SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I5P104

Volume 12 Issue 5, 32-44, May 2025

Original Article

Stochastic Lagrangian Krill Herd Optimized Quadratic Associative Boost Classification for Load Balancing in VANET

S. Sumathi[1], P. Tamilselvan[2]

[1,2]*Department of Computer Science, Karpagam Academy of Higher Education, Tamilnadu, India.*

[1]*Corresponding Author : sumathi3@gmail.com*

Received: 28 February 2025 Revised: 04 April 2025 Accepted: 18 April 2025 Published: 31 May 2025

Abstract - *VANETs are wireless technologies specifically designed for communication among vehicles and roadside infrastructure. VANETs face various challenges, including network connectivity issues due to high mobility and limited communication range, especially in dense urban environments. Load balancing in VANETs is crucial for ensuring efficient and reliable data communication among vehicles. The dynamic nature of VANETs, characterized by rapidly changing network topologies and varying traffic loads, poses unique challenges for achieving optimal communication performance. In this paper, a Stochastic Lagrangian Krill Herd Optimized Quadratic Associative Boost Classification (SLKHO-QABC) method is introduced for resource-efficient load balancing in VANETs. The main objective of the proposed method is designed* for load-balanced data transmission in VANETs *with minimum end-to-end delay. The SLKHO-QABC method includes two major processes namely resource optimization and classification in VANET. Initially, the Stochastic Universal Sampled Lagrangian Krill Herd Optimization is used to determine the resource-efficient vehicle nodes based on fitness functions. With the optimal vehicle nodes, the load capacity is identified through classification. Quadratic Associative Boost Classification is utilized to categorize the less or heavy-loaded vehicle nodes based on the likelihood ratio test. Finally, the vehicle node with a higher load broadcasts an information packet to the lesser-loaded vehicle node during the time of flight, which is used to achieve efficient load balancing in VANET. Experimental analysis is performed for various parameters. Performance comparison analyses show that the proposed SLKHO-QABC method improves the load balancing efficiency throughput and minimizes energy utilization, packet loss rate, and end-to-end delay. SLKHO-QABC method improves the load balancing efficiency by 5.5.% and throughput by 40%, reduces the Packet loss rate by 31%, energy consumption by 18%,* and *end-to-end delay by 18.5%.*

Keywords - *VANETs, load balancing, data communication, Stochastic Universal Sampled Lagrangian Krill Herd Optimization, Quadratic Associative boost Classification, likelihood ratio test, time of flight method.*

1. Introduction

VANET refers to a kind of ad hoc network that permits communication among vehicles and pavement infrastructure. In VANETs, all vehicles are utilized to share and exchange information. Load balancing in VANETs is essential to ensure network resources are utilized optimally and prevent congestion in specific regions. Different approaches have been developed. A Modified Social Spider Optimization (M-SSO) algorithm was introduced in [1] to enhance data transmission efficiency. The algorithm successfully increased throughput but did not include load balancing aware transmission strategies to optimize delivery ratio and reduce transmission delay. An integration PSO-SVNS-LBGB was introduced in [2] to find the optimal path. However, it fails to address the multi-objective optimization needed for further enhancing throughput and minimizing delay. A new DFACO method was presented [3] for achieving data transmission with minimal time and solution cost. However, achieving higher performance in terms of data transmission with minimal delay remains a challenging issue. A novel HFCHBO algorithm was developed in [4] to effectively establish victorious routing paths for data broadcast among vehicles. However, load balancing performance was not improved. A hybrid optimization approach, integrated with ensemble learning, was introduced in [5] to enhance throughput and reduce latency. However, resource optimization posed a significant challenge in this context. Server-Based Network Congestion Handling Mechanism (SBNC) was introduced in [6] to enhance network performance. But it failed to enhance energy consumption. ANFC and quantum glowworm swarm optimization-basis of routing were developed in [7] to enhance data communication. However, the designed routing method failed to improve the network throughput.MFO algorithm and K-Means clustering were developed in [8] for handling clustering optimization issues. However, it failed to reduce the delay. A hybrid optimization algorithm was designed in [9] for energy-aware load balancing. However, it failed to enhance the throughput performance. Whale Optimization Algorithm was introduced in [10] to select an optimum Cluster Head (CH) and improve data transmission. However, multi-objective functions remained unsolved in optimization techniques due to the rapid changes in vehicle topologies. The Rider Integrated Cuckoo Search (RI-CS) optimization algorithm was designed [11] to attain optimal route selection with minimal cost. VGBC, depending on the honey bee method, was developed [12] to minimize computational overhead. However, it did not address the minimization of communication workload.

The QoSR with Particle Swarm Optimization (QoSR-PSO) method was designed [13] to enhance the packet delivery ratio as well as minimize delay. An optimized and effective routing protocol was developed [14] to enhance throughput. However, it failed to analyze the average packet drop ratio results. A two-level communication routing algorithm was introduced in [15] to improve information transmission efficiency. However optimizing load balancing to reduce latency further posed a challenging task. The specific challenges of load balancing in vanet are due to the dynamic and unpredictable nature of vehicular networks. It includes Dynamic Network Topology, Scalability, Security, Limited Resources.

1.1. Research gap

An essential challenge associated with load-balanced data transmission in VANETs is minimum energy consumption. A Modified Social Spider Optimization (M-SSO) algorithm was used to enhance data transmission efficiency. However it failed to improve the efficiency of load balancing. An integration PSO-SVNS-LBGB was introduced to find the optimal path. However, the designed method did not reduce the energy consumption. To overcome the above issue, the SLKHO-QABC method is designed.

2. Literature Review

An Improved Harmony Search Optimization (EHSO) algorithm was introduced in [16] for data transmission among nodes. However, it failed to address load-aware data transmission. Optimization for Congestion Control System applying Machine Learning [OCCS-ML] was designed in [17] to diminish road accidents. However, bandwidth efficiency and packet loss in vehicular communication remained major concerns. The Lightweight Load Balancing method developed in [18] aimed to minimize the average Packet Loss Ratio. However, it did not improve throughput and network lifetime. Deep Reinforcement Learning-based Intelligent QoS-optimized efficient routing algorithm was employed in [19] to enhance network quality of service. However, the method did not achieve throughput. The Giraffe Kicking Optimization (GKO) was developed in [20] to improve throughput and minimize data transmission delay. However, the multi-objective version of the GKO algorithm has not been addressed.

A Q-learning-based routing protocol was developed in [21] to minimize historical traffic flows. However, handling multidimensional resources for intelligent routing in VANETs remained a challenging task. A particle swarm optimization-based multipath routing method was introduced in [22] to minimize time delay in data transmission. An integration of swarm intelligence-based optimization strategies was developed in [23]. However, it did not minimize data transmission complexity and cooperative communication among the vehicles.

The Spatio-Temporal Autonomous Load Balancing (STALB) routing protocol was introduced in [24] to minimize average latency and overload ratio. However, it did not achieve higher throughput performance. A capacity-based load-distribution method was developed in [25] to perform load-balancing with the aim of minimizing energy consumption and network delay. However, it did not implement learning-based scheduling to enhance energy consumption and network performance further.

Chaotic Harris Hawks Optimization Algorithm was introduced in [26] for efficient energy usage. A Q-learning-basis of routing protocol was designed [27] to reduce end-to-end communication latency. An integrated approach was examined in [28] to improve energy efficiency. However, it failed to minimize the communication overhead.

An intelligent machine learning-based routing method was developed for VANET with the aim of achieving higher throughput and reducing overall average delay [29]. However, the efficiency of the method was not improved in high-density environments. A new routing technique was designed [30] to enhance the Quality of Service during communication, which aims for a higher packet delivery ratio. An algorithm for Vehicular Edge Computing (VEC) with network slicing and load-balancing based on resource utilization, denoted as VECSlic-LB was proposed in [31] specifically dedicated to offloading tasks from vehicles to edge nodes at gNBs or RSUs but failed to reduce the energy consumption. An efficient algorithm, TAASLB-traffic-aware adaptive server load balancing, was designed in [32] to balance the flows to the servers in a data center network. However, end-to-end delay was not minimized. A Server-Based Network Congestion Handling Mechanism (SBNC) was developed in [6] VANETs to bridge this gap. However, load balancing efficiency was not enhanced.

2.1. The Novelty of the SLKHO-QABC Method

The major novelty of the proposed SLKHOQABC method is summarized as follows,

- To improve the resource-efficient load-balancing data transmission in VANET, the SLKHOQABC method is designed based on optimization and classification.
- First, Stochastic Universal Sampled Lagrangian Krill Herd Optimization (SLKHO) is applied to identify resource-efficient vehicle nodes based on energy, bandwidth, and signal strength. Stochastic Universal Sampling is employed within the Krill Herd Optimization framework to select the optimal vehicle nodes in terms of resources. This approach aims to enhance throughput and minimize delays.
- Quadratic Associative Boost Ensemble Classification is employed for analyzing the load capacity. The Time of Flight method is applied to determine the nearest node for load balancing, consequently enhancing load balancing efficiency and minimizing packet loss.
- Finally, an extensive simulation is carried out to estimate the performance of our SLKHOQABC method and other related works. The simulation result demonstrates that our SLKHOQABC method is highly efficient than the other methods.

3. Proposed Methodology

Wireless communication technology is advancing rapidly in various sectors, especially regarding effective data transmission. In VANET, load balancing is the process of distributing the data among a set of nodes to ensure optimal utilization of available resources and to prevent congestion or overloading of any single node or link. Ensuring load balancing in VANETs becomes challenging due to highly dynamic topology and constrained bandwidth. Incorporating a novel SLKHO-QABC method for load-balanced data transmission in VANETs helps improve network efficiency, reduce packet loss, and enhance overall network performance. Figure 1 depicts the architecture of the SLKHO-QABC method that helps for improving the load balanced data communication in VANET.

Let us consider the VANET network organized into the undirected graph $G = (v, e)$' where 'v' indicates a number of vehicle nodes. $Vn_1, Vn_2, Vn_3, \ldots., Vn_n$ and 'e' denotes the edges.

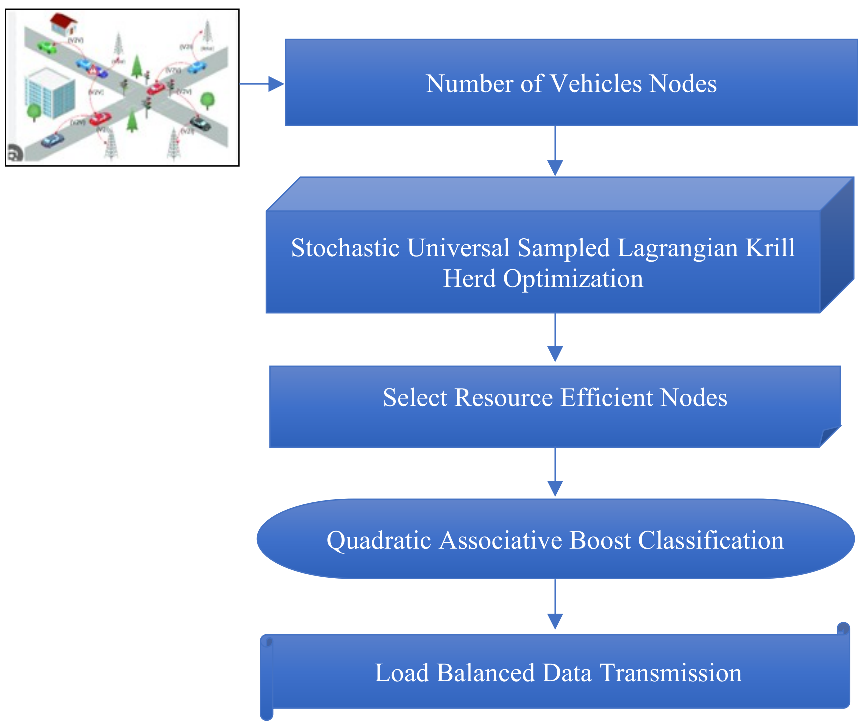

Fig. 1 Architecture of the SLKHO-QABC method

To achieve the load-balanced data communication in VANET, the resource of vehicle nodes is optimized by applying a Metaheuristic Krill Herd Optimization. Followed by the resource optimal vehicles nodes are identified from the entire network. Then, the Quadratic Associative Classification is applied to find the load capacity of the virtual machine. Finally, the data packets $DP_i = Dp_1, Dp_2, Dp_2, \ldots, Dp_n$ are transmitted to the destination node (Dn) through resource-optimal and lesser-loaded nodes $Nn_i = Nn_1, Nn_2, \ldots, Nn_n$.

3.1.Stochastic Universal Sampled Lagrangian Krill Herd Optimization

The initial process of the *SLKHO-QABC* method is to perform effective resource node selection using Metaheuristic Krill Herd Optimization. Krill Herd Optimization is a nature-inspired metaheuristic optimization method that depends on the collective activities of krill swarms. This optimization simulates the social interactions and movement patterns of krill to solve multi-objective optimization problems. The main advantages of Krill Herd Optimization than the other optimization techniques are providing global optimization capabilities, diversity maintenance, efficiency, robustness, and user-friendly implementation.

The behavior is inspired by the behavior of krill in nature is to search the food concentrations. They tend to move towards regions with higher food concentrations (better solutions) while avoiding regions with lower food concentrations (poorer solutions). This collective movement allows the population to explore the search space efficiently and converge towards optimal solutions over time.

Optimization process begins to generate a population of krills. Here, krills are related to vehicle nodes in VANET. So, an initial population of vehicle nodes is generated as follows,

$$Vn_i = Vn_1, Vn_2, Vn_3, \dots, Vn_n \quad (1)$$

Where, Vn_i indicates a number of vehicle nodes. After the population generation, the fitness of every vehicle node is estimated depending on multiple objective functions.

$$f(x) = \left[{E_i}^{Res}, {Bw_i}^{avail}, SS_i\ \right] \quad (2)$$

Where, $f(x)$ denotes multiple objective functions, ${E_i}^{Res}$ indicates a residual energy level of ''i^{th}'vehicle nodes, ${Bw_i}^{avail}$ indicates the bandwidth availability of 'i^{th}'vehicle nodes, SS_i denotes a signal strength of 'i^{th}'vehicle nodes.

The residual energy of the vehicle node is estimated by subtracting the consumed energy from the initial energy of the vehicle node.

$${E_i}^{Res} = [{E_i}^{Ini}] - [{E_i}^{Cons}] \quad (3)$$

Where, ${E_i}^{Res}$ indicates a residual energy level of 'i^{th}'vehicle nodes, ${E_i}^{Ini}$denotes a primary energy of vehicle nodes, ${E_i}^{Cons}$denotes the utilized energy of vehicle nodes.

Bandwidth is the highest information transfer rate of a network per unit time. The bandwidth availability is estimated as the total available bandwidth minus the consumed bandwidth.

$${Bw_i}^{avail} = \left[{Bw_i}^{Ini}\right] - [{Bw_i}^{Cons}] \quad (4)$$

Where, ${Bw_i}^{avail}$ designates the bandwidth availability, ${Bw_i}^{Ini}$ indicates an initial bandwidth, ${Bw_i}^{Cons}$ represents the consumed bandwidth.

Friis transmission equation is used as a fundamental formula for estimating the signal strength of the vehicle node in wireless communication systems. It is mathematically formulated as follows,

$$SS_i\ =\ St_i * g_t * g_r * \left(\frac{\lambda}{4\pi D}\right)^2 \quad (5)$$

Where, SS_i denotes a received signal strength or power of i^{th}'vehicle nodes,St_i the transmitted signal strength of i^{th}'vehicle nodes, g_t and g_r indicates a gain of transmitter and receiver antenna, $\lambda$is the wavelength of the signal, D is the distance among the transmitter and receiver. After computing the resource of the vehicle node, fitness is measured with a set of criterion functions as follows,

$$FF = \Big(({E_i}^{Res} > T_E) \&\& ({Bw_i}^{avail} > T_B) \&\& (SS_i > T_{SS_i})\Big) \quad (6)$$

Where FF indicates fitness function,T_E, T_B, T_{SS_i}represents the threshold for residual energy, bandwidth availability, signal strength or power of nodes, respectively.

After fitness measurement, the population's current best krill is chosen by applying a stochastic universal sampling procedure. The chosen of individuals are performed depending on probability evaluation as follows,

$$P_s = \frac{FF_i}{\sum_{j=1}^{n} FF_j} \quad (7)$$

Where, P_s indicates a selection probability computed depending on the ratio of each individual node fitness 'FF_i' to average fitness of a population in j^{th} individual 'FF_j'. As population generation varies, the fitness values as well as selection probabilities as well change. This means the greatest individuals are chosen through P_s. Likewise, the best individuals are chosen to identify the best global solution in the current methodology.

For each current best individual, there are three major behaviors executed, such as manipulation of additional krill individuals, activities of searching food sources, as well as random diffusion. Lagrangian model is employed to an n-dimensional decision space for integrating the above-said actions as follows,

$$\frac{dV_k}{dt} = I_k + FS_k + RD_k \quad (8)$$

Where, $\frac{dV_k}{dt}$ denotes a Lagrangian model, I_k indicates a manipulation of other krill individuals, FS_k denotes activities of searching for food sources, RD_k denotes a random diffusion.

For manipulation of additional krill individuals, the motion of krill is persuaded through other krill is expressed as below,

$$I_{k_{new}} = V_{mx}\,\vartheta_i + w_n * I_{k_{old}} \tag{9}$$

Where, $I_{k_{new}}$ denotes a motion of krill is induced through other krill, V_{mx} denotes a represents the maximum induced velocity, $w$indicates inertia weight as well as value range is (0,1), ϑ_i indicates which individual is concerned through the induction direction of surrounding neighbors, $I_{k_{old}}$ denotes formerly induced movement.

Next behavior $FS_k$is to get food, as follows:

$$FS_{k_{new}} = S_{mx}\,\varphi_i + w_f * FS_{k_{old}} \tag{10}$$

Where, $FS_{k_{new}}$denotes a behavior of searching for a food source, S_{mx} denotes the highest foraging speed, as well as its value is constant, (i.e.,) 0.02 (m/s),φ_i indicates the foraging direction, w_f represents inertia weight of foraging movement,$FS_{k_{old}}$ indicates the previous foraging movement.

The final behavior random diffusion is executed as follows,

$$RD_{k_{new}} = DS_{mx}\left(1 - \frac{t}{t_{mx}}\right)\beta \tag{11}$$

Where, $RD_{k_{new}}$denotes a behavior of random diffusion, DS_{mx} denotes a maximum random diffusion speed, t indicates a current iteration, t_{mx} represents the maximum number of iterations, β indicates the direction of random diffusion.

Based on the above-said behavior, the position of krill is modernized as below,

$$X_{t+1} = X_t + \Delta t \frac{dV_k}{dt} \tag{12}$$

$$\Delta t = \rho \sum (u_j - l_j) \tag{13}$$

Where, X_{t+1} updated position of krill, X_t denotes a current position of krill, Δt denotes a time interval related to the specific application, step factor 'ρ' is constant among 0 and 2, u_j and l_j denotes upper as well as lower bounds of equivalent variables.

After that, the fitness for every krill is computed along with its newly updated location. This procedure is iterated till maximum iteration obtains achieved. Lastly, the resource-optimal vehicle node is selected. The flowchart of the Stochastic Universal Sampled Lagrangian Krill Herd Optimization is given below,

Figure 2 illustrates an overall flow diagram of Stochastic Universal Sampled Lagrangian Krill Herd Optimization based resource optimal node selection. The algorithmic description of the Stochastic Universal Sampled Lagrangian Krill Herd Optimization is described as follows,

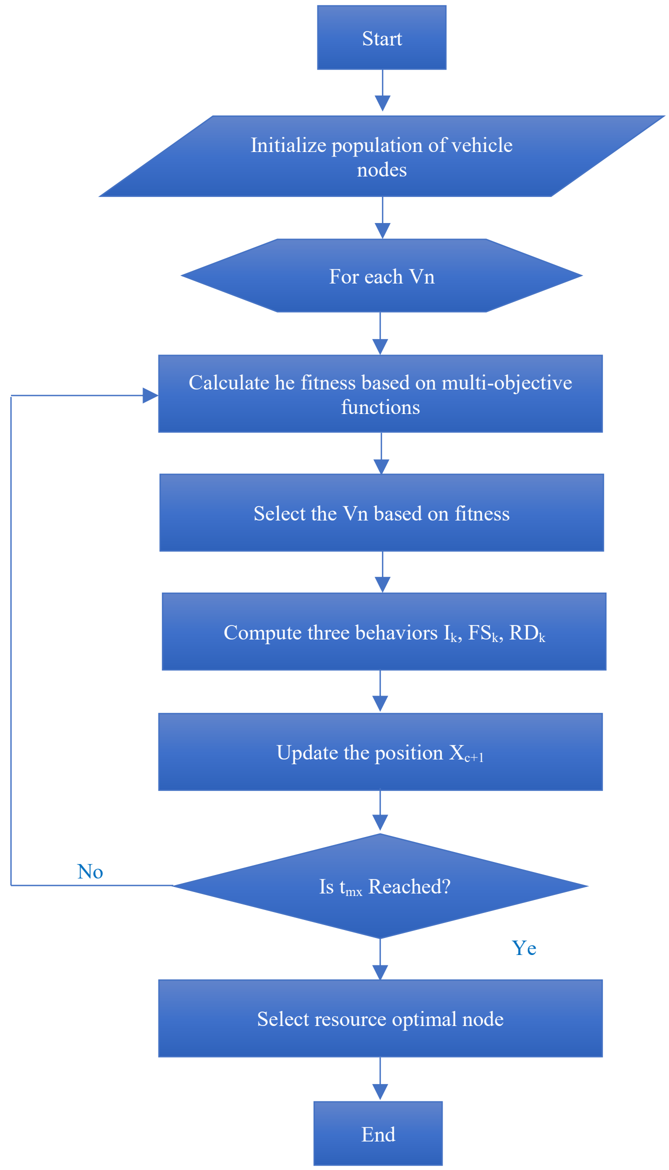

Fig. 2 Flow diagram of stochastic universal sampled lagrangian krill herd optimization

Algorithm 1 described above outlines the process of resource-optimal node selection. Initially, populations of vehicle nodes are randomly generated at search space (i.e., network). For every vehicle node, fitness is computed based on multiple objective functions. The current best vehicle nodes are then selected based on fitness estimation. Following this, the three behavior models of the krills are estimated. Afterwards, locations of krills are modernized. Fitness is calculated for recently generated locations. This procedure is frequent till maximum iteration is attained. Finally, the global best individual is chosen as the best vehicle node for improving data transmission with minimal delay.

Algorithm 1: Stochastic Universal Sampled Lagrangian Krill Herd Optimization
Input : Number of vehicle nodes $Vn_1, Vn_2, Vn_3, \ldots., Vn_n$,
Output : Select resource-efficient vehicle nodes
Begin
Step 1 : Initialize the population of vehicle nodes $Vn_1, Vn_2, Vn_3, \ldots., Vn_n$
Step 2 : For each Vn_i
Step 3 : Calculate E_i^{Res} and Bw_i^{avail}, SS_i using (3)(4)(5)
Step 4 : Compute the fitness using (6)
Step 5 : Select current best using (7)
Step 6 : While ($t < t_{mx}$) do
Step 7 : For each individual
Step 8 : Compute I_k, FS_k, RD_k using (9) (10) (11)
Step 9 : Update the positions of the krill using (12) (13)
Step 10 : Go to step 4
Step 11 : End for
Step 12 : t= t+1
Step 13 : end while
Step 14 : end for
Step 15 : End

3.2. Quadratic Associative Boost Classification based Load Balanced Data Transmission

After optimizing the resources of the vehicle nodes, the neighboring node with the least load capacity and minimal distance is identified by applying a quadratic associative boost classification. Quadratic Associative Boost Classification is an ML ensemble classification that translates weak learners into strong learners. The weak learner is a base classifier that is complex to give accurate categorization. In contrast, the strong learner is a classifier that gives true categorization. Figure 3 Portrays graphic construction of quadratic associative boost classification for precise classification with minimum time consumption. The proposed boost ensemble technique assumes input as the number of resource-optimal vehicle nodes.

$\{Vn_i, Y\}$

where $Vn_i = Vn_1, Vn_2, \ldots, Vn_m$ and Y indicates ensemble classification results. In Figure 4, the boost method primarily constructs the 'k' set of weak learners $L_1, L_2, L_3, \ldots. L_k$ as well as results are summed to construct strong categorization outcomes. Boost ensemble method employs weak learners as quadratic associative classifiers. For each optimal vehicle node with respect to available resources, the load capacity is computed based on the number of data packets performed through the node during a given time period.

$$L_i^{cap} = \left(\frac{NC_{dp}}{T}\right) \quad (14)$$

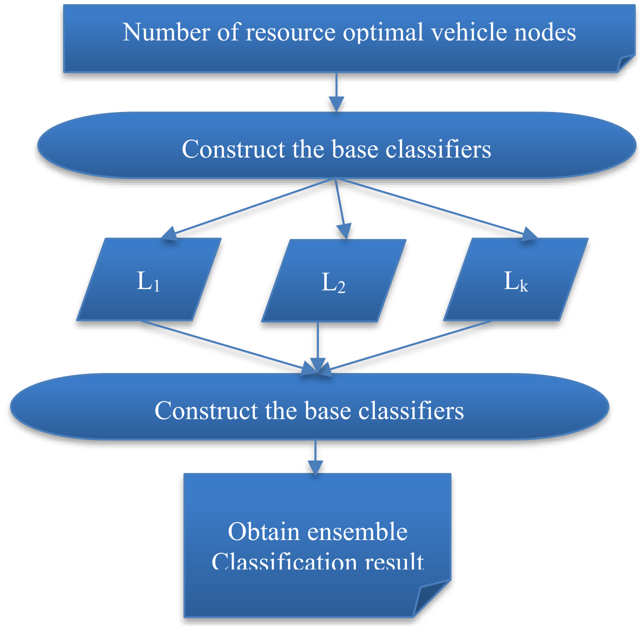

Fig. 3 Schematic structure of quadratic associative boost classification

Where, L_i^{cap} denotes a load of vehicle nodes, NC_{dp} designates a number of data packets that the node carries, T indicates the time in seconds (S). $L_1, L_2, L_3, \ldots. L_k$

The quadratic classifier performs the likelihood ratio test for the load capacity of vehicle nodes and the threshold value.

$$L = (2\pi\omega^2)^{-m/2} \exp\left(-\sum_{i=1}^{n} \frac{(L_i^{cap} - L_i^{T})^2}{2\omega^2}\right) \quad (15)$$

Where L represents the likelihood ratio test, ω represents deviation, L_i^T indicates a threshold of the load capacity, L_i^T represents the load capacity of nodes.

Based on the likelihood ratio test, the quadratic classifier utilizes the association rule mining concept to improve the accuracy of node classification based on support and confidence values. Here, the rule indicates a likelihood ratio test. Let us consider the $Vn_i \Rightarrow Q$ where Vn_i denotes the number of vehicle nodes, and Q denotes the output of the base learner. The support is an indication of how the vehicle nodes are more related to that particular class based on the rule, i.e., the Likelihood ratio test, which is formulated as follows,

$$sup(Vn_i \Rightarrow Q) = \left(\frac{Vn_i\, satisfy\ the\ rule}{n}\right) \quad (16)$$

Where, $sup(Vn_i \Rightarrow Q)$ denotes a support value of an Vn_i and output class Q, 'n' denotes the number of nodes, $Vn_i\ satisfies\ the\ rule$ indicates a vehicle node satisfies the rule 'i.e. better likelihood ratio test '.

Depend on support value, confidence is measured as below,

$$Con(Vn_i \Rightarrow Q) = \left(\frac{Vn_i \, satisfy \; the \; rule}{Vn_i \, not \; satisfy \; the \; rule}\right) \quad (17)$$

Where, $Con(Vn_i \Rightarrow Q)$ represents the confidence of how the nodes Vn_i is more related to the particular class. If the estimated support and confidence are lower than the threshold range, the node is classified as less loaded. Otherwise, it is classified as a heavy-loaded vehicle node. In this way, less-loaded and heavy-loaded vehicle nodes are identified. The observed weak learner outcomes are summed up to create strong classification outcomes, as follows,

$$Y = \sum_{i=1}^{k} Q_i \quad (18)$$

Where Y indicates ensemble output, Q_i indicates the output of weak learners. For every weak learner, the weight is initialized as follows,

$$Y = \sum_{i=1}^{k} Q_i * h_i \quad (19)$$

Where, 'h_i ' denotes the weight assigned to the weak learner results. After combining, an error is calculated as the dissimilarity among expected and actual outcomes. The error rate is computed as below,

$$ER = (Y_{ex} - Y)^2 \quad (20)$$

Where ER denotes an error, Y_{ex} represents the expected results, Y denotes the actual results. Depending on ER value, the primary weight gets modernized. If a weak learner correctly classifies nodes, its weight is decreased. Otherwise, the primary weight value is enhanced. Therefore, weak learner results with minimum error are selected to contribute more to the final classification result, leading to higher accuracy. In this way, less-loaded and heavy-loaded nodes are classified. To balance the traffic load, heavy-loaded vehicle nodes distribute the data packets to the nearest less-loaded vehicle nodes. This helps to enhance data broadcast through minimal delay. The ToF method is used to identify the nearest lesser-loaded nodes in a network. Each heavy-loaded node distributes beacon communication to other less-loaded nodes. Then, the nearest vehicle nodes receive the beacon message and send a reply.

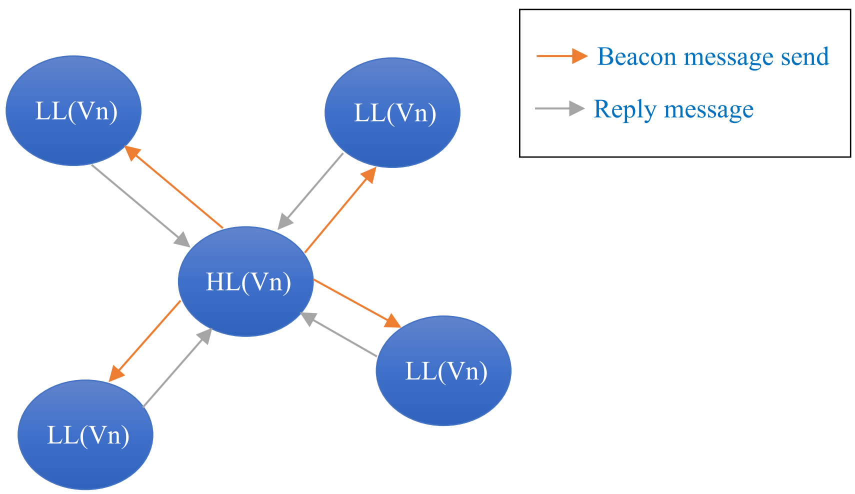

Fig. 4 Process of ToF method

Figure 4 illustrates the process of the time of flight method, where the beacon message distribution between the nodes. Based on message distribution, the distance between the nodes is estimated. Time of Flight (ToF) is time dissimilarity among beacon messages broadcasted as of heavily loaded node ' HL(Vn)' and the reply message sent to that node from the less loaded node '$LL(Vn)$'. It is calculated as given below,

$$d = [\mathrm{T_{Btr}}] - [\mathrm{T_{Rrx}}] \quad (21)$$

Where d represents a heavy-loaded node and less loaded node, $\mathrm{T_{Btr}}$ indicates the time for a beacon message broadcasted as a heavily loaded node and $\mathrm{T_{Rrx}}$ denotes a reply message returned from the less loaded node. Therefore, the minimal time is used to identify the nearest node. After that, the node distributes information packets to the nearest less loaded nodes within the network. In this way, load-balanced data communication is performed in VANET. The algorithm of load balancing is described as follows.

Algorithm 2: Quadratic Associative Boost Classification-Based Load Balancing
Input : Number of optimal vehicle nodes $Vn_1, Vn_2, Vn_3 \ldots\ldots Vn_k$, number of data packets $dp_1, dp_2, dp_3, \ldots dp_n$
Output : Improve the load balancing efficiency
Begin

Step 1 : For each resource-efficient optimal node 'Vn_k'
Step 2 : Measure the load capacity using (14)
Step 3 : Construct 'k' number of weak learners
Step 4 : Measure the likelihood test using (15)
Step 5 : Measure support value using (16)
Step 6 : Measure confidence value using (17)
Step 7 : $If(Con < Th)$then
Step 8 : Node is classified as lesser loaded
Step 9 : Else
Step 10 : Node is classified as heavily loaded
Step 11 : End if
Step 12 : End for
Step 13 : Combine all weak learners $Y = \sum_{i=1}^{k} Q_i$
Step 14 : for eachQ_i
Step 15 : Assign the weight 'h_i '
Step 16 : Compute the error ' ER'
Step 17 : Adjust the weight
Step 18 : Find the weak learner with minimum error
Step 19 : Return (strong classification results)
Step 20 : end for
Step 21 : for each heavy-load vehicle node
Step 22 : Send beacon message to other less loaded node
Step 23 : Compute the distance using (21)
Step 24 : Find the nearest less-loaded vehicles
Step 25 : Distribute the data packets to less-loaded vehicles
Step 26 : Return (load balanced data transmission)
Step 27 : End for
Step 28 : End

Algorithm 2 illustrates the various processes involved in load balancing during data transmission. For each vehicle node, the load capacity is estimated. The proposed ensemble technique sets the number of weak learners depend on input amount of vehicle nodes. Then, the likelihood ratio test is computed for each vehicle node. By applying association rule mining, the support value and confidence value are computed. If the estimated support and confidence are lower than the threshold range, the node is classified as less loaded.

Otherwise, it is classified as a heavily loaded vehicle node. The results from weak learners are summed, and weights are assigned. The error of each weak learner result is measured. Weak learner through minimum error is chosen as the last strong categorization result.

Then, the heavily loaded node distributes the data packets to the nearest less loaded node to enhance data broadcast and reduce delay.

4. Results and Discussions

Simulations of the *SLKHO-QABC* technique and conventional techniques M-SSO and PSO-SVNS-LBGA are executed in the NS2.34 simulator. The simulation duration is set to 300 seconds. The nodes' movement speed is configured to be within the range of 0-20 m/sec. The number of data packets considered for simulation varies from 100 to 1000. Simulation parameters, along with their respective values, are given in Table 1.

Table 1. Simulation parameters settings

Simulation Parameters	Values
Network Simulator	NS2.34
Simulation Area	1500 m * 1500 m
Number of Vehicle Nodes	100, 200, 300, 400, 500, 600, 700, 800, 900, 1000
Number of Data Packets	5000, 10000….50000
Mobility Model	Random Waypoint Model
Nodes Speed	0–20 m/s
Simulation Time	300 sec
Routing Protocol	DSR
Number of Runs	10

5. Performance Comparison Analyses

Performance of *SLKHO-QABC* method re compared through M-SSO and PSO-SVNS-LBGA with dissimilarparameters.

5.1. Energy Consumption

It is measured as the amount of energy utilized through vehicle nodes for distributing information packets. It is calculated as below,

$$EC = \sum_{i=1}^{n} Vn_i * CE(Vn) \quad (22)$$

Where EC indicates energy consumption, n indicates a vehicle node, $'CE(Vn)$ indicates the amount of energy utilized by a single vehicle node (Vn).It is measured in joule (J).

5.2. Load Balancing Efficiency

It typically refers to how effectively the data packets are distributed among the nodes in the network to avoid congestion and optimize resource utilization. It is calculated as the ratio of the number of data packets correctly distributed among vehicle nodes to the total number of data packets.

$$LBE = \sum_{i=1}^{n} \frac{Dp\ correctly\ distributed}{DP_i} * 100 \quad (23)$$

Where LBE symbolizes the Load balancing efficiency, DP_i indicates the number of data packets. It is calculated in percentage (%). Packet loss rate: It is calculated as the ratio of the number of data packets lost to the whole number of data packets sent. It is calculated as below,

$$RA_{LSS} = \sum_{i=1}^{n} \frac{Dp\ lost}{DP_i} * 100 \quad (24)$$

Where, RA_{LSS} indicates packet loss rate, $Dp\ lost$ symbolize the number of data packets lost. It is measured in percentage (%).

5.3. Throughput

It is calculated as the size of packets successfully received at the destination within the specific time period. It is measured in bits per second (bps).

$$T_{put} = \left(\frac{Dp\ received\ (bits)}{t\ (sec)}\right) \tag{25}$$

Where, 'T_{put}' denotes the size of data packets successfully delivered in terms of bits at destination and time (t) in seconds (sec).

5.4. End-to-End Delay

It is referred to as the time taken through the algorithm to deliver packets from source to destination.

$$D_{ED} = [DP_{arr}(T) - DP_{sed}(T)] \tag{26}$$

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

Figure 5 illustrates the result outcomes of EC versus number of vehicle nodes. The graph compares EC of *SLKHO-QABC* method, M-SSO, and PSO-SVNS-LBGA. Among these methods, the SLKHOQABC method demonstrates better performance than conventional methods.

Considering 50 sensor nodes for measuring energy consumption, the *SLKHO-QABC* method exhibits an energy consumption of 10.5 joules for data packet distribution.

In contrast, the energy consumption using M-SSO and PSO-SVNS-LBGA was observed to be 16.5 joules and 12.5 joules, respectively.

Table 2. *EC*

Number of Nodes	*EC* (Joule)		
	SLKHO-QABC	M-SSO	PSO-SVNS-LBGA
50	10.5	16.5	12.5
100	12.23	18.56	14.2
150	14.2	18.74	16.41
200	15.82	20.2	17.2
250	16.33	22.02	19.65
300	18.2	23.65	21.2
350	20.56	25.02	23.01
400	22.45	27.52	25.02
450	24.2	30.1	27.65
500	26.32	31.05	28.14

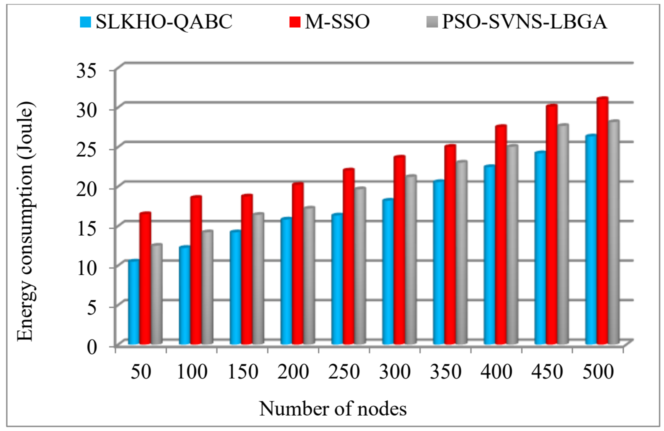

Fig. 5 Impact of EC

Various statistical results were observed and compared. Finally, the comparison reveals which EC performance of the *SLKHO-QABC* method is significantly minimized by 24% and 12% to the M-SSO and PSO-SVNS-LBGA. This is because of the *SLKHO-QABC* method's ability to identify resource-effective nodes for effectual data broadcast using Stochastic Universal Sampled Lagrangian Krill Herd Optimization. By selecting nodes with higher residual energy, the method enhances data transmission performance and contributes to increasing network lifetime.

Table 3. *LBE*

Number of Data Packets	*LBE* (%)		
	SLKHO-QABC	M-SSO	PSO-SVNS-LBGA
100	95	90	92
200	95.6	88.45	90.36
300	94.65	87.56	91.2
400	95.12	89.1	91.63
500	94.13	88.56	90.1
600	94.56	87.2	91.75
700	95.12	88.1	90.52
800	94.6	87.02	89.85
900	95.65	89.1	91.36
1000	94.52	88.74	90.56

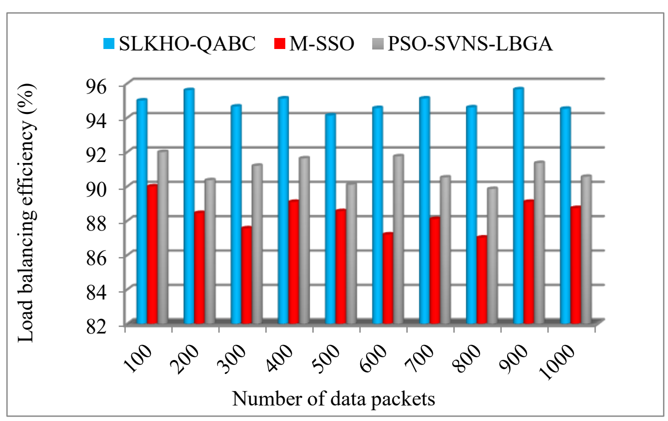

Fig. 6 Impact of load balancing efficiency

Figure 6 illustrates the result analysis of LBE versus the number of data packets. The outcomes demonstrate variations among three methods, namely *SLKHO-QABC*, M-SSO, and PSO-SVNS-LBGA. Overall, the *SLKHO-QABC* method outperforms the other two existing methods, consistently achieving higher load balancing efficiency. Specifically, when 100 data packets are considered, the SLKHOQABC method demonstrates 95% efficiency, while methods M-SSO and PSO-SVNS-LBGA achieve 90% and 92%, respectively. Ten dissimilar outcomes were examined for every technique. Comparing examined outcomes of the *SLKHO-QABC* method with other existing methods, the average comparison reveals a significant increase in load balancing efficiency of 7% and 4% compared to methods M-SSO and PSO-SVNS-LBGA, respectively. This is because of the Quadratic Associative Boost Classification application for identifying heavily and less loaded vehicle nodes. Subsequently, the ToF method is employed to determine neighboring less loaded vehicle nodes for forwarding data packets, enhancing efficiency.

Table 4. RA_{LSS}

Number of Data Packets	RA_{LSS}(%)		
	SLKHO-QABC	**M-SSO**	**PSO-SVNS-LBGA**
100	5	8	7
200	4.5	8.5	6
300	6	8.66	7.33
400	4.5	8	6.25
500	5.8	8.4	7
600	5.83	9.16	7.16
700	5.71	9.85	7.42
800	5.62	9.5	7.75
900	5.88	9.44	7.22
1000	6.5	11.4	8.5

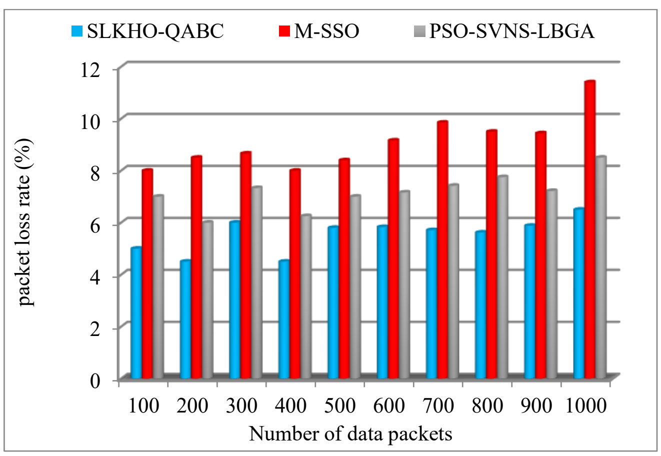

Fig. 7 Impact of RA_{LSS}

Figure 7 depicts the graphical analysis of RA_{LSS} using three different methods. The figure demonstrates which RA_{LSS} of *SLKHO-QABC* technique are minimized compared to conventional methods. This improvement is achieved by the *SLKHO-QABC* method through load capacity analysis of vehicle nodes before distributing data packets to all vehicle nodes. By employing Quadratic Associative Boost Classification, less or heavily loaded vehicle nodes within the network are identified. Additionally, the ToF technique is employed to identify neighboring vehicle nodes with lower load capacity for data packet distribution. This approach enhances data transmission and minimizes loss rates. The average of ten comparison outcomes denotes which RA_{LSS} the *SLKHO-QABC* method is significantly reduced by 39% and 23% to the M-SSO and PSO-SVNS-LBGA.

Table 5. Throughput

Data Packet Size (KB)	Throughput (bps)		
	SLKHO-QABC	**M-SSO**	**PSO-SVNS-LBGA**
25	315	185	208
50	358	205	222
75	412	265	302
100	585	347	395
125	623	412	485
150	725	563	612
175	825	610	695
200	985	715	798
225	1023	810	895
250	1185	914	1015

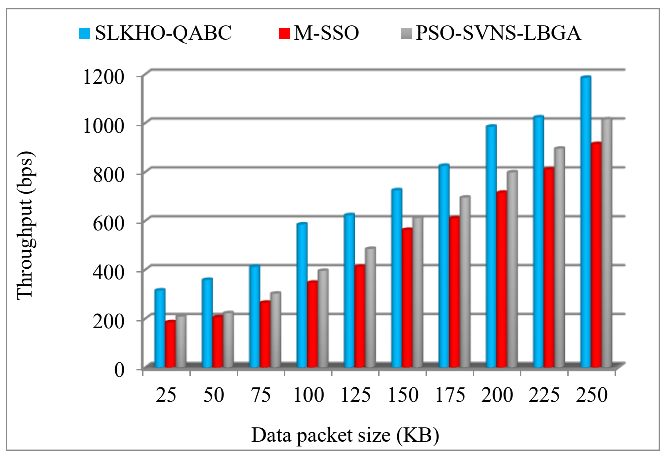

Fig. 8 Impact of throughput

Figure 8 illustrates the simulation analysis of throughput versus size of data packets. Observed outcomes denote which proposed *SLKHO-QABC* method attains superior performance in terms of achieving superior. T_{put} than the existing techniques. This important improvement of the *SLKHO-QABC* method is attained through effectual communication among vehicle nodes within the VANET. Let us take the 25KB size of the information packet being sent, the result of T_{put} was examined at 315bps, whereas the observed result of throughputs using two existing methods was found to be 185bps and 208bps, respectively. Similarly, the difference performance outcomes were performed and compared entire outcomes. Overall comparison outcome shows T_{put} is found to be increased by 48% and 32% using the *SLKHO-QABC* method than the conventional methods M-SSO, and PSO-SVNS-LBGA, respctively. This is owing to the choice of resource-effective nodes and less-loaded vehicle nodes, which are determined by employing Stochastic Universal Sampled Lagrangian Krill Herd Optimization. This optimization technique identifies vehicle nodes with higher residual energy, available bandwidth, and stronger signal strength. Consequently, it enhances the rate of data delivery per unit of time.

Table 6. D_{ED}

Number of Data Packets	D_{ED}(ms)		
	SLKHO-QABC	**M-SSO**	**PSO-SVNS-LBGA**
100	14	19.6	18
200	16.2	22.5	21.2
300	20.6	25.9	23.5
400	22.3	28	26.5
500	25.1	30.5	28.9
600	26.3	32	30.4
700	28.5	35.7	33.5
800	30.5	38	36
900	32	40.2	38.2
1000	34.6	42.9	40.6

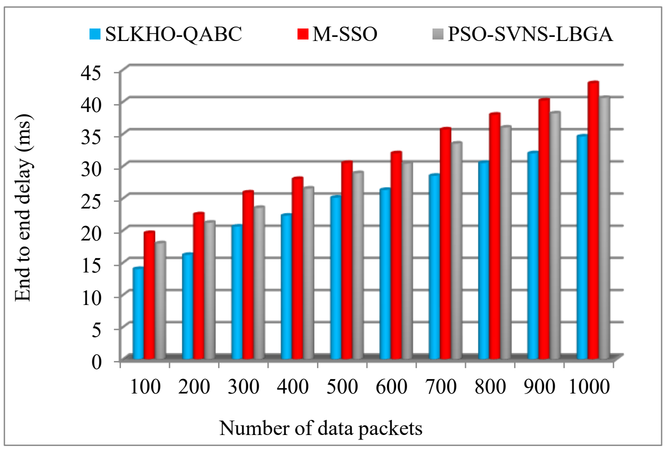

Fig. 9 Impact of D_{ED}

Performance analysis of D_{ED} using the *SLKHO-QABC* method and the other conventional methods, M-SSO and PSO-SVNS-LBGA, are shown in Figure 9. When the number of data packets increases (100, 200, 300… 1000), the overall D_{ED} of every three techniques is improved.

Simulations are conducted with 100 data packs, and the delay of data transmission was observed using the SLKHOQAB method, which was found to be $14ms$. The delay of M-SSO and PSO-SVNS-LBGA were found to be $19.6ms$ and $18ms$respectively. From the observed results, the proposed *SLKHO-QABC* method minimizes the delay by 21% and 16% when compared to existing M-SSO and PSO-SVNS-LBGA. This is accomplished by identifying vehicle nodes with higher bandwidth availability, greater energy efficiency, and stronger signal strength. These selected nodes enhance the rate of data communication, facilitating faster transmission. Furthermore, load balancing among vehicle nodes contributes to the continuous distribution of data with reduced delay.

6. Discussion

This study compares the proposed *SLKHO-QABC* method with the existing M-SSO and PSO-SVNS-LBGA are discussed with NS2.34 simulator based on various parameters, such as load balancing efficiency, throughput, and energy utilization, packet loss rate, as well as end-to-end delay.

The proposed *SLKHO-QABC* method is evaluated on a test dataset with different performance metrics, namely, load balancing efficiency, throughput, energy utilization, and packet loss rate, with respect to different numbers of data packets.

The results confirm that the proposed *SLKHO-QABC* method improved load balancing efficiency by 5.5.%, throughput by 40%, and reduced the Packet loss rate by 31% when compared to the existing methods M-SSO and PSO-SVNS-LBGA.

7. Conclusion and Future work

VANET includes a variety of applications demanding efficient data delivery. Due to the dynamic nature of topologies and frequent path disruptions in VANETs, an effective approach is essential to establish reliable data transmission paths from source to destination. This paper introduces the *SLKHO-QABC* method to address the load balancing issue by integrating resource optimization and load capacity analysis. Stochastic Universal Sampled Lagrangian Krill Herd Optimization is employed to optimize resource allocation among vehicle nodes within the network, thereby enhancing throughput and minimizing transmission delays.

Additionally, the load capacity of nodes is evaluated using Quadratic Associative Boost Classification to facilitate efficient data distribution. These processes collectively improve load balancing efficiency and mitigate packet loss rates. A comprehensive simulation is conducted by comparing the proposed *SLKHO-QABC* method with existing techniques. Results indicate superior performance of SLKHOQAB in terms of minimizing energy consumption, transmission delay, and packet loss rates while enhancing throughput and load balancing efficiency compared to conventional techniques. SLKHO-QABC method improves the load balancing efficiency by5.5.% and throughput by 40%, reduces the Packet loss rate by 31%, energy consumption by 18%, and end-to-end delay by 18.5%.

References

[1] Achyut Shankar et al., “A Modified Social Spider Algorithm for an Efficient Data Dissemination in VANET,” *Environment, Development and Sustainability*, pp. 1-44, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] S. Harihara Gopalan et al., “Data Dissemination Protocol for VANETs to Optimize the Routing Path using Hybrid Particle Swarm Optimization with Sequential Variable Neighbourhood Search,” *Telecommunication Systems*, vol. 84, no. 2, pp. 153-165, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Sahar Ebadinezhad, “Design and Performance Evaluation of Improved DFACO Protocol based on Dynamic Clustering in VANETs,” *SN Applied Sciences*, vol. 3, no. 486, pp. 1-15, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Madhuri Husan Badole, and Anuradha D. Thakare, “An Optimized Framework for VANET Routing: A Multi-Objective Hybrid Model for Data Synchronization with Digital Twin,” *International Journal of Intelligent Networks*, vol. 4, pp. 272-282, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Gagan Preet Kour Marwah, and Anuj Jain, “A Hybrid Optimization with Ensemble Learning to Ensure VANET Network Stability Based on Performance Analysis,” *Scientific Reports*, vol. 12, no. 10287, pp. 1-20, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] Syed Ehsan Haider, Muhammad Faizan Khan, and Yousaf Saeed, “Adaptive Load Balancing Approach to Mitigate Network Congestion in VANETS,” *Computers*, vol. 13, no. 8, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Koppisetti Giridhar, C. Anbuananth, and N. Krishnaraj, “Energy Efficient Clustering with Heuristic Optimization based Ro/uting Protocol for VANETs,” *Measurement: Sensors*, vol. 27, pp. 1-8, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Sham Rizal Bin Ramlee, Sazlinah Hasan, and Shamala K. Subramaniam, “Cluster Optimization in VANET Using MFO Algorithm and K-Means Clustering: A Bibliometric Review,” *International Journal for Multidisciplinary Research*, vol. 6, no. 2, pp. 1-65, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Ren Qun, and S.M. 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 Communication*, vol 15, no. 13, pp. 1665-1676, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[10] Ghassan Husnain, and Seyedeh Maryam Arefzadeh, “An Intelligent Cluster Optimization Algorithm based on Whale Optimization Algorithm for VANETs (WOACNET),” *Plos One*, vol. 16, no. 4, pp. 1-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Tony Santhosh Gnanasekar, and Dhandapani Samiappan, “Impact of Hybridized Rider Optimization with Cuckoo Search Algorithm on Optimal VANET Routing,” *International Journal of Communication System*, vol. 34, no. 16, pp. 1-21, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Masood Ahmad et al., “Optimized Clustering in Vehicular Ad Hoc Networks Based on Honey Bee and Genetic Algorithm for Internet of Things,” *Peer-to-Peer Networking and Applications*, vol. 13, no. 2, pp. 532-547, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] Amir Javadpour et al., “Enhancement in Quality of Routing Service Using Metaheuristic PSO Algorithm in VANET Networks,” *Soft Computing*, vol. 27, no. 5, pp. 2739-2750, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Kiran Afzal et al., “An Optimized and Efficient Routing Protocol Application for IoV,” *Mathematical Problems in Engineering*, vol. 2021, no. 1, pp. 1-32, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] Chenguang He et al., “A Two-Level Communication Routing Algorithm Based on Vehicle Attribute Information for Vehicular Ad Hoc Network,” *Wireless Communications and Mobile Computing*, vol. 2021, no. 1, pp. 1-14, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ravie Chandren Muniyandi et al., “An Improved Harmony Search Algorithm for Proactive Routing Protocol in VANET,” *Journal of Advanced Transportation*, vol. 2021, no. 1, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[17] V.M. Niaz Ahamed, and K. Sivaraman, “Congestion Control System Optimization with the Use of Vehicle Edge Computing in VANET Powered by Machine Learning,” *International Journal of Computer Networks and Applications*, vol. 11, no. 4, pp. 1-13, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Ali Seyfollahi, and Ali Ghaffari, “A Lightweight Load Balancing and Route Minimizing Solution for Routing Protocol for Low-Power and Lossy Networks,” *Computer Networks*, vol. 179, pp. 1-21, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[19] Shitong Ye et al., “A Deep Reinforcement Learning-Based Intelligent QoS Optimization Algorithm for Efficient Routing in Vehicular Networks,” *Alexandria Engineering Journal*, vol. 107, no. 6, pp. 317-331, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Aradhana Behura, M. Srinivas, amd Manas Ranjan Kabat, “Giraffe Kicking Optimization Algorithm Provides Efficient Routing Mechanism in the Field of Vehicular Ad Hoc Networks,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 8, pp. 3989-4008, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Long Luo et al., “Intersection-Based V2X Routing via Reinforcement Learning in Vehicular Ad Hoc Networks,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 6, pp. 5446-5459, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Dhwani Desai, Hosam El-Ocla, and Surbhi Purohit, “Data Dissemination in VANETs Using Particle Swarm Optimization,” *Sensors*, vol. 23, no. 4, pp. 1-21, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Nitin Singh Rajput et al., "Swarm Intelligence Inspired Meta-Heuristics for Solving Multi-Constraint QoS Path Problem in Vehicular Ad Hoc Networks," *Ad Hoc Networks*, vol. 123, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] Yujie Song et al., "STALB: A Spatio-Temporal Domain Autonomous Load Balancing Routing Protocol," *IEEE Transactions on Network and Service Management*, vol. 20, no. 1, pp. 73-87, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[25] Ahmad Raza Hameed et al., "Energy- and Performance-Aware Load-Balancing in Vehicular Fog Computing," *Informatics and Systems*, vol. 30, pp. 1-21, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[26] V. Manoj Kumar et al., "Chaotic Harris Hawks Optimization Algorithm for Electric Vehicles Charge Scheduling," *Energy Reports*, vol. 11, pp. 4379-4396, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] Arbelo Lolai et al., "Reinforcement Learning based on Routing with Infrastructure Nodes for Data Dissemination in Vehicular Networks (RRIN)," *Wireless Networks*, vol. 28, pp. 2169-2184, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Yixin He et al., "Joint Task Offloading, Resource Allocation, and Security Assurance for Mobile Edge Computing-Enabled UAV-Assisted VANETs", *Remote Sensors*, vol. 13, no. 8, pp. 1-26, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[29] Khalid Kandali et al., "An Intelligent Machine Learning Based Routing Scheme for VANET," *IEEE Access*, vol. 10, pp. 74318-74333, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[30] Arindam Debnath et al., "A Routing Technique for Enhancing the Quality of Service in Vanet," *IETE Journal of Research*, vol. 69, no. 4, pp. 2193-2206, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] Khaled Hejja, Sara Berri, and Houda Labiod, "Network Slicing with Load-Balancing for Task Offloading in Vehicular Edge Computing," *Vehicular Communications*, vol. 34, pp. 1-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[32] C. Fancy, and M. Pushpalatha, "Traffic-Aware Adaptive Server Load Balancing for Software Defined Networks" *International Journal of Electrical and Computer Engineering*, vol. 11, no. 3, pp. 2211-2218, 2021. [CrossRef] [Google Scholar] [Publisher Link]