Golden jackal optimization-based clustering scheme for energy-aware vehicular ad-hoc networks

Mahalakshmi Baladhandapani[1], Shoaib Kamal[2], Chevella Anil Kumar[3], Jegajothi Balakrishnan[4], Segu Praveena[5], Ezudheen Puliyanjalil[6]
[1]Department of School of Computer Studies, RVS College of Arts and Science, Sulur, India
[2]Department of ECE, Dr. B. R. Ambedkar Institute of Technology, Port Blair Andaman and Nicobar Islands, India
[3]Department of Artificial Intelligence and Data Science, Saveetha Engineering College, Chennai, India
[4]Department of ECE, Saveetha School of Engineering, Chennai, India
[5]Department of Electronic and Communication Engineering, Mahatma Gandhi Institute of Technology is a Technological Institution, Hyderabad, India
[6]Computer Science and Engineering, Government Engineering College Thrissur, Thrissur Engineering College P O, Thrissur, India

Article Info

Article history:

Received Feb 12, 2024
Revised Jun 11, 2024
Accepted Jun 24, 2024

Keywords:

Clustering
Communication
Energy efficiency
Metaheuristics
VANET

ABSTRACT

Clustering in vehicular ad-hoc networks (VANETs) plays a pivotal role in enhancing the reliability and efficiency of transmission among vehicles. VANET is a dynamic and highly mobile network where vehicles form clusters to enable effective data exchange, resource allocation, and cooperative actions. Clustering algorithm, helps vehicles self-organize into clusters based on connectivity and proximity, thus improving scalability and reducing transmission overhead. This cluster enables critical applications such as traffic management, collision avoidance, and data dissemination in VANET, which contribute to more efficient and safer transportation systems. Effective clustering strategy remains an active area of research to address the unique challenges posed by the diverse and rapidly changing environments of VANET. Therefore, this article presents a golden jackal optimization-based energy aware clustering scheme (GJO-EACS) approach for VANET. The presented GJO-EACS technique uses a dynamic clustering approach which adapts to the varying network topologies and traffic conditions, intending to extend the network lifetime and improve energy utilization. The results highlight the potential of the GJO-EACS technique to contribute to the sustainable operation of VANETs, making it a valuable contribution to the field of vehicular networking and smart transportation systems.

Corresponding Author:

Jegajothi Balakrishnan
Department of ECE, Saveetha School of Engineering
Chennai, India
jegajothibalakrishnan@gmail.com

1. INTRODUCTION

Vehicular ad hoc network (VANET) contains automobiles associated with each other through a short-term link without any access to central point. VANETs increase road security as well as offer safety for passengers and drivers via periodic sharing of messages [1]. The shared data includes status information like direction, speed, and position of all vehicles, threat warnings, and data regarding present traffic situations [2]. Every automobile is prepared with transceivers in order to interconnect by employing wireless access for vehicular environments (WAVE) [3]. Nonstop movement of vehicles means that a VANET topology is extremely vigorous. Frequent interruptions between vehicles and loss of messages are common particularly below increasing amount of vehicles in a dynamic topology [4]. So, it's a highly challenging task for a message protocol to make sure trustworthy messages for applications of vehicular and be accessible at an equal time [5]. The network undergoes different issues like scalability, whole network basic variability, and network convenience owing to quick and casual node flexibility in VANETs. It damages system quality of service (QoS) so that frequent communication failure happens. In order to solve all these kinds of problems, several protocols are proposed where intelligent clustering protocol is one among others.

Clustering a system is main procedure of separating it into tiny consistent clusters [6]. The procedure depends on dissimilar parameters, for instance; internode distance and message association ability. It is used to enhance entire network outcome. Small clusters can be able to achieve more successfully. Many models only depend upon the clustering. Clustering devices also vary from each other due to various development criteria. These measures can differ according to domain of application and functionality [7]. Moreover, nodes perform as cluster members (CMs) or can be selected as cluster heads (CHs) in the cluster system vehicles. CM nodes are said to be ordinary nodes while CHs are answerable for intra-cluster and inter-cluster data furthering in VANETs [8]. So, CHs are chosen as the foundation of their improved efficiency for obtaining optimal network results. Overall, CH's range is very important for achieving trustworthy communication [9]. For instance, CHs with double wireless support network (cellular) are ideal choices when compared to ordinary nodes. Then the selection of appropriate CH, which is a challenging job for VANETs [10]. For this reason, the optimal clustering in VANETs also fits non-polynomial-hard type issues.

This article presents a golden jackal optimization-based energy aware clustering scheme (GJO-EACS) approach for VANET. The presented GJO-EACS technique uses a dynamic clustering approach, which adapts to the varying network topologies and traffic conditions, intending to extend the network lifetime and improve energy utilization. The GJO-EACS technique mainly derives a fitness function comprising three parameters: distance to neighbours, energy, and trust level. With comprehensive experimental analysis, it is demonstrated that the GJO-EACS technique exhibits maximum energy efficiency with no compromise in reliability.

2. RELATED WORKS

Mohan *et al.* [11] proposed a BC-assisted chaotic chameleon swarm optimizer-based energy aware clustering (BCCSO-EAC) method in VANET. This architecture builds clusters and chooses CHs employing a fitness function (FF) including node degree (ND), intra-cluster distance parameters, and residual energy (RE). Besides, BC technology has been implemented to allow secure intra-cluster and inter-cluster VANET communication. Kumar *et al.* [12], a trust-based energy-aware routing employing golden eagle optimized secure routing (GEOSR) protocol for ad-hoc sensor networks was designed. GEOSR algorithm has been developed to choose the optimum routing path depending on the parameters. Therefore, secured routing and efficiency could be executed with the help of GEOSR protocol. GEOSR procedure was further applied for the NS-2 simulation tool followed by comparing with present methods.

Lee *et al.* [13], a fuzzy logic (FC)-based routing technique was introduced that can be 2 stages such as route discovery stage and route maintenance stage. Firstly, an approach for computing the score of all nodes in the network was developed, and similarly, the score has been evaluated depending on different parameters. Secondly, a fuzzy system was devised for choosing routes. It contains two phases. Lastly, this presented routing method could be executed in NS2 to determine its effectiveness and its proficiency. Bhabani and Mahapatro [14], a cluster-based road side unit (RSU)-assisted message aggregation protocol (CluRMA) that implements global and local aggregation was developed. This work employs cosine distance for similarity examination among the data to remove the duplications. Next, the syntactic aggregation was achieved by utilizing data compression method adaptive Huffman compression algorithm for secure data, and arithmetic coding method for non-safety data.

Aissa *et al.* [15], a novel CH selection (CHS) method was presented. This technique depends on an FL-powered, k-hop distributed clustering method. This study developed a new approach for designing FL-based clustering techniques. This approach mainly derives mathematically, a new average distance approximation form, which could be utilized as a metric for choosing CHS. Besides, the novel developed method generates unchanging clusters by decreasing reclustering above and extending cluster' lifetimes. Tian *et al.* [16], the notion of centralized control was implemented for optimizing network energy consumption from an overall viewpoint. Particularly, a centralized control-enabled clustering method (CCCS) for underwater acoustic sensor networks (UASNs) has been developed. A node density-based adaptive clustering method was implemented, intra-cluster controllers have been developed in clusters, and selection of both relay clusters and relay nodes could be improved for attaining route optimization and energy balancing. Authors introduced traffic-aware clustering-based routing protocol (TACRP) for large-scale dynamic VANETs in this paper. The protocol regulates network traffic, including mobility data, vehicle neighborhood details, RSU data, and cluster management, with the traffic management unit (TMU). The author recommends grouping by relative mobility and merging by similar mobility patterns to produce a stable, continuous network [17]-[23].

3. THE PROPOSED MODEL

In this article, an effective GJO-EACS clustering approach has been developed for VANET. The presented GJO-EACS technique uses a dynamic clustering approach which adapts to the varying network topologies and traffic conditions, intending to extend the network lifetime and improve energy utilization. Figure 1 represents the entire flow of GJO-EACS methodology.

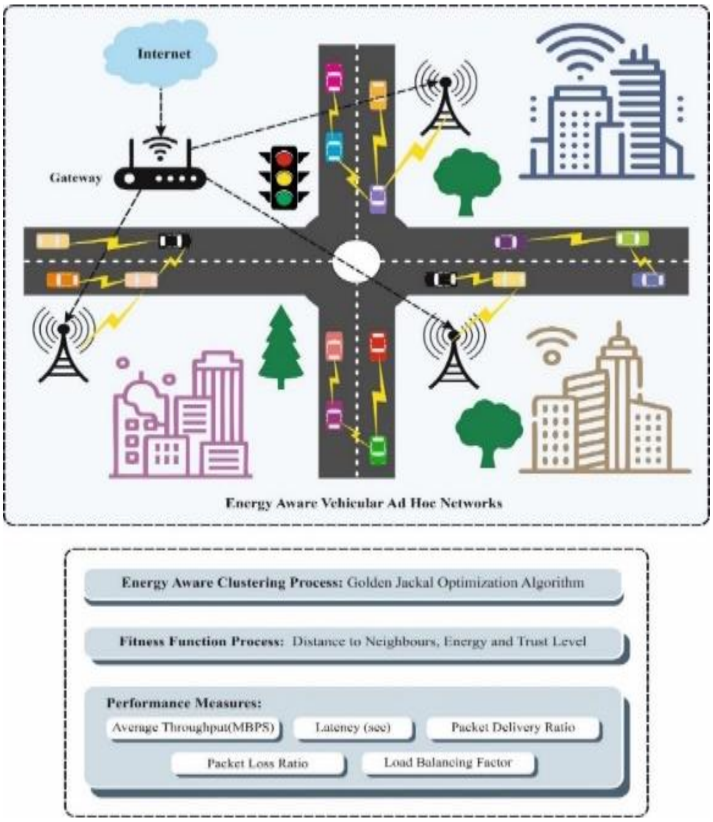

Figure 1. Overall flow of GJO-EACS algorithm

3.1. Design of GJO algorithm

The classical GJO method is based on the pursuing tactic of golden jackal pairs and a swarm-based method is adopted [24]. The foraging process includes attacking prey, looking for catching prey, and chasing nearby prey. Similar to other metaheuristic techniques, the starting point of GJO method is uniformly distributed on the search range and it is shown as follows:

$$Y_0 = Y_{\min} + rand \times (ub - lb) \quad (1)$$

where Y_0 denotes the key arbitrary population. The early process involves the creation of first prey matrix, with FMJ and MJ conquering the primary and succeeding places, correspondingly. And ub and lb characterize the upper along with lower restrictions of the search space. $rand$ represents the random number within [0,1]. The prey composition is given as follows:

$$Prey = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,\mathrm{d}} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,\mathrm{d}} \\ \vdots & \vdots & \vdots & \vdots \\ Y_{n,1} & Y_{n,2} & \cdots & Y_{n,\mathrm{d}} \end{bmatrix} \quad (2)$$

In (2), Y_{ij} denotes the i^{th} preys at j^{th} parameter. There are n preys in total and d variables. The target place is taken into account as an optimal solution.

During the optimization method, a fitness function assesses each target with the resulting value as follows:

$$F_{OA} = \begin{bmatrix} f\left(Y_{1,1}; Y_{1,2}; \dots; Y_{1,d}\right) \\ f\left(Y_{2,1}; Y_{2,2}; \dots; Y_{2,d}\right) \\ \vdots \\ f\left(Y_{\mathrm{n},1}; Y_{\mathrm{n},2}; \dots; Y_{\mathrm{nd}}\right) \end{bmatrix} \tag{3}$$

In (3), Y_{ij} shows the values of j^{th} parameter at i^{th} target, f represents the fitness function, and F_{OA} specifies the matrix for storing the prey fitness. The jackal couples find an appropriate target spot.

Commonly, jackal tracks down food efficiently with the remarkable capacity to detect and pursue targets. Nevertheless, there are instances when the effort has been unsuccessful, and the potential target avoids capture prompting them to find and abandon alternative sources of food. During pursuit, the MJ takes the lead, while the FMJ carefully follow them, and the mathematical modelling is formulated by:

$$Y_1(t) = Y_M(t) - E.\left|Y_M(t) - rl.Prey(t)\right| \tag{4}$$

$$Y_2(t) = Y_{FM}(t) - E.\left|Y_{FM}(t) - rl.Prey(t)\right| \tag{5}$$

Now, $Prey(t)$ shows the vector of victim spot, t denotes the present iteration. $YM(t)$ and $YFM(t)$ correspondingly represent the positions of MJ and FMJ. The revised places of MJ and FMJ concerning the victim are indicated by $Y(t)$ and $Y_2(t)$. The E evasive energy of prey is evaluated by the following expression:

$$E = E_1 * E_0 \tag{6}$$

$$E_0 = 2 * r - 1 \tag{7}$$

$$E_1 = c_1 * \left(1 - \left(\frac{t}{T}\right)\right) \tag{8}$$

In the equation, E_1 represents the prey's diminished energy, r shows the random integer within [0,1] and E_0 indicates the initial state of target's energy. T shows the maximum iteration number and c_1 signifies the constant values of 1.5. E_1 linearly dropped from 1.5 to 0. In (4) and (5), the distance between the jackal and the target is estimated by $|Y(t) - rl.Prey(t)|$. This distance can be deducted either added to or from its present locality based on how well the prey manages to prevent the jackal. The vector of random integers rl in (4) and (5) characterize the Levy's motion as follows:

$$rl = 0.05 * LP(y) \tag{9}$$

In (9), LP represents the LF algorithm that is represented as follows:

$$LF(y) = 0.01 \times \frac{(\mu \times \sigma)}{\left(\left|v^{\left(\frac{1}{\beta}\right)}\right|\right)}; \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times \left(2^{\frac{\beta-1}{2}}\right)}\right)^{\frac{1}{\beta}} \tag{10}$$

In (10), the β value is set as 1.5, and u, v represents arbitrarily produced value in $[0,1]$. The jackal position is updated by balancing (4) and (5).

$$Y(t+1) = \frac{Y_1(t) + Y_2(t)}{2} \tag{11}$$

Meanwhile, the target was chased by jackals, and their elusive decay of energy, led to last surrounding of the target via the jackals pair identified at first. The victim was attacked after being encircled and consumed by the jackal couples. The mathematical model of chasing strategy of MJ and FMJ jackals that chase in couples is shown (12).

$$Y_1(t) = Y_M(t) - E.\left|rl.Y_M(t) - Prey(t)\right| \tag{12}$$

$$Y_2(t) = Y_{FM}(t) - E.\,|rl.\,Y_{FM}(t) - Prey(t)| \tag{13}$$

In which $Prey\ (t)$ denotes the vector location of prey at t present iteration, and $Y(t)$ and $YM(t)$ characterize the location of MJ and FMJ. The new MJ and FMJ positions from association with the target are indicated as $Y(t)$ and $Y_2(t)$. In (6) describes escaping energy of the prey or E. In this work, the FF employed is intended for taking a balance between the count of features designated in the classifier accuracy (greater) and performance (lower) attained by using the features elected, in (14) describes the FF for appraising the outcome.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{14}$$

Now, $\gamma_R(D)$ describes the classifier error of the presented classifier. $|R|$ represents the cardinality of subset chosen and $|C|$ refers to the overall amount of features from the dataset, the parameters α and β are respective to the effect of subset length and classifier quality. $\in [1,0]$ and $\beta = 1 - \alpha$.

4. RESULTS AND DISCUSSION

This section inspects the clustering results of the GJO-EACS technique on the VANET environment. Figure 2 represent the number of clusters (NC) results of the GJO-EACS system with recent models [25]. The results indicate that the GJO-EACS method reaches increased number of NCs. On transmission range (TR) of 100, the GJO-EACS technique offers increased NC of 43.55 while the grey wolf optimizer (GWO), ant lion optimizer (ALO), and particle - whale optimization algorithm (P-WOA) models obtain decreased NC of 42.99, 48.31, and 48.45, respectively. Also, with TR of 100, the GJO-EACS methodology provides raised NC of 72.78 whereas the GWO, ALO, and P-WOA systems get reduced NC of 73.91, 75.04, and 77.07 individually. Additionally, based on TR of 150, the GJO-EACS technique provides improved NC of 65.48 but, the GWO, ALO, and P-WOA models acquire diminished NC of 74.95, 82.2, and 68.54. At last, on TR of 100, the GJO-EACS approach offers increased NC of 86.87 while the GWO, ALO, and P-WOA algorithms get minimized NC of 90.7, 93.7, and 96.43 correspondingly.

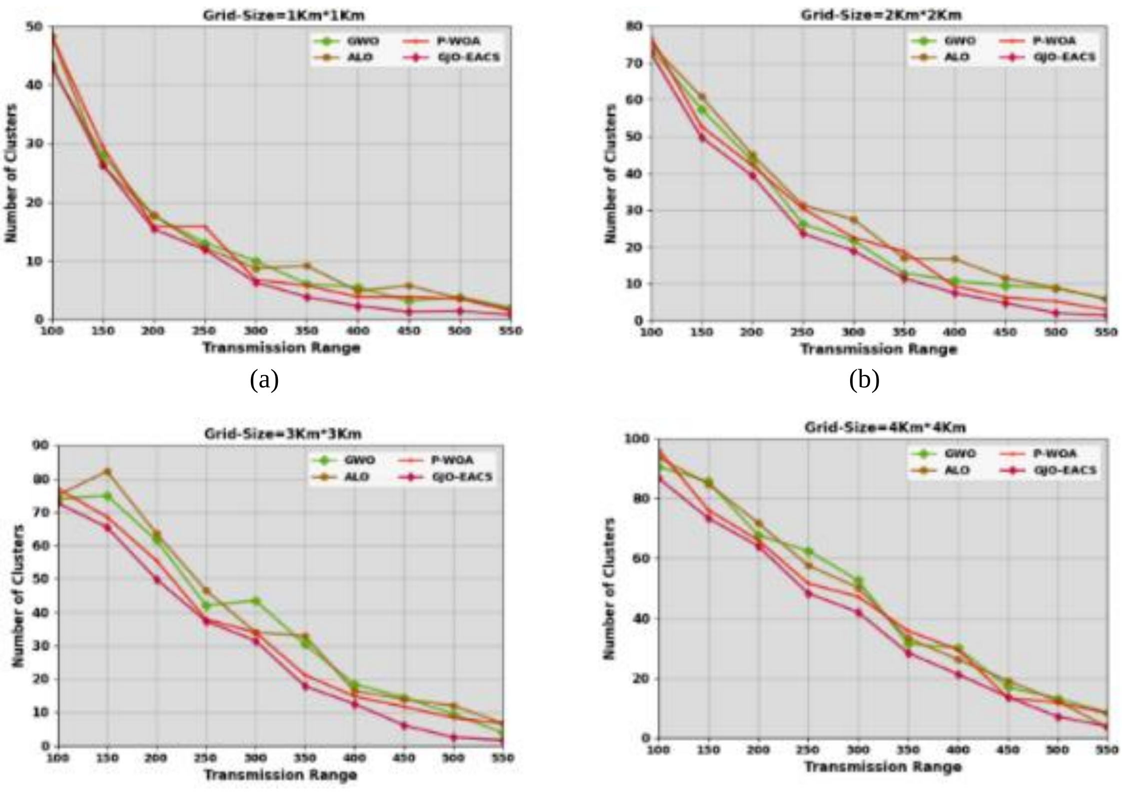

Figure 2. NC outcome of GJO-EACS approach: (a) grid-size=1 km×1 km, (b) grid-size=2 km×2 km, (c) grid-size=3 km×3 km, and (d) grid-size=4 km×4 km

Table 1 and Figure 3 report the packet delivery ratio (PDR) results of the GJO-EACS technique with existing models. The results stated that the GJO-EACS method reaches increased PDR values. With 30 vehicles, the GJO-EACS technique gains increased PDR of 94.51% while the P-WOA, GWO, and ALO models obtain decreased PDR values of 89.76%, 79.53%, and 74.05%, respectively. Meanwhile, based on 40 vehicles, the GJO-EACS approach achieves improved PDR of 83.91% whereas the P-WOA, GWO, and ALO systems acquire reduced PDR values of 75.14%, 59.80%, and 44.45%, individually. Eventually, with 50 vehicles, the GJO-EACS method attains better PDR of 66.01% whereas the P-WOA, GWO, and ALO systems acquire reduced PDR values of 58.33%, 55.41%, and 38.97% respectively.

Table 1. PDR outcome of GJO-EACS algorithm with existing systems under various vehicles

	Packet delivery ratio			
No. of vehicles	GJO-EACS	P-WOA	GWO	ALO
30	94.51	89.76	79.53	74.05
40	83.91	75.14	59.80	44.45
50	66.01	58.33	55.41	38.97
60	57.60	49.57	48.10	33.85
70	48.83	37.87	28.74	28.37
80	40.07	30.93	20.33	22.89
90	32.03	20.70	15.59	19.60
100	29.10	19.60	14.12	15.59
	Packet loss ratio			
30	5.49	10.24	20.47	25.95
40	16.09	24.86	40.20	55.55
50	33.99	41.67	44.59	61.03
60	42.40	50.43	51.90	66.15
70	51.17	62.13	71.26	71.63
80	59.93	69.07	79.67	77.11
90	67.97	79.30	84.41	80.40
100	70.90	80.40	85.88	84.41

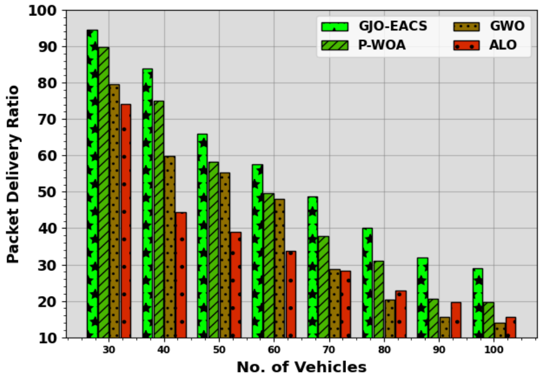

Figure 3. PDR outcome of GJO-EACS algorithm under various vehicles

Figure 4, packet loss ratio (PLR) results of the GJO-EACS technique with existing models are compared. The obtained values inferred that the GJO-EACS system provides minimal PLR values. On 30 vehicles, the GJO-EACS model offers minimal PLR of 5.49% while the P-WOA, GWO, and ALO models gained higher PLR of 10.24%, 20.47%, and 25.95%, respectively. Also, based on 40 vehicles, the GJO-EACS system gives lower PLR of 16.09% but, the P-WOA, GWO, and ALO techniques acquired increased PLR values of 24.86%, 40.20%, and 55.55%. Meanwhile, with 50 vehicles, the GJO-EACS approach offers reduced PLR of 33.99% but, the P-WOA, GWO, and ALO techniques acquired increased PLR values of 41.67%, 44.59%, and 61.03% correspondingly.

In Table 2 and Figure 5, latency analysis of the GJO-EACS system with existing methods is compared. The outcome values show that the GJO-EACS system gives lowest latency values. According to 30 nodes, the GJO-EACS model provides reduced latency of 4.32 s whereas the P-WOA, GWO, and ALO techniques attained higher latency of 9.40 s, 30.35 s, and 21.67 s, individually. Similarly, based on 40 nodes, the GJO-EACS method gives lower latency of 2.22 s but, the P-WOA, GWO, and ALO techniques get increased latency values of 12.99 s, 36.04 s, and 42.02 s. Then, with 50 nodes, the GJO-EACS methodology provides minimal latency of 3.42 s however, the P-WOA, GWO, and ALO techniques acquired raised latency values of 15.69 s, 35.14 s, and 42.02 s respectively.

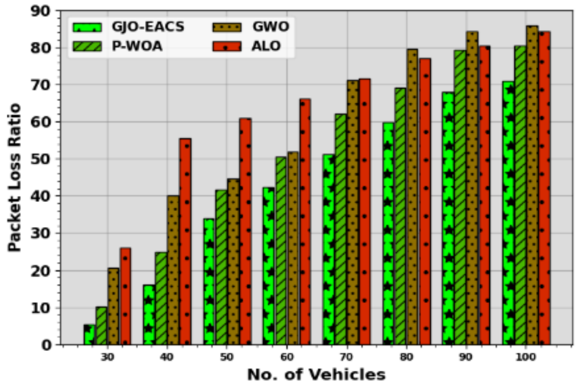

Figure 4. PLR outcome of GJO-EACS algorithm under various vehicles

Table 2. Latency analysis of GJO-EACS system with recent models under various nodes

Number of nodes	Latency (sec) GJO-EACS	P-WOA	GWO	ALO
30	4.32	9.40	30.35	21.67
40	2.22	12.99	36.04	42.02
50	3.42	15.69	35.14	42.02
60	7.31	19.28	39.63	51.90
70	7.91	19.58	50.70	55.79
80	11.50	20.77	49.80	61.77
90	17.18	32.45	57.28	70.75
100	19.58	31.55	64.17	82.12

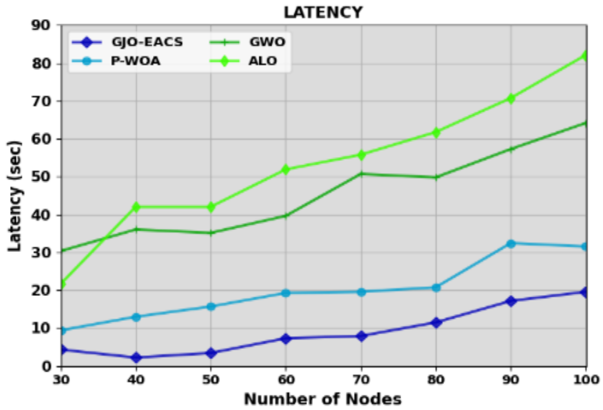

Figure 5. Latency outcome of GJO-EACS method under various nodes

Table 3 and Figure 6 represent average throughput (ATHRO) analysis of the GJO-EACS method with existing systems. The outcome values described that the GJO-EACS technique achieves increased ATHRO values. With 30 vehicles, the GJO-EACS technique attains better ATHRO of 27.55 Mbps whereas the P-WOA, GWO, and ALO systems get decreased ATHRO values of 13.03 Mbps, 12.66 Mbps, and 1.11 Mbps, individually.

Table 3. ATHRO analysis of the GJO-EACS technique with other approaches under various vehicles

No. of vehicles	Average throughput (Mbps) GJO-EACS	P-WOA	GWO	ALO
30	27.55	13.03	12.66	1.11
40	56.59	48.40	10.79	-0.75
50	83.40	74.09	23.83	48.40
60	88.61	75.58	31.27	24.20
70	90.10	52.87	49.89	23.45
80	94.57	72.60	62.92	61.06
90	98.29	90.10	51.38	72.60
100	96.81	86.38	75.95	49.15

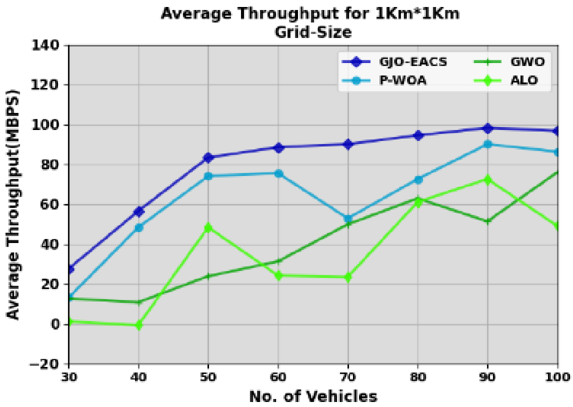

Figure 6. ATHRO analysis of GJO-EACS system under various vehicles

According to 40 vehicles, the GJO-EACS technique achieves improved ATHRO of 56.59 Mbps but, the P-WOA, GWO, and ALO methodologies obtain diminished ATHRO values of 48.40 Mbps, 10.79 Mbps, and -0.75 Mbps. Besides, on 50 vehicles, the GJO-EACS approach gains higher ATHRO of 83.40 Mbps. While the P-WOA, GWO, and ALO systems get decreased ATHRO values of 74.09 Mbps, 23.83 Mbps, and 48.40 Mbps correspondingly.

5. CONCLUSION

In this article, an effective GJO-EACS clustering approach has been developed for VANET. The presented GJO-EACS technique uses a dynamic clustering approach which adapts to the varying network topologies and traffic conditions, intending to extend the network lifetime and improve energy utilization. The GJO-EACS technique mainly derives a fitness function comprising three parameters: distance to neighbours, energy, and trust level. With comprehensive experimental analysis, it is demonstrated that the GJO-EACS technique exhibits maximum energy efficiency with no compromise in reliability. The results highlight the potential of the GJO-EACS technique to contribute to the sustainable operation of VANETs, making it a valuable contribution to the field of vehicular networking and smart transportation systems.

REFERENCES

[1] A. B. Tambawal, R. M. Noor, R. Salleh, C. Chembe, and M. Oche, "Enhanced weight-based clustering algorithm to provide reliable delivery for VANET safety applications," *PLoS ONE*, vol. 14, no. 4, p. e0214664, 2019, doi: 10.1371/journal.pone.0214664.

[2] M. Ren, J. Zhang, L. Khoukhi, H. Labiod, and V. Vèque, "A review of clustering algorithms in VANETs," *Annales des Telecommunications/Annals of Telecommunications*, vol. 76, no. 9–10, pp. 581–603, 2021, doi: 10.1007/s12243-020-00831-x.

[3] C. S. Kalita and M. Barooah, "Li-Fi based handoff technique in VANET," *2020 International Conference on Computational Performance Evaluation, ComPE 2020*, pp. 654–658, 2020, doi: 10.1109/ComPE49325.2020.9200013.

[4] S. Belmekki, M. Wahl, P. Sondi, D. Gruyer, and C. Tatkeu, "Toward the integration of V2V based clusters in a global infrastructure network for vehicles," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12574 LNCS, pp. 113–122, 2020, doi: 10.1007/978-3-030-66030-7_10.

[5] T. Qiu, X. Wang, C. Chen, M. Atiquzzaman, and L. Liu, "TMED: a spider-web-like transmission mechanism for emergency data in vehicular ad hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 9, pp. 8682–8694, 2018, doi: 10.1109/TVT.2018.2841348.

[6] G. Husnain and S. Anwar, "An intelligent probabilistic whale optimization algorithm (i-WOA) for clustering in vehicular ad hoc networks," *International Journal of Wireless Information Networks*, vol. 29, no. 2, pp. 143–156, 2022, doi: 10.1007/s10776-022-00555-w.

[7] O. Senouci, A. Zibouda, and S. Harous, "Survey: routing protocols in vehicular ad hoc networks," in *ACM International Conference Proceeding Series*, 2017, pp. 1–6, doi: 10.1145/3231830.3231838.

[8] T. K. Bhatia, R. K. Ramachandran, R. Doss, and L. Pan, "Data congestion in VANETs: research directions and new trends through a bibliometric analysis," *Journal of Supercomputing*, vol. 77, no. 7, pp. 6586–6628, 2021, doi: 10.1007/s11227-020-03520-7.

[9] S. Zaidi, S. Bitam, and A. Mellouk, "Enhanced user datagram protocol for video streaming in VANET," in *2017 IEEE International Conference on Communications (ICC)*, 2017, pp. 1–6, doi: 10.1109/ICC.2017.7997020.

[10] N. Magaia and Z. Sheng, "ReFIoV: a novel reputation framework for information-centric vehicular applications," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 2, pp. 1810–1823, 2019, doi: 10.1109/TVT.2018.2886572.

[11] R. Mohan, G. Prabakaran, and T. Priyaradhikadevi, "Blockchain assisted chaotic chameleon swarm optimization based clustering technique in vehicular ad hoc networks," *International Journal of Computer Networks and Applications*, vol. 10, no. 3, pp. 325–341, 2023, doi: 10.22247/ijcna/2023/221888.

[12] R. Kumar, S. Tripathi, and R. Agrawal, "Trust-based energy-aware routing using GEOSR protocol for ad-hoc sensor networks," *Wireless Networks*, vol. 28, no. 7, pp. 2913–2936, 2022, doi: 10.1007/s11276-022-02991-1.

[13] S. W. Lee *et al.*, "An energy-aware and predictive fuzzy logic-based routing scheme in flying ad hoc networks (FANETs)," *IEEE Access*, vol. 9, pp. 129977–130005, 2021, doi: 10.1109/ACCESS.2021.3111444.

[14] B. Bhabani and J. Mahapatro, "CluRMA: a cluster-based RSU-enabled message aggregation scheme for vehicular ad hoc networks," *Vehicular Communications*, vol. 39, p. 100564, 2023, doi: 10.1016/j.vehcom.2022.100564.

[15] M. Aissa, B. Bouhdid, A. Ben Mnaouer, A. Belghith, and S. AlAhmadi, "SOFCluster: safety-oriented, fuzzy logic-based clustering scheme for vehicular ad hoc networks," *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 3, p. e3951, 2022, doi: 10.1002/ett.3951.

[16] W. Tian *et al.*, "A centralized control-based clustering scheme for energy efficiency in underwater acoustic sensor networks," *IEEE Transactions on Green Communications and Networking*, vol. 7, no. 2, pp. 668–679, 2023, doi: 10.1109/TGCN.2023.3249208.

[17] M. I. Habelalmateen, A. J. Ahmed, A. H. Abbas, and S. A. Rashid, "TACRP: traffic-aware clustering-based routing protocol for vehicular ad-hoc networks," *Designs*, vol. 6, no. 5, p. 89, 2022, doi: 10.3390/designs6050089.

[18] A. R. Mohindra and Charu, "A weight based energy-aware hierarchical clustering scheme for mobile ad hoc networks," in *2014 7th International Conference on Contemporary Computing, IC3 2014*, 2014, pp. 518–524, doi: 10.1109/IC3.2014.6897227.

[19] W. S. Alnumay, P. Chatterjee, and U. Ghosh, "Energy aware secure routing for wireless Ad Hoc Networks," *IETE Journal of Research*, vol. 60, no. 1, pp. 50–59, 2014, doi: 10.1080/03772063.2014.890822.

[20] R. K. Yadav and R. P. Mahapatra, "Energy aware optimized clustering for hierarchical routing in wireless sensor network," *Computer Science Review*, vol. 41, p. 100417, 2021, doi: 10.1016/j.cosrev.2021.100417.

[21] S. A. Sharifi and S. M. Babamir, "The clustering algorithm for efficient energy management in mobile ad-hoc networks," *Computer Networks*, vol. 166, p. 106983, 2020, doi: 10.1016/j.comnet.2019.106983.

[22] H. S. Mansour *et al.*, "Cross-layer and energy-aware AODV routing protocol for flying ad-hoc networks," *Sustainability (Switzerland)*, vol. 14, no. 15, p. 8980, 2022, doi: 10.3390/su14158980.

[23] H. Taheri, P. Neamatollahi, O. M. Younis, S. Naghibzadeh, and M. H. Yaghmaee, "An energy-aware distributed clustering protocol in wireless sensor networks using fuzzy logic," *Ad Hoc Networks*, vol. 10, no. 7, pp. 1469–1481, 2012, doi: 10.1016/j.adhoc.2012.04.004.

[24] E. H. Houssein, D. A. Abdelkareem, M. M. Emam, M. A. Hameed, and M. Younan, "An efficient image segmentation method for skin cancer imaging using improved golden jackal optimization algorithm," *Computers in Biology and Medicine*, vol. 149, p. 106075, 2022, doi: 10.1016/j.compbiomed.2022.106075.

[25] G. Husnain, S. Anwar, G. Sikander, A. Ali, and S. Lim, "A bio-inspired cluster optimization schema for efficient routing in vehicular ad hoc networks (VANETs)," *Energies*, vol. 16, no. 3, p. 1456, 2023, doi: 10.3390/en16031456.

BIOGRAPHIES OF AUTHORS

Dr. Mahalakshmi Baladhandapani, is an Associate Professor in School of Computer Studies at RVS College of Arts and Science, Coimbatore, India. She obtained her M.Phil in Computer Science from Periyar University. She obtained her Ph.D. in Computer Science from Bharathiar University. She has 16 years of teaching experience. Her area of specialization is ad-hoc Networks and also Programming. She has published and also presented research papers in National/International Conferences. She can be contacted at email: jegajothibalakrishnan@gmail.com.

Dr. Shoaib Kamal (B.E, M.Tech, Ph.D, LMISTE) is currently working as an Associate Professor in the Department of ECE, Dr. B.R. Ambedkar Institute of Technology, Port Blair, A&N Islands. He has completed his Ph.D. from Jodhpur National University and has published around 80 papers in refereed international journals and conferences. He has published 6 patents on emerging technologies and has published books and book chapters on emerging technologies. His areas of interest are image processing, digital communication, and 5G Technology. He can be contacted at email: shoaibkamal87@gmail.com.

Chevella Anil Kumar is an Assistant Professor in the ECE Department of the VNR Vignana Jyothi Institute of Engineering and Technology in Hyderabad, Telangana, India. He was awarded a Doctor of Philosophy (Ph.D.) from JNT University Hyderabad. His research focuses on image, speech, and video signal processing, neural networks, machine learning, and deep learning. He can be contacted at email: chevellaanilkumar@gmail.com.

Dr. Jegajothi Balakrishnan obtained her B.E in Electrical and Electronics Engineering from Anna University, Chennai, Tamil Nadu, India in the year of 2006 and Master of engineering in Power Electronics and Drives in St. Peter's University, Chennai, Tamil Nadu, India in the year of 2011 respectively. She received his Ph.D. in Electrical Engineering from Anna University, Chennai, Tamil Nadu, India in the year of 2022. She has over ten years of Teaching Experience and currently and five years full time research experience. Currently, she is working as an Assistant Professor in Saveetha School of engineering, Chennai. She has presented many papers in national and international conferences. Her research interest covers renewable energy systems, artificial intelligence techniques, neural networks and embedded systems. She can be contacted at email: jegajothibalakrishnan@gmail.com.

Dr. Segu Praveena is an Associate Professor with 21 years of teaching experience. She joined MGIT on June 16, 2005, and has a Ph.D. in Electronics and Communication Engineering, specializing in Image Processing. Dr. Praveena has published 30 papers, attended 6 conferences, and authored 4 books. She has organized 3 events and attended 25. Her professional memberships include LMIETE and LMISTE. Dr. Praveena has held various institutional and departmental responsibilities, such as member of the incubation and startup committee. She teaches courses in both undergraduate and postgraduate programs. She can be contacted at email: praveenas897@gmail.com.

Dr. Ezudheen Puliyanjalil is working as an assistant professor at the Government Engineering College Thrissur. He completed his Ph.D. from the Indian Institute of Science Bangalore in the area of Software Verification in the year 2022. He completed his M-Tech with a gold medal from the National Institute of Technology Calicut in the year 2009. He is currently engaged in collaborative research with Prof. Rahul Gopinath of The University Sydny, Prof. Pavithra Prabhakar of Kansas State University and Prof. Deepak D'souza of Indian Institute of Science. His current research interest are automated reasoning, formal verification and small language models. He can be contacted at email: ezudheenpuliyanjalil@gmail.com.