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Original Article

Search and Rescue with Continuous Butterfly Optimization Algorithm for Secure Routing in Clustered Vehicular Networks

M V B Murali Krishna M [1], C. Anbu Ananth [2], N. Krishnaraj[3]

[1] *Department of Computer Science & Engineering, Annamalai University, Tamil Nadu, India.*
[2] *Department of Computer Science & Engineering, Annamalai University, Tamil Nadu, India.*
[3] *Department of Networking and Communications, School of Computing, SRM Institute of Science and Technology, Kattankulathur 603203, Tamilnadu, India.*

[1]*Corresponding Author : muralimk786@gmail.com*

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Abstract *- Recently, vehicular ad hoc network (VANET) has gained significant interest among research communities owing to the rapid innovations in autonomous driving technologies. The vehicles in VANET can interact with one another using the clusters and optimal routes. But the adequate changes in the VANET topology result in abrupt link distortions and high Delay. Besides, security is also a challenging issue in the VANET, which needs to be considered in designing a clustered-based routing approach for VANET. This study develops a novel search and rescue with a continuous butterfly optimization algorithm for multihop secure routing (SRCBO-MHSR) protocol for clustered VANET. The major intention of the SRCBO-MHSR model is to accomplish secure data transmission in VANET. The SRCBO-MHSR model initially derives a search and rescue optimization-based clustering (SAROC) technique for proficiently election cluster heads (CHs). Besides, the continuous butterfly optimization-based multihop routing (CBO-MHR) technique has been developed for optimal path selection. The CBO-MHR technique derives a fitness function with the inclusion of trust factors for secure data transmission in the network. The results of the SRCBO-MHSR technique are carried out, and outcomes are compared with existing models. The obtained results portrayed the efficiency of the SRCBO-MHSR technique with other benchmark models.*

Keywords *- Clustering, Multihop Routing, Metaheuristics, Secure Routing, VANET.*

1. Introduction

A vehicular adhoc network (VANET) mainly acts as a mesh network comprising fixed and mobile nodes. It is a kind of mobile adhoc network (MANET) that aims at providing transmission amongst nearby fixed equipment and adjacent vehicles. It is determined as a network with no centralized administration and architecture [1]. Intelligent VANET (IVANET) offers a smart means of utilizing vehicular networks [2]. It supports traffic monitoring, accident prevention, vehicular safety, etc. Even though VANET is a subgroup of MANET having distinct features from different kinds of adhoc networks, including wireless sensor network (WSN) and delay-tolerant network (DTN), the node in VANET is armed with a router and host simultaneously [3].

The capability and special property qualify VANET to set up and form network connectivity in outstanding environments involving forests, mountains, deserts, and natural disaster circumstances, whereby normal transmission architecture is lacking.

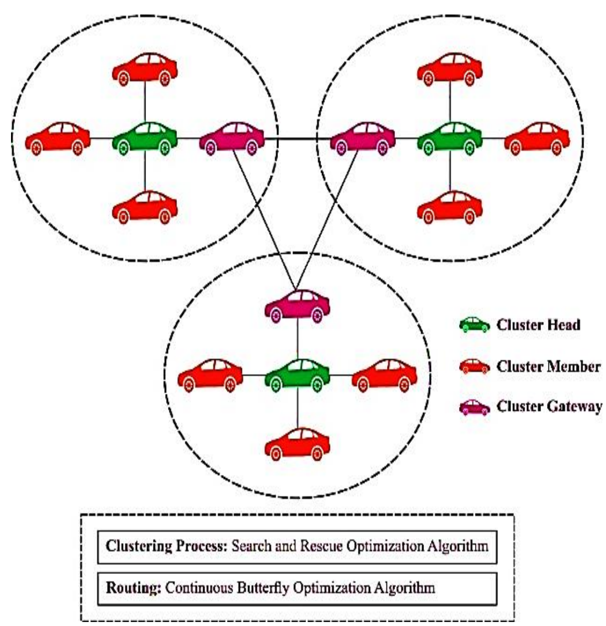

Fig. 1 VANET structure

Moreover, the dynamic topological characteristic enables VANET to operate as a part of public networks or as a standalone network, namely the Internet, with satellites and other transmission connections [4]. Fig. 1 depicts the framework of VANET.

In VANET, it is significant to progress an efficient and stable route to assist V2X communication. Services in VANET, including vehicle-safety-based transmission, need V2X messages must be transported fast and reliably [5]. Data regarding safety, all the data must be communicated correctly and timely through this route. Even though VANET suffers from several problems, including high node mobility, limited spectral bandwidth, and scalability, it has distinctive features, such as unlimited power and calculation capabilities and limited vehicle mobility patterns employed for mitigating this problem's effects [6].

Another aspect of this exploitation is the usage of the VANET cluster. Clustering in a VANET aim is to change the network architecture from flat to hierarchical by separating the networks into virtual groups of vehicles named clusters [7]. All the clusters have a leader, generally contributing as many cluster members (CMs) as the cluster head (CH). The CH servers as an access point or an infrastructure of the cluster. Next, rather than handling a perfect adhoc network, a virtual-architecture-based network is proposed with no requirement of exclusive physical architecture deployment [8].

Furthermore, once the clustering is performed considering the vehicle's mobility data, the cluster's topology becomes comparatively stable. Therefore, the extremely dynamic topology challenges become less dangerous [9]. Usually, this type of clustering is named mobility-based clustering [10].

Using a Support Vector Machine (SVM) based approach for estimating the node location and a hybrid Genetic Algorithm-Particle Swarm Optimization (GAPSO) based model for clustering optimise, the paper [11] presents a clustering routing method for the Internet of Things perception layer called GAPSO-SVM. This method uses a Genetic Algorithm-Particle Swarm Optimization (GAPSO) based model to cluster optimise. The encounter-aware and clustering-based routing technique (ECRA) for data-centric VANET were described by Zhang et al. [12]. The preparedness of the encounter makes it possible for the vehicle that is recording the movement track of the vehicle to find the terminal node quickly. K-Medoid Clustering is a technique established by researchers in [13] to cluster the vehicle node. Afterwards, the researchers selected the energy-effective node to compel transmission. A cluster-based reliable routing technique has been given for VANET [14]. This approach is intended for use with reliable applications. For the purpose of appropriate node clustering in this technique, simulated annealing has been applied.

Additionally, the parameter of node degree, as well as coverage and capacity, have been taken into consideration in the strategy that has been provided. Using the assumption that real-time transmission is available in VANET, Zhang et al. [15] introduced a routing approach called FLHQRP. The virtual grid is offered to segment the vehicle networks into groups. To choose the optimal CH in the cluster with a reliable transmission link, the node mobility and centrality, as well as the bandwidth efficiency, are considered by applying the fuzzy logic technique.

This study develops a novel search and rescue with a continuous butterfly optimization algorithm for multihop secure routing (SRCBO-MHSR) protocol for clustered VANET. The major intention of the SRCBO-MHSR model is to accomplish secure data transmission in VANET. The SRCBO-MHSR model initially derives a search and rescue optimization-based clustering (SAROC) technique for proficiently election cluster heads (CHs). Besides, the continuous butterfly optimization-based multihop routing (CBO-MHR) technique has been developed for optimal path selection. The CBO-MHR technique derives a fitness function with the inclusion of trust factors for secure data transmission in the network.

2. The Proposed Model

In this study, a new SRCBO-MHSR protocol has been developed for achieving energy efficiency and security in VANET. It mainly intends to attain secure data transmission in VANET. The SRCBO-MHSR model performs two major processes: the SAROC technique for CH selection and CBO-MHR technique for optimal route selection. The CBO-MHR technique derives a fitness function with the inclusion of trust factors for secure data transmission in the network.

2.1. Process involved in SAROC Technique

At the initial stage, the SAROC technique was applied to choose CHs and organize clusters in VANET. The location of the lost human is an important simulation of SAR optimized technique to optimize issues, and the effect of clues established under this place defines the cost of solutions. At this point, an optimum technique exposes an optimum place with further hints [16]. An individual looks to an optimum option throughout the search but exits several clues. But, the left clue has been kept from the memory matrix (matrix M), and the searching places to individuals were kept from the conditioned matrix (matrix X) with similar sizes of memory matrix, $n \times d$, particulars the problem dimensional and n refers the individual quantity from the group. In this case, the clue is attained by the subsequent formula:

$$M = \begin{bmatrix} X \\ M \end{bmatrix} = \begin{bmatrix} X_{1,1} & \dots & X_{1,d} \\ \vdots & \ddots & \vdots \\ X_{n,l} & \dots & X_{n,d} \\ M_{1,1} & \cdots & M_{1,d} \\ \vdots & \ddots & \vdots \\ M_{n,l} & \cdots & M_{n,d} \end{bmatrix} \quad (1)$$

As before declared, by considering an arbitrary clue amongst the attained clues, the searching way has achieved as:

$$sp_i = (X_j - C_k), k \neq i \quad (2)$$

where k refers to the arbitrary value amongst one and twoN, X_i and C_k implies the place of i^{th} humans and k^{th} clue correspondingly. It is noticeable because $i = k,\ C_i$ equivalents $X_i,\ k \neq i.$ In order to prevent repetitive place searches, the dimensional of X_i is not be changed utilized move from the way in Eq. (2).

The SAR technique utilizes a binomial crossover function for applying to constraint. In addition, when the considered clue is further significant than the present clue, the region was searched to sp_i direction and assumed clue. If not so, afterwards search for the place of the present place from sp_i has continued. A novel place of j^{th} dimensional is so expressed as follows to the i^{th} human:

$$X_{ij} = \begin{cases} Matrix_{X_{ii}-C_{ki}}^{X_{ii}-C_{ki}})\ i \dots, d \\ X_i\ otherwise \end{cases} \quad (3)$$

$$X_{ij} = \begin{cases} \begin{cases} c_{k,j} + r_1 \times (X_{i,j} - C_{k,j}) & (X_i) \\ X_{i,j} + r_1 \times (X_{i,j} - C_{k,j}) & otherwise \end{cases} \\ \quad X_i \end{cases} \quad (4)$$

where, $c_{k,j}$ indicates the place of dimensional number j and clue number $k.j_r$, r_1 and r_2 denotes the 3 uniform arbitrary values from the ranges $[1, d]$, $[-1,1]$ and $[0,1]$ correspondingly. The following stage is individuals. During this stage, the exploitation term is complete about the present human place. This stage employs the various clues linking ideas in the social stage. The place upgrade by the human number i has attained by the subsequent:

$$X_i' = X_j + r_3 \times (C_k - C_m), \quad (5)$$

where, r_3 implies the uniformly arbitrary distributing values amongst zero and one, and m and k refer to the 2 arbitrary values amongst one and two$N$ and $i \neq k \neq m.$ It might seem that the solution area that comes later has attained the solution in the phases that came before it. This stage is referred to as the Boundary stage. In this scenario, the ensuing formula is used whenever the answer is located outside the boundaries.

$$X_{ij}' = \begin{cases} \frac{(X_{ij} + X_j^{\max})}{2}\ if\ X_{ij}' > X_j^{\max} \\ \frac{(X_{i,j} + X_j^{\min})}{2}\ if\ X_{ij}' < X_j^{\min} \end{cases} \quad (6)$$

where, $j = 1,2, \dots, d, X_j^{min}$ and X_j^{max} stands for the minimal and maximal threshold to dimensional number j, correspondingly. According to this stage, the lost human candidate was searched dependent upon the previously described technique. When the count of cost function from the condition $X_i'(f(X_i'))$ has superior to the current one $(f(X_i))$, the preceding place (X) is kept from the accidental place from the memory matrix (M) and has described a novel condition. Then, this condition has left, and the memory has not been enhanced. Fig. 2 illustrates the flowchart of the SAR technique.

$$M_n = \begin{cases} X_j\ if\ f(X_i') > f(X_i) \\ M_n\ otherwise \end{cases} \quad (7)$$

$$X_i = \begin{cases} X_i'\ if\ f(X_i') > f(X_i) \\ X_i\ otherwise \end{cases} \quad (8)$$

where n refers to the arbitrary integer amongst 1 and N, and M_n represents the place of clue numbers n from the memory matrix. Because of the reason for hurting himself, time is vital for placing the missing people; some more delay in the search also leads to death. Thus, when the person under his quest doesn't define the notable clue, it exits a novel one with the existing place. The subsequent formula was utilized for solving these abandonment clues:

$$usn_i = \begin{cases} usn_i + 1\ if\ f(X_i') < f(X_i) \\ 0\ otherwise \end{cases} \quad (9)$$

whereas usn determines the unproductive search numbers. In this case, the SAR technique was obtainable for selecting a group of nodes for working as CH, so it minimalized the energy used to broadcast data. An optimized purpose is to define an optimum group of nodes to work as heads that minimalize energy consumption and extend the network's lifespan. The main function is to increase the network lifespan (δ_n^n) that terminates when the primary node exit:

$$\delta_n^1 = \min_{s \in S} \delta_s \quad (10)$$

At this point, δ_s signifies the node lifespan s and S denotes the set of nodes. Whereas n sensor is uniformly distributed, and k refers to the clusters. Therefore, there are n/k nodes to all the clusters (one CH and $(n/k) - 1$ CM). The entire energy utilized by CH (e_{CH}) to individual's iteration has expressed as:

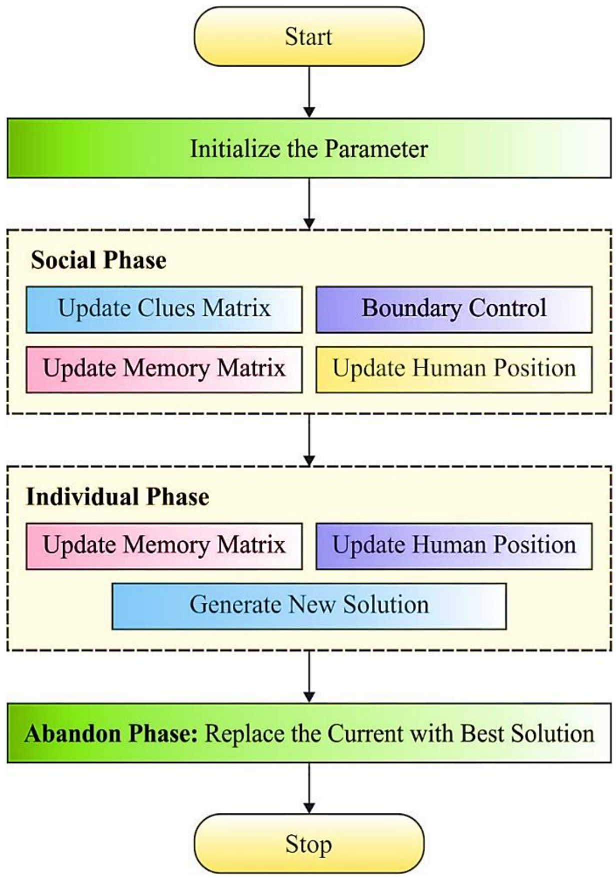

Fig. 2 Flowchart of SAR technique

$$e_{CH} = \left(\frac{n}{k} - 1\right). E_{Rx}(b) + \frac{n}{k}. b. E_{DA} + E_{Tx}(b, d_{toBS}) \quad (11)$$

The CM node transfers its data to its CH; thus, the entire energy utilized by the CM nodes over iteration by Eq. (12):

$$e_{CM} = E_{Tx}(b, d_{toCH}). \quad (12)$$

Where as d_{toBS} and d_{toCH} defines the average distance amongst the head node and BS, as well as the average distance amongst CH and member nodes correspondingly. The entire utilized energy from the cluster at the iteration

$$E_{consumed}^{cluster} = e_{CH} + e_{CM} \quad (13)$$

The purpose is to improving δ_n^1 with reducing the entire energy utilized from the networks to all iterations, CH rotation has been obtained to balance the energy utilized. Therefore, the FF is demonstrated as follows:

$$F = \frac{\sum_{i=1}^{k} E_{consumed}^{cluster}(i)}{a + \sum_{i=1}^{k} E_{consumed}^{cluster}(i)} + \left(\frac{\beta}{a + \beta}\right) \quad (14)$$

Where as the count of CHs referred to as k, β refers to the entire count of times the node chosen as CH a implies the constant superior to 0.

2.2. Process involved in CBO-MHR Technique

Next, the CBO-MHR technique was developed in the second stage to choose routes for secure data transmission. CBO is fundamentally simulated as the food foraging performance of butterflies (BFs), and these BFs are utilized as a searching agent for implementing optimized from CBO [17]. In the CBO, the fragrance has been expressed as a purpose of the physical intensity of the stimulus as follows:

$$pf_i = cI^a \quad (15)$$

Where pf_i refers to the perceived magnitude of fragrances; for instance, they strongly the fragrance of i^{th} BF has supposed that another BFs current from the area, c represents the sensory modality, I denotes the stimulus intensity, and a indicates the power exponents depend on modality that accounts for changing the degree of absorptions. During the CBO, an artificial BF is a place vector that is upgraded utilizing in the optimized procedure utilizing:

$$x_{i^{t+1}} = x_{i^t} + F_i^{t+1} \quad (16)$$

Where x_i^t stands for the solution vectors x_i to i^{th} BF from the iteration number t and F_i stands for the fragrance that is employed by x_i^{th} BF for updating their place under the course of iterations. Moreover, there are 2 key stages of the technique, for instance, global and local searching phases. During the global searching stage, the BF gets a step near the fittest BF or solution g^* that is expressed as:

$$F_i^{t+1} = (r^2 \times g^* - x_i^t) \times pf_i \quad (17)$$

At this point, g^* denotes the present optimum solutions initiate amongst every solution of existing iteration. The supposed fragrance of i^{th} BF has signified as pf_i and r refers to the uniform arbitrary number from zero and one. The local searching stage is demonstrated as follows:

$$F_i^{t+1} = \left(r^2 \times x_{j^t} - x_{k^t}\right) \times pf_i \quad (18)$$

Where x_{j^t} and x_{k^t} are j^{th} and k^{th} BFs in the solution spaces. When x_{j^t} and x_{k^t} goes to the similar population, and r refers to the uniform arbitrary number from zero, and one afterwards develops the arbitrary local walk. The switch probability p has been utilized from CBO for switching amongst usual global searching for intensive local searching. The CBO-MHR technique derives an objective function for secure and energy-efficient data transmission in the network. Consider $h1$ as a parameter of residual energy, which needs to be high for routing the data. Next, $h2$ be another parameter denoting the distance, which needs to be lower.

Finally, $h3$ be the third objective function which indicates the trust factor of the nodes, which needs to be high. All the trust metrics have a particular weight that provides the capability for controlling/adjusting the priority of all metrics based on the needed applications. Eq. (19) refers to the denes how to direct trust value has been computed as node i to node j.

$$DT(i,j) = \sum_{k=1}^{m} W_k * T_k(i,j) \quad (19)$$

Whereas m implies the amount of trust metrics; W_k demonstrates the weighted value of metrics k such that $\sum_{k=1}^{m} W_k = 1; T_k(i,j)$ is the trust value fixed by node i on metric k to node j.

Consider b_{ij} be a Boolean variable which can be represented as follows.

$$b_{ij} = \begin{cases} 1 & if\ nexthop(CH_i) = CH_j, \forall_{i,j} 1 \le i,j \le m \\ 0 & Otherwise \end{cases} \quad (20)$$

Minimization of

$$F = \frac{1}{h_1} \times \beta_1 + h_2 \times \beta_2 + \frac{1}{h_3} \times \beta_3 \quad (21)$$

Subjected to,

$$dis(CH_i, CH_j) \times \le d_{\max} CH_j \varepsilon \{C + BS\} \quad (22)$$

$$\sum_{j=1}^{m} b_{ij} = 1\ and\ 1 \ne j \quad (23)$$

where $0 < \beta_1, \beta_2, \beta_3 < 1$.

3. Performance Validation

This section aims to evaluate the clustering and routing efficacy of the SRCBO-MHSR model. Table 1 and Fig. 3 inspect the end-to-end Delay (ETED) examination of the SRCBO-MHSR model with recent methods under distinct nodes. The figure shows that the SRCBO-MHSR model has accomplished effectual outcomes with the least ETED over the other methods. For example, under 100 nodes, the SRCBO-MHSR model has led to decreased ETED of 0.4643s, whereas the GA-AODV, LEACH-GA, and GA-AOMDV models have reached an increased ETED of 0.5903s, 0.5492s, and 0.4815s respectively. Moreover, under 350 nodes, the SRCBO-MHSR model has attained a reduced ETED of 0.5769s, whereas the GA-AODV, LEACH-GA, and GA-AOMDV models have obtained higher ETED of 0.7678s, 0.7057s, and 0.6418s respectively.

Table 1. ETED analysis of SRCBO-MHSR technique with the count of nodes

End-to-End Delay (sec)				
No. of Nodes	GA-AODV	LEACH-GA	GA-AOMDV	SRCBO-MHSR
100	0.5903	0.5492	0.4815	0.4643
150	0.6084	0.5626	0.5225	0.4815
200	0.6361	0.6122	0.5292	0.4910
250	0.6981	0.6246	0.5779	0.5053
300	0.7420	0.6752	0.6132	0.5416
350	0.7678	0.7057	0.6418	0.5769

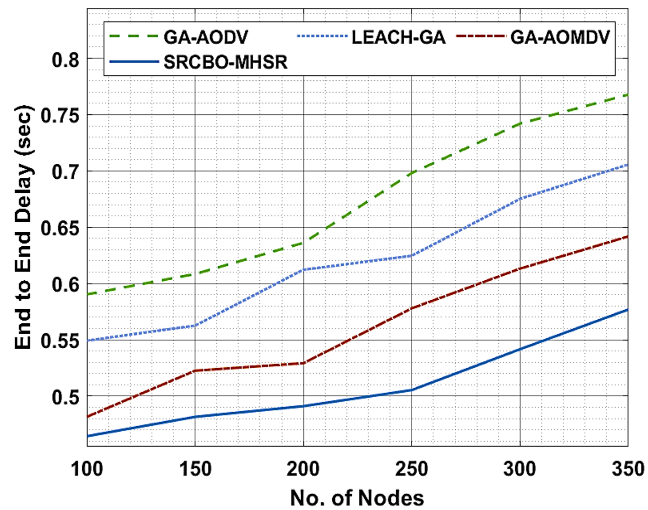

Fig. 3 ETED analysis of SRCBO-MHSR technique with recent approaches

Table 2. ECM analysis of SRCBO-MHSR technique with the count of nodes

Energy Consumption (J)				
No. of Nodes	GA-AODV	LEACH-GA	GA-AOMDV	SRCBO-MHSR
100	154.94	145.86	131.61	116.45
150	189.03	175.25	155.80	129.23
200	229.81	213.58	190.70	144.48
250	283.71	260.73	233.24	207.91
300	346.59	319.72	283.03	237.48
350	397.14	370.65	340.11	303.16

Table 2 and Fig. 4 examine the ECM examination of the SRCBO-MHSR technique with recent approaches under different nodes. The figure shows that the SRCBO-MHSR methodology has accomplished effectual outcomes with the least ECM over the other methods. For example, under 100 nodes, the SRCBO-MHSR model has reduced ECM of 116.45J whereas the GA-AODV, LEACH-GA, and GA-AOMDV techniques have reached maximum ECM of 154.94J, 145.86J, and 131.61J correspondingly.

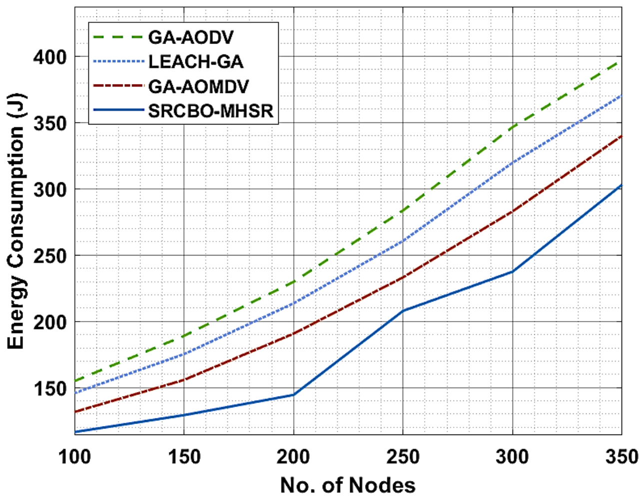

Fig. 4 ECM analysis of SRCBO-MHSR technique with recent approaches

At the same time, under 350 nodes, the SRCBO-MHSR method has obtained a reduced ECM of 303.16J, whereas the GA-AODV, LEACH-GA, and GA-AOMDV approaches have obtained a superior ECM of 397.14J, 370.65J, and 340.11J correspondingly.

A comparative throughput (THRP) investigation of the SRCBO-MHSR model with existing ones is provided in Table 3 and Fig. 5. The experimental results stated that the SRCBO-MHSR model has resulted in increased values of THRP under several nodes.

For instance, with 100 nodes, the SRCBO-MHSR model has gained effective performance with an increased THRP of 3.08Mb/s, whereas the GA-AODV, LEACH-GA, and GA-AOMDV models have demonstrated reduced THRP of 2.25Mb/s, 2.35Mb/s, and 2.57Mb/s respectively.

Furthermore, under 350 nodes, the SRCBO-MHSR model has depicted a maximum THRP of 4.02Mb/s, whereas the GA-AODV, LEACH-GA, and GA-AOMDV models have provided minimal THRP of 2.91Mb/s, 3.20Mb/s, and 3.34Mb/s respectively.

Table 3. Throughput analysis of the SRCBO-MHSR technique with the count of nodes

Throughput (Mb/sec)				
No. of Nodes	GA-AODV	LEACH-GA	GA-AOMDV	SRCBO-MHSR
100	2.25	2.35	2.57	3.08
150	2.21	2.55	2.43	3.07
200	2.29	2.79	2.92	3.78
250	2.74	2.87	3.12	3.81
300	2.70	2.97	3.10	3.91
350	2.91	3.21	3.34	4.02

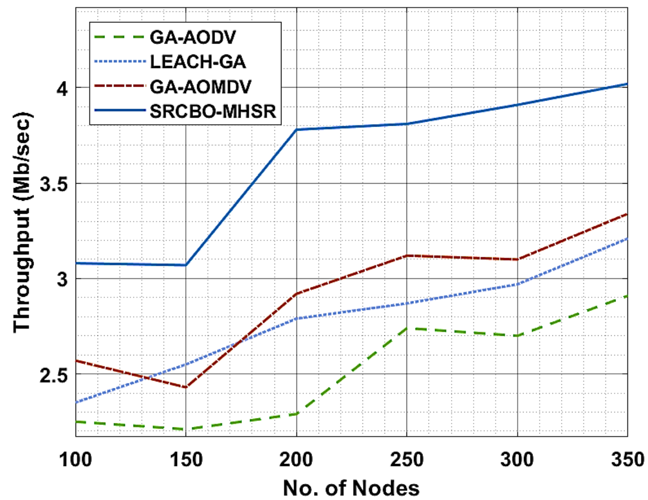

Fig. 5 Throughput analysis of SRCBO-MHSR technique with recent approaches

Table 4. PDR analysis of the SRCBO-MHSR technique with the count of nodes

Packet Delivery Ratio (%)				
No. of Nodes	GA-AODV	LEACH-GA	GA-AOMDV	SRCBO-MHSR
100	87.65	88.37	89.27	90.43
150	88.62	89.36	90.49	91.10
200	89.00	90.13	91.18	91.94
250	89.75	90.83	92.39	93.23
300	90.45	91.82	92.85	93.51
350	91.33	92.36	93.90	94.26

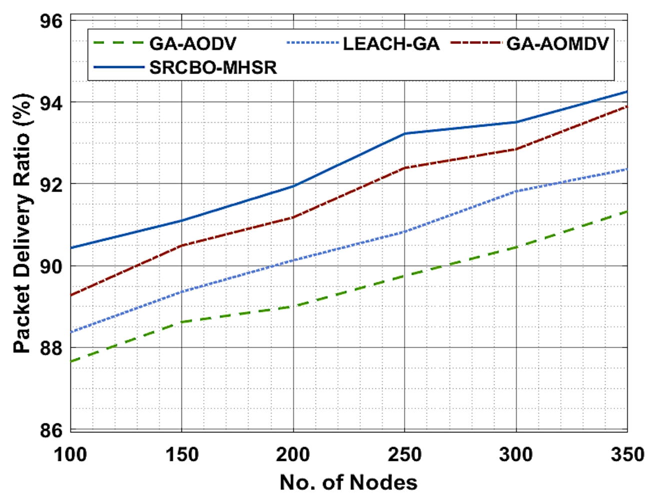

Fig. 6 PDR analysis of SRCBO-MHSR technique with recent approaches

A detailed PDR analysis of the SRCBO-MHSR technique with existing ones is offered in Table 4 and Fig. 6. The experimental outcomes revealed that the SRCBO-MHSR system has resulted in higher values of PDR under several nodes. For the sample with 100 nodes, the SRCBO-MHSR model has gained effective performance with an increased PDR of 90.43%, whereas the GA-AODV, LEACH-GA, and GA-AOMDV models have outperformed decreased PDR of 87.65%, 88.37%, and 89.27% correspondingly. Eventually, under 350 nodes, the SRCBO-MHSR methodology has portrayed an increased PDR of 494.26%, whereas the GA-AODV, LEACH-GA, and GA-AOMDV algorithms have provided lower PDR of 91.33%, 92.36%, and 93.90% correspondingly.

Table 5 and Fig. 7 determine the PLR investigation of the SRCBO-MHSR system with recent techniques under distinct nodes. The figure demonstrated that the SRCBO-MHSR method had accomplished effectual outcomes with minimum PLR over the other approaches. For example, under 100 nodes, the SRCBO-MHSR technique has led to decreased PLR of 9.57%, whereas the GA-AODV, LEACH-GA, and GA-AOMDV techniques have achieved increased PLR of 12.35%, 11.63%, and 10.73% correspondingly.

Under 350 nodes, the SRCBO-MHSR model has attained a reduced PLR of 5.74%, whereas the GA-AODV, LEACH-GA, and GA-AOMDV methodologies have obtained a maximum PLR of 8.67%, 7.64%, and 6.10% respectively.

Table 5. PLR analysis of SRCBO-MHSR technique with the count of nodes

Packet Loss Rate (%)				
No. of Nodes	**GA-AODV**	**LEACH-GA**	**GA-AOMDV**	**SRCBO-MHSR**
100	12.35	11.63	10.73	9.57
150	11.38	10.64	9.51	8.90
200	11.00	9.87	8.82	8.06
250	10.25	9.17	7.61	6.77
300	9.55	8.18	7.15	6.49
350	8.67	7.64	6.10	5.74

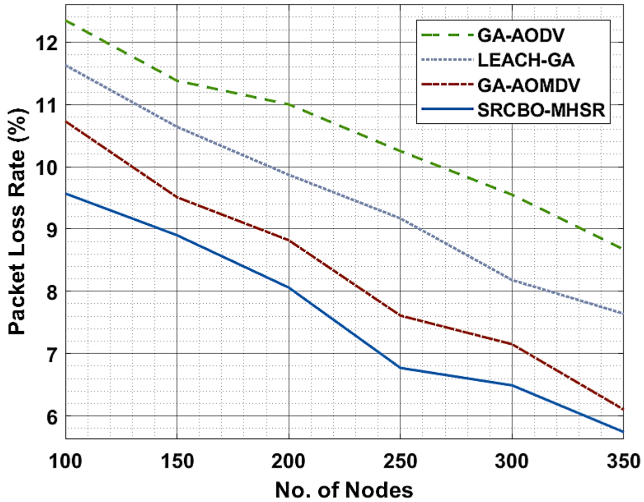

Fig. 7 PLR analysis of SRCBO-MHSR technique with recent approaches

Table 6. Transmission overhead analysis of the SRCBO-MHSR technique with the count of nodes

Transmission Overhead (kb)				
No. of Nodes	**GA-AODV**	**LEACH-GA**	**GA-AOMDV**	**SRCBO-MHSR**
100	3.302	3.581	1.964	1.277
150	5.871	6.404	2.799	2.407
200	7.392	10.468	3.315	2.810
250	8.717	15.605	3.921	3.470
300	12.809	20.849	5.226	4.605
350	16.387	21.554	5.945	4.812

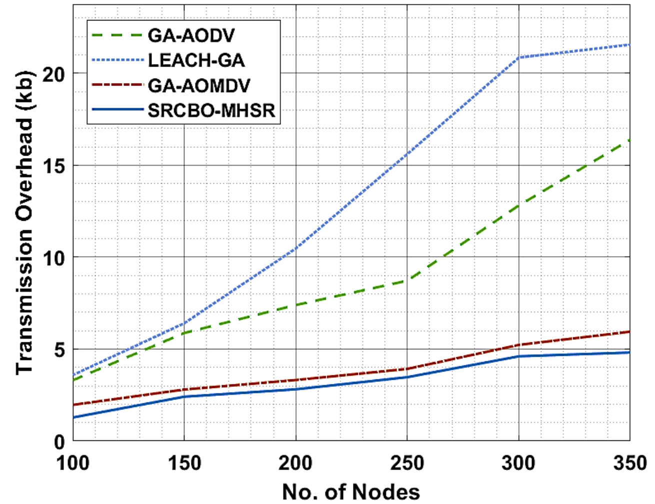

Fig. 8 TOH analysis of SRCBO-MHSR technique with recent approaches

Table 6 and Fig. 8 illustrate the transmission overhead (TOH) analysis of the SRCBO-MHSR model with recent algorithms under distinct nodes [18]. The figure outperformed that the SRCBO-MHSR model has accomplished effectual outcomes with the least TOH over the other methods.

For example, under 100 nodes, the SRCBO-MHSR model has led to decreased TOH of 1.277kb, whereas the GA-AODV, LEACH-GA, and GA-AOMDV techniques have reached an increased TOH of 3.302kb, 3.581kb, and 1.964kb correspondingly. In addition, under 350 nodes, the SRCBO-MHSR methodology has attained a reduced TOH of 4.812kb, whereas the GA-AODV, LEACH-GA, and GA-AOMDV techniques have obtained higher TOH of 16.387kb, 21.554kb, and 5.945kb correspondingly.

From the results and discussion, it can be concluded that the SRCBO-MHSR model can attain maximum performance over the other methods in clustered VANET.

4. Conclusion

In this study, a new SRCBO-MHSR protocol has been developed for achieving energy efficiency and security in

VANET. It mainly intends to attain secure data transmission in VANET. The SRCBO-MHSR model performs two major processes: the SAROC technique for CH selection and CBO-MHR technique for optimal route selection. The CBO-MHR technique derives a fitness function with the inclusion of trust factors for secure data transmission in the network. The experimental analysis of the SRCBO-MHSR technique is carried out, and the results are compared with existing models. The obtained results portrayed the betterment of the SRCBO-MHSR technique over the other recent models. In future, lightweight cryptographic solutions can be designed to improve the security of the VANET.

References

[1] D.Chandramohan, A.Dumka and L.Jayakumar, . 2M2C-R2ED: “Multi-Metric Cooperative Clustering Based Routing for Energy Efficient Data Dissemination in Green-Vanets,” *Technology and Economics of Smart Grids and Sustainable Energy*, vol. 5, no. 1, pp.1-14, 2020.

[2] M.Mohammadnezhad,and A.Ghaffari, “Hybrid Routing Scheme Using Imperialist Competitive Algorithm and RBF Neural Networks for Vanets,” *Wireless Networks*, vol. 25, no. 5, pp.2831-2849,2019.

[3] M.A.Mujahid, K.Abakar, T.S Darwish and F.T Zuhra, “Cluster-Based Location Service Schemes in Vanets: Current State, Challenges and Future Directions,” *Telecommunication Systems*, vol. 76, no. 3, pp.471-489,2021.

[4] R.Kolandaisamy, R.M noor, I.Kolandaisamy, I.Ahmedy, M.L.M Kiah, M.E.M Tamil and T.Nandy, 2 “A Stream Position Performance Analysis Model Based on Ddos Attack Detection for Cluster-Based Routing in VANET,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 6, pp.6599-6612,2021.

[5] H.Fatemidokht and M.K Rafsanjani, QMM-VANET: “An Efficient Clustering Algorithm Based on Qos and Monitoring of Malicious Vehicles in Vehicular Ad Hoc Networks,” *Journal of Systems and Software*, vol. 165, pp..110561,2020.

[6] R.Kolandaisamy, R.M noor, I. Kolandaisamy, I. Ahmedy, M.L.M Kiah, M.E.M Tamil and T.Nandy, “A Stream Position Performance Analysis Model Based on Ddos Attack Detection for Cluster-Based Routing in VANET, “ *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 6, pp. 6599-6612, 2021.

[7] S.Hosmani and B.Mathapati, “Efficient Vehicular Ad Hoc Network Routing Protocol Using Weighted Clustering Technique,” *International Journal of Information Technology*, vol. 13, no. 2, pp. 469-473, 2021.

[8] A. Javadpour, S.Rezaei, A.K. Sangaiah, A.Slowik and S.Mahmoodi Khaniabadi, “Enhancement in Quality of Routing Service Using Metaheuristic PSO Algorithm in VANET Networks,” *Soft Computing*, pp.1-12,2021.

[9] Y.Azzoug and A.Boukra, “Bio-Inspired VANET Routing Optimization: An Overview. *Artificial Intelligence Review,*” vol. 54, no. 2, pp.1005-1062,2021.

[10] R.Kaur,R.K. Ramachandran,R.Doss and L.Pan, “The Importance of Selecting Clustering Parameters in Vanets,”: A Survey, *Computer Science Review*, vol. 40, pp. 100392,2021.

[11] M.norouzi Shad, M.Maadani and M.Nesari Moghadam, GAPSO-SVM: “An IDSS-Based Energy-Aware Clustering Routing Algorithm for Iot Perception Layer” *Wireless Personal Communications*, pp.1-20, 2021.

[12] W.Zhang,R.Zheng,M. Zhang,J. Zhu and Q. Wu, ECRA: “An Encounter-Aware and Clustering-Based Routing Algorithm for Information-Centric Vanets,” *Mobile Networks and Applications*, vol. 25, no. 2, pp. 632-642,2020.

[13] M. Elhoseny. and K.Shankar, “Energy Efficient Optimal Routing for Communication in Vanets Via Clustering Model. in Emerging Technologies for Connected Internet of Vehicles and Intelligent Transportation System Networks,” *Springer, Cham*, pp. 1-14, 2020.

[14] H.Bagherlou and A.Ghaffari, “A Routing Protocol for Vehicular Ad Hoc Networks Using Simulated Annealing Algorithm and Neural Networks,” *The Journal of Supercomputing*, vol. 74, no. 6, pp.2528-2552,2018.

[15] W.L.Zhang, X.Y Yang, Q.X Song, and L.Zhao, “V2V Routing in VANET Based on Fuzzy Logic and Reinforcement Learning,” *International Journal of Computers, Communications & Control*, vol. 16, no. 1, 2021.

[16] C.Muppala, and V.Guruviah, “Detection of Leaf Folder and Yellow Stemborer Moths in the Paddy Field Using A Deep Neural Network With Search and Rescue Optimization,” *Information Processing in Agriculture*, , vol. 8, no. 2, pp. 350-358,2021.

[17] Z.Sadeghian, E.Akbari and H.Nematzadeh, “A Hybrid Feature Selection Method Based on Information Theory and Binary Butterfly Optimization Algorithm,” *Engineering Applications of Artificial Intelligence*, vol. 97, pp. 104079, 2021.

[18] L. Tan Et Al., "Speech Emotion Recognition Enhanced Traffic Efficiency Solution for Autonomous Vehicles in A 5G-Enabled Space–Air–Ground Integrated Intelligent Transportation System," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 3, pp. 2830-2842, March 2022, Doi: 10.1109/TITS.2021.3119921.

[19] F. Ding, G. Zhu, Y. Li, X. Zhang, P. K. Atrey and S. Lyu, "Anti-Forensics for Face Swapping Videos Via Adversarial Training," *IEEE Transactions on Multimedia*, Doi: 10.1109/TMM.2021.3098422.

[20] M.Supriya, Dr.T.Adilakshmi, "Secure Routing Using ISMO for Wireless Sensor Networks," *SSRG International Journal of Computer Science and Engineering*, vol. 8, no. 12, pp. 14-20, 2021. Crossref, https://doi.org/10.14445/23488387/IJCSE-V8I12P103.

[21] L. Zhao, Z. Bi, A. Hawbani, K. Yu, Y. Zhang, M. Guizani, "ELITE: An Intelligent Digital Twin-Based Hierarchical Routing Scheme for Softwarized Vehicular Networks," *IEEE Transactions on Mobile Computing*, 2022, DOI: 10.1109/TMC.2022.3179254.

[22] J.Patel and H. El-Ocla, "Energy Efficient Routing Protocol in Sensor Networks Using Genetic Algorithm," *Sensors*, vol. 21, no. 21, pp. 7060,2021.

[23] Kishor N Tayade, M U Kharat, "Mobility Prediction and Enhancement of Link Stability in VANET Using MGPSR and MAODV Protocol," *International Journal of Engineering Trends and Technology*, vol. 70, no. 3, pp. 66-74, 2022.

[24] K.A Theodore Shaji, K. Rajiv Gandhi, V. Palanisamy, "Privacy Preserving Lightweight Cryptography Scheme for Clustered Vehicular Adhoc Networks" *International Journal of Engineering Trends and Technology*, vol. 70, no. 7, pp. 24-31, 2022.
Crossref, https://doi.org/10.14445/22315381/IJETT-V70I7P203.

[25] Md. Humayun Kabir. "Research Issues on Vehicular Ad Hoc Network" *International Journal of Engineering Trends and Technology (IJETT),* vol. 6, no. 4, pp.174-179 , 2013.

[26] Q. Zhang Et Al., "Graph Neural Networks-Driven Traffic Forecasting for Connected Internet of Vehicles," *IEEE Transactions on Network Science and Engineering,* Doi: 10.1109/TNSE.2021.3126830.