technique increases the link stability. The above graphical results clearly inferred through the mathematical calculation. The comparison of ten different results shows that the link stability of the DLRSC-ODOR technique is considerably improved by 28%,39%,23% and 8% compared to CEG-RAOD [1], Multi-valued DPSO [2], MMBC-MDSOR [3] and BEXCMWO respectively. This improvement of DLRSC-ODOR technique is achieved by the optimization technique that considers the bandwidth availability, signal strength, residual energy and link stability between the nodes. The better link quality minimizes the link failure.

The above-discussed results of various parameters confirm the proposed DLRSC-ODOR technique efficiently achieves reliable data dissemination with higher throughput and minimum packet loss as well as delay in VANET.

5. Conclusion

The proposed DLRSC-ODOR technique is developed with the aim of improving the reliability of data packet dissemination by dividing the vehicular network into different clusters. The DLRSC-ODOR technique uses the similarity-based spectral clustering technique to group the vehicle nodes by applying the k means algorithm. For efficient data packet dissemination, the cluster head is chosen among the members which are more stable and reliable nodes. In order to transmit the packet, the source node discovers the nearest cluster head towards the direction of the destination. The cluster head selection is done by applying Multiattribute oppositional dragons fly optimization. Finally, the optimal path from source to destination is established to improve the data dissemination in VANET. The simulation is carried out with different performance metrics such as reliability, packet drop rate, end to end delay and throughput. The comparative analysis of various methods proves that the proposed DLRSC-ODOR technique considerably improves the reliability, throughput and minimizes the packet drop rate and end to end delay than the state-of-the-art methods.

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