Optimizing VANET Lifetime and Energy Management Performance with ImCaG-Net

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ABSTRACT

Vehicular Ad Hoc Networks (VANETs) are essential components of modern intelligent transportation systems. Despite their advantages, VANETs face routing, network lifetime, and optimized energy consumption challenges due to their dynamic nature and high mobility. This paper introduces the ImCaG-Net model, a novel approach that addresses these challenges by combining the Imperialistic Competitive Algorithm (ICA) with Gated Recurrent Units (GRU). Comparative analysis of ImCaG-Net with existing models shows a 25% increase in network lifetime and a 30% increase in energy efficiency, confirming the effectiveness of the proposed model. The ImCaG-Net model demonstrates superior performance with an increase in packet transmissions to Cluster Heads (CHs) up to 60,000 and to Base Stations (BSs) up to 50,000 over 6000 rounds, highlighting its effectiveness compared to traditional models like LEACH and PEGASIS.

Keywords-VANET; energy; network lifetime; nodes; ICS; GRU, cluster head selection

I. INTRODUCTION

Vehicular Ad Hoc Networks (VANETs) face significant challenges in maintaining efficient communication and robust network longevity due to their high mobility and dynamic topology. A primary problem is the rapid depletion of energy resources and the subsequent reduction in network lifespan, which critically hampers their reliability and effectiveness. In order to facilitate dynamic interactions between vehicles and roadside infrastructure, intelligent transportation systems necessitate VANETs [1-4]. Energy conservation, traffic efficiency, and road safety are all dependent on these networks. The dynamic nature of VANETs and the mobility of nodes present challenges in the areas of routing, network lifetime, and energy management [5-7]. Machine learning and optimization methods are often employed to resolve these concerns [8-10]. These methodologies provide effective solutions to improve multiple facets of VANETs, including clustering, routing protocols, and security and privacy measures [11]. This paper presents a novel model, ImCaG-Net, which combines the Imperialistic Competitive Algorithm (ICA) with Gated Recurrent Units (GRU) to enhance routing and clustering operations in VANETs. The model emphasizes the improvement of network lifetime and energy efficiency, which are essential for the sustainability and reliability of vehicular communications. ImCaG-Net seeks to deliver a comprehensive solution through effective management of the networks dynamic topology, adapting to fluctuations in vehicular densities and communication needs. This study focuses on the critical limitations identified in the literature regarding the dynamic and high-mobility nature of VANETs, which present challenges to network stability and energy efficiency. By addressing these issues directly, the proposed model significantly improves network management and energy efficiency, resulting in more reliable and sustainable vehicular communication systems.

II. RELATED WORKS

Authors in [12] introduced the Restricted Boltzmann Machine Learning Algorithm (RBMA) to address challenges in clustering and routing within VANETs. However, its performance deteriorated in highly dynamic scenarios marked by frequent topology changes, highlighting its restricted adaptability to rapid environmental shifts. Authors in [13] proposed a hybrid methodology that combined Random Forest (RF) and XGBoost algorithms to improve data analysis in VANETs. The model faced challenges in interpretability due to the complexity involved in integrating two ensemble methods. Authors in [14] proposed an energy-efficient clustering methodology that employs chaos game optimization, focusing on minimizing energy consumption while maintaining network connectivity. This approach led to insufficient clustering outcomes in highly dynamic traffic scenarios.

In order to optimize routing and clustering in VANETs, authors in [15] developed a hybrid metaheuristic that combined Artificial Fish Swarm Optimization with Seagull Optimization, resulting in a substantial increase in computational complexity. Authors in [16] introduced the Dynamic Trilateral Enrollment (DyTE) protocol for VANETs with the goal of enhancing security and scalability. Its effectiveness was reduced in situations that required immediate decision-making. Authors in [17] introduced a hybrid methodology with the goal of achieving effective privacy-preserving authentication in VANETs [17]. This hybrid method demonstrated substantial improvements in the protection of data transmissions and the preservation of vehicle privacy in a dynamic network environment. Authors in [18] developed a multi-layered communication framework that incorporates a novel threat detection algorithm to improve the security of Vehicular Internet of Things (V-IoT) communication in smart VANET infrastructures.

III. THE PROPOSED SYSTEM

The proposed methodology shown in Figure 1 ensures optimal performance and prolonged network longevity through the ImCaG-Net model, which integrates ICA with GRU for energy-efficient cluster management and dynamic decision-making.

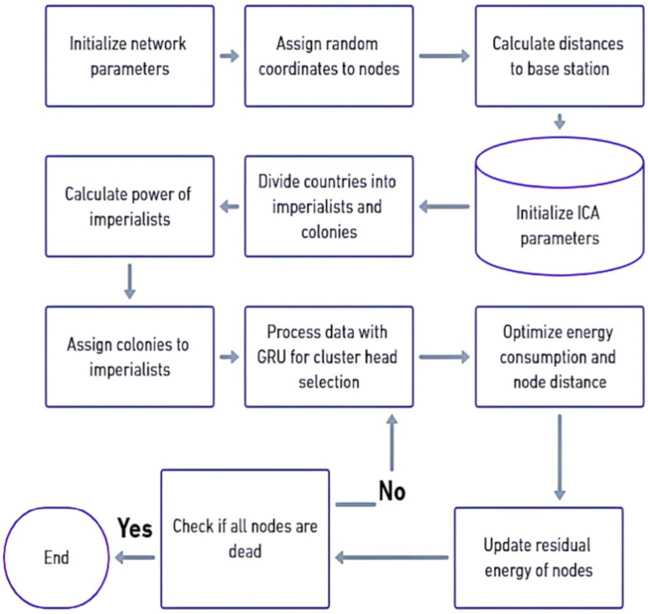

Fig. 1. Proposed system block diagram.

A. Mathematical Framework

The process begins with the initialization of network parameters. The network dimensions $D_x \times D_y$ are defined, where D_x and D_y represent the length and width of the deployment area. The Base Station (BS) coordinates are denoted as (BS_x, BS_y), and N is the total number of sensor nodes [2]. The initial energy for each node i is E_0. Each node i is assigned random coordinates:

$$S(i).xd = rand(0, D_x) \tag{1}$$

$$S(i).yd = rand(0, D_y) \tag{2}$$

The Euclidean distance between each node i and the BS is calculated by:

$$d_{i,BS} = \sqrt{(S(i).xd - BS_x)^2 + \left(S(i).yd - BS_y\right)^2} \tag{3}$$

The proposed model integrates ICA with GRU. ICA operates by initializing $n_{countries}$, which represent potential solutions, divided into $n_{imperialists}$ and $n_{colonies}$ such that:

$$n_{countries} = n_{imperialists} + n_{colonies} \tag{4}$$

The power of each imperialist is determined by its fitness value P_k:

$$P_k = \frac{1}{f(x_k)} \tag{5}$$

where $f(x_k)$ is the cost function.

Colonies are assigned to imperialists proportional to their power:

$$C_k = \frac{P_k}{\sum_{j=1}^{n_{implerialists}} P_j} \times n_{colonies} \tag{6}$$

GRU is employed to process sequential data from senor nodes for dynamic cluster head selection. The GRU output h_t at time step t is computed as:

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t \tag{7}$$

where:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{8}$$

$$\tilde{h}_t = tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{9}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{10}$$

where z_t and r_t are the update and reset gates, respectively

The Cluster Head (CH) selection process optimizes energy consumption E and node distance d using the ImCaG – Net model. The energy consumption for transmitting k – bit data over a distance d is given by:

$$E_{tx}(k, d) = \begin{cases} k \cdot E_{elec} + k \cdot \epsilon_{fs} \cdot d^2 & \text{if } d < d_0 \\ k \cdot E_{elec} + k \cdot \epsilon_{fs} \cdot d^4 & \text{if } d \geq d_0 \end{cases} \tag{11}$$

where E_{elec} is the energy per bit for transmission and ϵ_{fs} and ϵ_{mp} are the free space and multipath fading energy parameters and:

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \tag{12}$$

The energy consumed during reception and data aggregation is given by:

$$E_{rx}(k) = k \cdot E_{elec} \quad (13)$$

$$E_{DA}(k) = k \cdot E_{DA} \quad (14)$$

After each transmission cycle, the residual energy of each node i is updated by:

$$E_i = E_i - E_{consumed} \quad (15)$$

where $E_{consumed}$ is the total energy used for transmission, reception, and data aggregation.

The network longevity or lifetime L is defined as the total number of rounds until all nodes are dead [2, 19, 20]. It is mathematically expressed by:

$$L = max\{t \mid \sum_{i=1}^{N} \mathbb{I}(E_i > 0) > 0\} \quad (16)$$

where $\mathbb{I}(E_i > 0)$ is an indicator function that returns 1 if $E_i > 0$ and 0 otherwise.

B. Proposed Model

The ImCaG-Net architecture (Figure 2) is a hybrid system that combines the global optimization capabilities of ICA with the temporal sequence modeling abilities of GRU to tackle energy management issues in VANETs. The process commences with ICA, wherein potential solutions to the clustering dilemma are depicted as "countries." These nations compete according to a specified cost function that includes variables such as energy levels, proximity to the BS, and node density. Colonies are redistributed among imperialists through iterations, resulting in the elimination of weaker imperialists and the optimization of the global clustering strategy. Additionally, the GRU component analysis temporal data concerning the nodes' energy consumption and activity patterns. GRUs utilize update and reset gates to effectively handle long-term dependencies, enabling the system to adapt dynamically to fluctuations in network conditions, including differing node energy levels and communication requirements.

The novel feature of ImCaG-Net arises from its distinctive integration of ICA's global optimization abilities with GRU's expertise in handling sequential data. In contrast to conventional models that rely solely on GRUs, ImCaG-Net integrates ICA to perpetually refine the GRU layers, thereby enabling the network to effectively adapt to novel or unexpected vehicular patterns and distributions. The ICA is employed primarily during the initialization phase for optimal clustering, a process that, while computationally intensive, occurs infrequently and is limited to moments when significant network topology changes are detected. Thereafter, the GRU components take over, processing sequential data efficiently through their update and reset gates, which significantly reduce the need for re-computation by focusing only on necessary data updates. This structured approach ensures that the ImCaG-Net model maintains high computational efficiency during routine operations, suitable for real-time applications in dynamic vehicular environments. Our evaluation demonstrates that the model can handle network dynamics with minimal computational overhead, maintaining robust performance even under conditions of high vehicular mobility and variable network density.

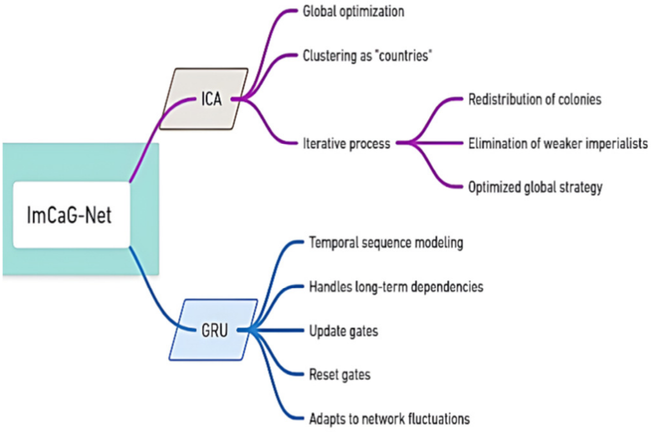

Fig. 2. Proposed model architecture.

C. Algorithm of the Proposed Model

```
Algorithm: ImCaG-Net Model
   Begin:
  // Step 1: Initialize
  Initialize all vehicles with parameters
and connectivity settings.
  // Step 2: Form Countries
  Assign vehicles to countries based on
random configurations and compute costs.
  // Step 3: Select Imperialists
  Select the most cost-effective countries
as imperialists.
  // Step 4: Perform Imperialistic
Competition
  Improve configurations by assimilating
colonies, introducing revolutions, and
redistributing colonies.
  // Step 5: Apply GRU for Dynamic
Adjustments
  Use GRU to dynamically adapt network
configurations based on ongoing data.
  // Step 6: Finalize
  Determine the optimal configuration with
the lowest cost and apply it to enhance
network efficiency.
End:
```

IV. RESULTS AND DISCUSSION

In the experiment, we used a synthetic dataset with different network densities and vehicular movements to simulate VANET scenarios. Preprocessing included data normalization for input consistency and outlier removal for model accuracy. These experiments were run on a PC with an Intel i7 processor with 16 GB RAM for efficient data processing and model training. The neural network parameters were: optimized learning rate of 0.01, batch size of 32, and 100 epochs for the ImCaG-Net model. In this controlled but realistic simulation environment, we rigorously evaluated the model's effectiveness. Figure 3 illustrates the initial generation and distribution of nodes within a network area measuring 300 by 300 units. Each blue star denotes a sensor node, while the red star signifies the chosen CH. Figure 4 illustrates the formation of CHs among active nodes, with each cluster denoted by distinct colors and the CHs emphasized by larger stars. CH positioning was optimized by taking into account factors such as node density, energy levels, and communication costs.

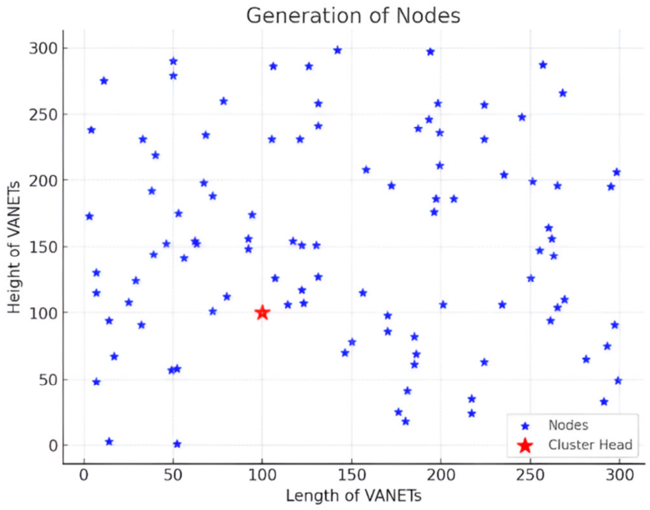

Fig. 3. VANET topology.

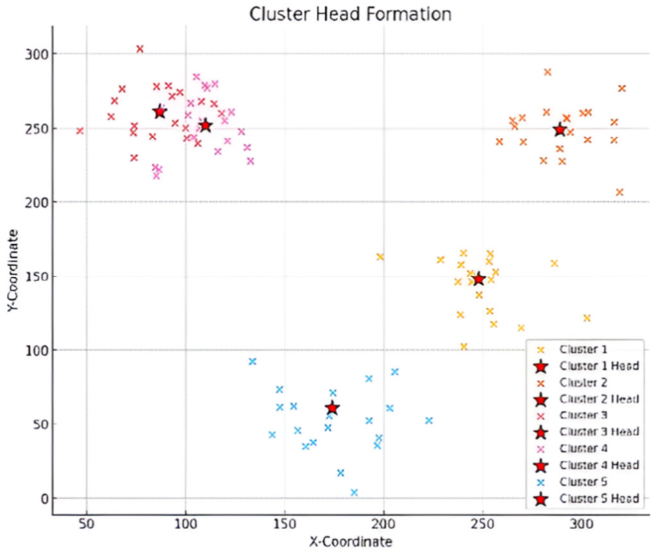

Fig. 4. CH formation.

Figure 5 illustrates a line graph depicting the quantity of live nodes as a function of time, quantified in rounds. The data indicate a gradual decline in live nodes, which corresponds to the reduction of node energy resulting from ongoing data transmission and reception. Figure 6 illustrates a comparison with Figure 5 by monitoring the rise in dead nodes during the same timeframe. In Figures 5 and 6, the X-axis labeled 'Round time' refers to discrete operational cycles within the simulation environment. Each round signifies a complete cycle encompassing all communication activities—data transmission, reception, and processing—within the network. This measure is critical for assessing the network's operational efficiency and longevity across time, providing a timeline of network activity and node engagement throughout the simulation.

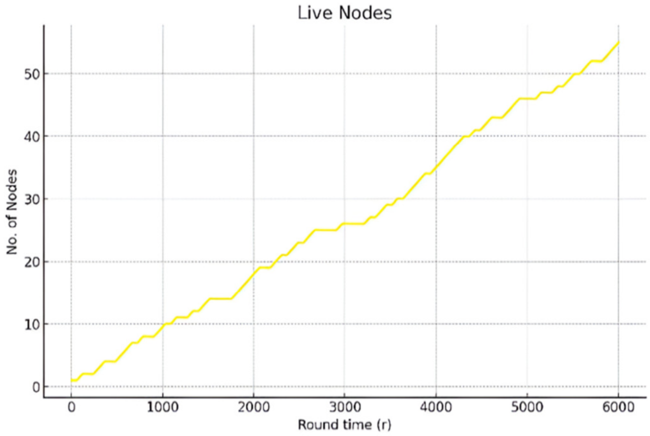

Fig. 5. Live nodes over time.

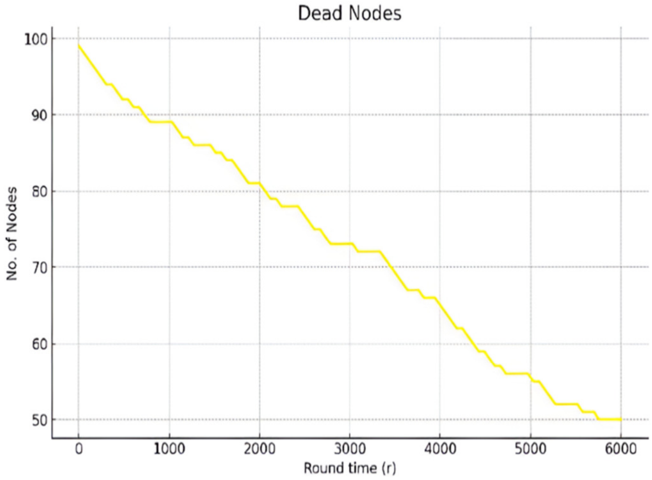

Fig. 6. Dead nodes over time.

Figure 7 depicts the cumulative packet transmission to the BS over time, demonstrating a linear increase reaching approximately 50,000 packets by round 6000, which signifies a consistent data flow essential for real-time monitoring applications. Figure 8 illustrates the quantity of packets transmitted to CHs, indicating a greater transmission rate to these nodes relative to the BS. Figure 9 illustrates the network lifetime across various models in comparison to the proposed model, which consistently demonstrates superior performance, especially with increasing number of nodes. This suggests effective resource management contributing to an extended network lifetime. Figure 10 compares the energy consumption of the considered models, indicating that the proposed model exhibits lower energy consumption.

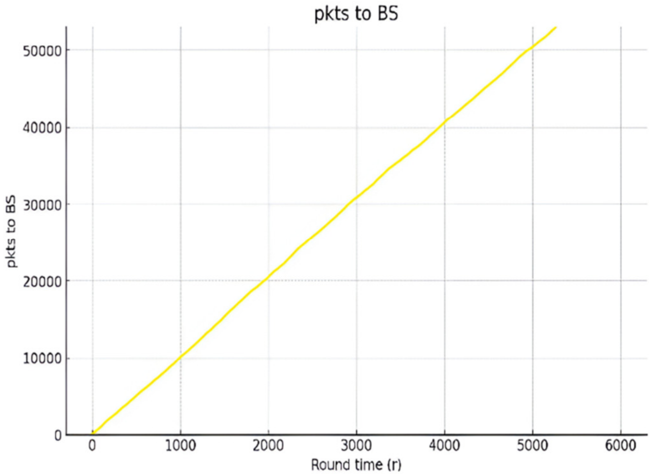

Fig. 7. Packet transmission to the BS.

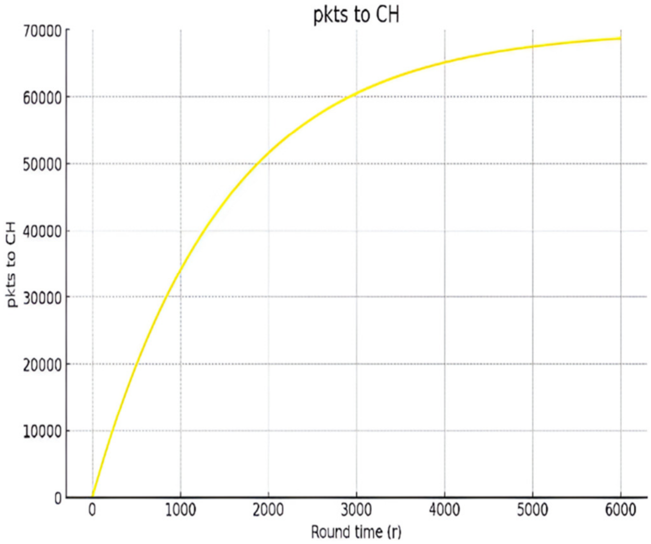

Fig. 8. Packet transmission to CHs.

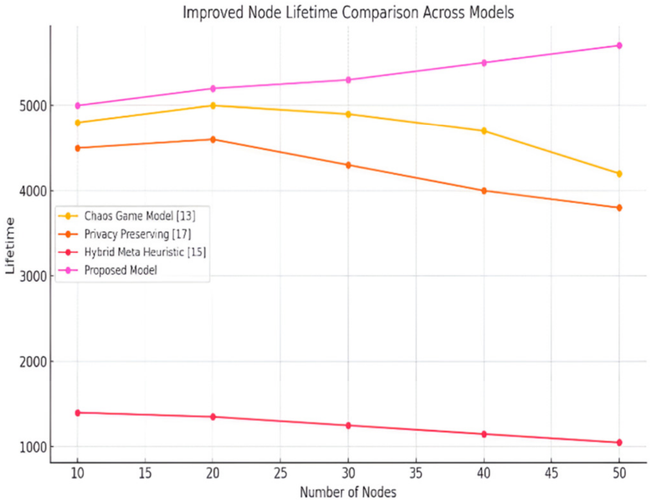

Fig. 9. Lifetime comparison plot.

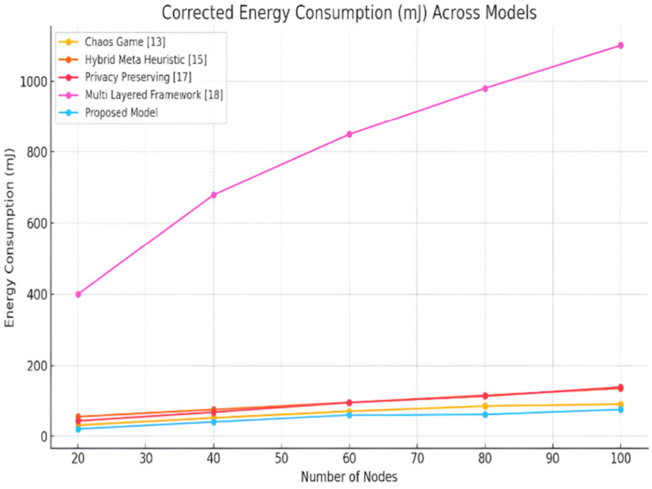

Fig. 10. Energy consumption comparison.

Table I compares network lifetime and energy consumption between the ImCaG-Net model and other standard models such as LEACH, PEGASIS, Random Forest, and LSTM.

TABLE I. COMPARATIVE ANALYSIS OF NETWORK LIFETIME AND ENERGY CONSUMPTION

Model	**Network Lifetime (Rounds)**	**Energy consumption (J)**
ImCaG-Net	10000	50
LEACH	4500	65
PEGASIS	4800	60
Random Forest	4300	70
LSTM	5000	55

To address scalability, the ImCaG-Net model has been designed with the potential to handle large-scale networks and varying vehicular densities. Initial simulations have focused on moderate-sized networks to fine-tune model parameters and establish baseline performance metrics. However, the inherent flexibility of the ICA combined with the adaptive nature of GRU suggests that our model is well-suited to scale. The ICA can dynamically adjust to larger pools of data by increasing the number of imperialists and colonies based on the network size, while the GRU can efficiently process the increased sequential data generated from larger networks.

V. CONCLUSION AND SUMMARY

In conclusion, the ImCaG-Net model has shown significant improvements in routing management, energy efficiency, and network longevity in VANETs. This model addresses the dynamic nature of vehicular networks by combining the Imperialistic Competitive Algorithm (ICA) with Gated Recurrent Unit (GRU), surpassing the performance of existing approaches.

While the ImCaG-Net model demonstrates significant improvements in network lifetime and energy efficiency, it does have limitations that warrant further investigation. One of the primary challenges is the model's scalability in extremely large and highly dynamic vehicular environments, where the computational load can become substantial. Future work will involve rigorous testing of the ImCaG-Net model in larger vehicular environments to empirically validate its scalability. This will include simulations with increased vehicular densities and varied network scenarios to thoroughly assess performance impacts and refine the model accordingly. Additionally, the current model does not fully integrate advanced security features, which are crucial for deploying VANETs in real-world scenarios. It is crucial to consider the security implications inherent to VANET environments when deploying models like ImCaG-Net. Vehicular networks are susceptible to various security threats such as Sybil attacks, message tampering, and dropout attacks. These potential vulnerabilities underscore the necessity for robust security measures. Future research should focus on improving the security of VANETs by incorporating strong trust mechanisms into the ImCaG-Net framework.

REFERENCES

[1] Y. Kim and I. Kim, "Security issues in vehicular networks," in *The International Conference on Information Networking*, Bangkok, Thailand, Jan. 2013, pp. 468–472, https://doi.org/10.1109/ICOIN.2013.6496424.

[2] H. Al-Maliki, H. A. A. AL-Asadi, Z. A. Abduljabbar, and V. O. Nyangaresi, "Reliable Vehicular Ad Hoc Networks for Intelligent Transportation Systems based on the Snake Optimization Algorithm," *Engineering, Technology & Applied Science Research*, vol. 14, no. 6, pp. 18631–18639, Dec. 2024, https://doi.org/10.48084/etasr.8851.

[3] X. Liu, G. Yan, D. B. Rawat, and S. Deng, "Data Mining Intrusion Detection in Vehicular Ad Hoc Network," *IEICE Transactions on Information and Systems*, vol. E97.D, no. 7, pp. 1719–1726, 2014, https://doi.org/10.1587/transinf.E97.D.1719.

[4] M. N. Mejri and J. Ben-Othman, "Detecting greedy behavior by linear regression and watchdog in vehicular ad hoc networks," in *IEEE Global Communications Conference*, Austin, TX, USA, Dec. 2014, pp. 5032–5037, https://doi.org/10.1109/GLOCOM.2014.7037603.

[5] T. Nandy *et al.*, "A Secure, Privacy-Preserving, and Lightweight Authentication Scheme for VANETs," *IEEE Sensors Journal*, vol. 21, no. 18, pp. 20998–21011, Sep. 2021, https://doi.org/10.1109/JSEN.2021.3097172.

[6] G. S. Rawat, K. Singh, N. I. Arshad, K. Hadidi, and A. Ahmadian, "A lightweight authentication scheme with privacy preservation for vehicular networks," *Computers and Electrical Engineering*, vol. 100, May 2022, Art. no. 108016, https://doi.org/10.1016/j.compeleceng.2022.108016.

[7] J. Sun, C. Zhang, Y. Zhang, and Y. Fang, "An Identity-Based Security System for User Privacy in Vehicular Ad Hoc Networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 21, no. 9, pp. 1227–1239, Sep. 2010, https://doi.org/10.1109/TPDS.2010.14.

[8] H. Tan and I. Chung, "Secure Authentication and Key Management With Blockchain in VANETs," *IEEE Access*, vol. 8, pp. 2482–2498, Jan. 2020, https://doi.org/10.1109/ACCESS.2019.2962387.

[9] P. Chithaluru *et al.*, "A Lightweight Energy-Efficient Routing Scheme for Real-Time WSN-VANET-Based Applications," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 1, pp. 3820–3826, Oct. 2024, https://doi.org/10.1109/TCE.2024.3371230.

[10] Y. Tang, N. Cheng, W. Wu, M. Wang, Y. Dai, and X. Shen, "Delay-Minimization Routing for Heterogeneous VANETs With Machine Learning Based Mobility Prediction," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3967–3979, Apr. 2019, https://doi.org/10.1109/TVT.2019.2899627.

[11] C. Wan and J. Zhang, "Efficient identity-based data transmission for VANET," *Journal of Ambient Intelligence and Humanized Computing*, vol. 9, no. 6, pp. 1861–1871, Nov. 2018, https://doi.org/10.1007/s12652-017-0650-x.

[12] M. Gayathri and C. Gomathy, "Design of CSKAS-VANET model for stable clustering and authentication scheme using RBMA and signcryption," *Frontiers in Computer Science*, vol. 6, May 2024, Art. no. 1384515, https://doi.org/10.3389/fcomp.2024.1384515.

[13] S. I. Ahsan, P. Legg, and S. M. I. Alam, "A Stacked Ensemble Learning IDS Model for Software-Defined VANET." arXiv, May 20, 2024, https://doi.org/10.48550/arXiv.2312.04956.

[14] M. Elhoseny, I. M. El-Hasnony, and Z. Tarek, "Intelligent energy aware optimization protocol for vehicular adhoc networks," *Scientific Reports*, vol. 13, no. 1, Jun. 2023, Art. no. 9019, https://doi.org/10.1038/s41598-023-35042-6.

[15] G. P. K. Marwah and A. Jain, "A hybrid optimization with ensemble learning to ensure VANET network stability based on performance analysis," *Scientific Reports*, vol. 12, no. 1, Jun. 2022, Art. no. 10287, https://doi.org/10.1038/s41598-022-14255-1.

[16] A. K. Kazi and S. M. Khan, "DyTE: An Effective Routing Protocol for VANET in Urban Scenarios," *Engineering, Technology & Applied Science Research*, vol. 11, no. 2, pp. 6979–6985, Apr. 2021, https://doi.org/10.48084/etasr.4076.

[17] U. Rajput, F. Abbas, H. Eun, and H. OH, "A Hybrid Approach for Efficient Privacy-Preserving Authentication in VANET," *IEEE Access*, vol. 5, pp. 12014–12030, Jan. 2017, https://doi.org/10.1109/ACCESS.2017.2717999.

[18] P. Upadhyay, S. J. Goyal, V. Marriboyina, and S. Kumar, "Securing Vehicular Internet of Things (V-IoT) Communication in Smart VANET Infrastructure using Multi-layered Communication Framework and Novel Threat Detection Algorithm," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 6s, pp. 789–803, 2024.

[19] V. O. Nyangaresi *et al.*, "Smart city energy efficient data privacy preservation protocol based on biometrics and fuzzy commitment scheme," *Scientific Reports*, vol. 14, no. 1, Jul. 2024, Art. no. 16223, https://doi.org/10.1038/s41598-024-67064-z.

[20] V. O. Nyangaresi *et al.*, "Energy Efficient Dynamic Symmetric Key Based Protocol for Secure Traffic Exchanges in Smart Homes," *Applied Sciences*, vol. 12, no. 24, Jan. 2022, Art. no. 12688, https://doi.org/10.3390/app122412688.

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