Crayfish-Inspired Cluster Optimization for Efficient Routing in Vehicular Ad Hoc Networks (COANET)

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Abstract- Vehicular Ad Hoc Networks (VANETs) enables real-time communication between vehicles. VANETs address issues like Urban traffic congestion and frequent accidents that pose challenges to commuters leading to delays, inefficiencies, and safety hazards. However, the effectiveness of VANET could be hampered via high node mobility and sparse vehicle distribution, necessitating novel and efficient optimization approaches. This study introduces the Crayfish Optimization Algorithm (COA) for Vehicular Ad Hoc Networks (COANET), designed to intelligently optimize clusters within the VANET framework. To evaluate the efficacy of COA, comprehensive experiments were conducted, benchmarking the results against two state-of-the-art algorithms: Intelligent cluster optimization algorithm. based on whale optimization algorithm for VANETs (WOACNET) and An Intelligent Harris Hawks Optimization Based Cluster Optimization Scheme for VANETs (HHO). The comparison is focused on key performance metrics, including cluster stability, communication efficiency, and resource utilization. The findings demonstrate that the developed method outperforms both well-established methods WOACNET and HHO by 10%. The proposed method optimized clusters exhibit increased stability, reduced communication latency, and improved overall system performance. These results highlight the potential of COANET as a promising optimization tool for improving the effectiveness and functionality of VANETs as part of the larger framework of Intelligent Transportation System.

Index Terms- Crayfish Optimization Algorithm, Vehicular Ad Hoc Networks, Crayfish Optimization Algorithm for VANETs, Whale Optimization Algorithm for Clustering in VANETs, Harris Hawk Optimization.

I. Introduction

The complexity of real-world optimization problems in computer science, especially in the domain of AI and ML, is constantly rising. Optimization issues can take on several forms, such as discrete, continuous, non-linear, multi-model, multi-dimensional, etc. [1]. Research also exhibits that these techniques are not necessarily the best choice for issues that continuous, discrete, or differentiable [2]. Meta-heuristic algorithms, known for their independence and broad applicability to real-world optimization problems. Their inclusion of stochastic operators facilitates extensive exploration of the solution space for optimal results. However, their sensitivity to user-defined parameters is a common limitation. Recent decades have seen a rise in meta-heuristic approaches in computer vision and machine learning. Well-known meta-heuristics include Particle Swarm Optimization (PSO) [3], Genetic Algorithms (GA) [4], and ANT Colony Optimization (ACO) [5]. Meta-heuristic techniques are important in computer science and related fields. Many meta-heuristic methods incorporate random variables to solve problems without variation. The techniques are applicable to the present problems since they start with a random solution and less involve computations to find space. Inspiration for these solutions comes from Birds, animals, nature and insects. These algorithms are user friendly. These algorithms effectively explore the whole working space, eliminating the need for local optimization. A vital network field, is growing and updating daily for a brighter future [6]. Various kinds of networks come together to form the Internet of Things (IoT). The transportation sector, constituting the legal means of moving goods or individuals between locations, has encountered various challenges over time, Issues such as elevated accidents, blockade and carbon emissions have emerged. Given the intricate nature of these challenges, researchers have endeavored to integrate virtual technologies into transportation, leading to the development of what is known as Intelligent Transport Systems [7]. The aforementioned problems highlight the importance of intelligent clustering techniques for ITS, which can make them more scalable, optimized, managed, and load balanced [8]. In ITS, vehicles share information via ad hoc connections. There are also transient network creations in VANETs for resource sharing. ITS have proceeded to supplemental divisions based on communication method. VANETs include Communication between vehicles (V2V), as well as Communication between vehicles and infrastructure (V2I) as shown in Figure 1. A vehicular network is a constantly changing network in which nodes move in an random manner, resulting in frequent variations in the node arrangement [9].

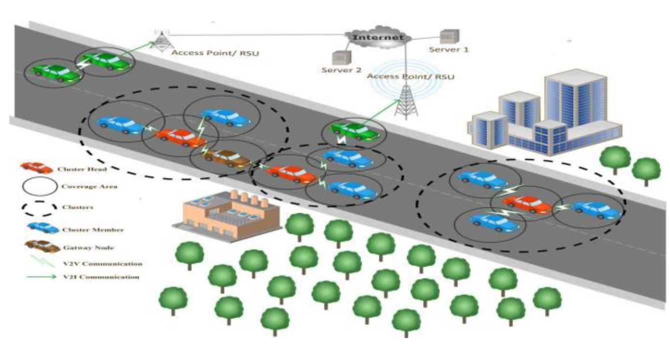

Figure 1: Clustering in VANETs [10]

Dynamic cluster formation is a critical network management method in the context of ITS, Clusters are virtual sets that are generated by an algorithm for clustering [11]. In most circumstances, any node might be chosen to be the CH [12]. Intelligent clustering algorithms play a key role in making VANETs more scalable, maintainable, optimized, and traffic balanced. In ITS, cluster formation refers to the spontaneous as well as adaptive formation of clusters, which are groups of vehicles, for effective data exchange and communication [13]. In a clustering configuration, one node is designated as the Cluster node or Cluster Head, while the other nodes form a collection or group. Node similarity could be determined using factors such as distance, bandwidth availability, speed, and direction of vehicular nodes. Certain grouping rules determine how various clustering approaches differ. Important parameters to consider when building these clusters include transmission ranges, grid size, number of nodes, speed, and direction of nodes, via optimizing these factors, the lifetime could be increased of the clusters and, by extension, the network's performance. Performance improves as nodes remain in a cluster for longer periods of time. Establishing networks. The clustering procedure relies heavily on CH selection [8]. CH is responsible for creating and destroying clusters, allocating resources to cluster members, and choosing the topology for maintenance. In vehicle networks, CH essential for tasks such as creating and breaking clusters, maintaining topology, and distributing resources. Their job is to make sure the clusters can talk to one other. The cluster node-to-CH conversion ratio and the CH change ratio are crucial metrics for gauging clustering stability, a key performance indicator of networks. Performance, reliability, and communication delays are all enhanced by cluster optimization [14]. Following are few key points addressed in this study.

1. The study employs nature-inspired meta-heuristic algorithm for ITS to address combinatorial optimization challenges, specifically clustering.
2. A novel clustering method is proposed, where every target is assigned a weight depending on the fitness function of each vehicle.
3. Vehicles have been equipped with self-imposed weights to decrease inaccuracy by reducing unpredictability.
4. In order to evaluate the developed approach, was compared with other methods considering variables in the system such as communication range and load balancing factor.

II. LITERATURE REVIEW

bio-inspired algorithms have given outstanding solutions when it comes to vehicle network routing, safety, and efficient parking, In VANET networks, routing mostly involves communicating with different vehicles to disseminate information about road conditions, accidents, and emergencies [15]. A renowned algorithm that takes its inspiration from nature is PSO, which uses the idea of a community of fish and birds as its foundation. Optimizing vehicle routes is another area where this approach has lately found use in VANET networks. To discover the best routes in VANETs, for example, a PSO-based clustering routing protocol (CRBP) is introduced [16]. The author examines V2V VANETs to improve vehicle communication within ITS. The focus was on clustering vehicles through bio-inspired routing algorithms (CLPSO and MOPSO) [17], with a comparison of their effectiveness in terms of transmission range, cluster and node quantities, and grid size. By only considering into account nodes that are moving at the same speed and direction, an improved Particle Swarm Optimization (PSO) approach for clustering is introduced in [16, 18]. ITS provide a number of design issues, some of which are a changing network layout, Variety of devices, transmission range, Node distribution, privacy and security. The right network topology is necessary for effective communication systems because it influences how nodes communicate with one another. Due to the limited transmission range along with constant movement of Mobile nodes in VANETs. ACO-Based Clustering method was suggested by researchers in [19] as an additional method for VANET (CACONET). In order to save network resources, CACONET optimizes two clustering operations: cluster minimization and CH stability. The iCHHO algorithm, inspired by Harris Hawks' Optimizes intelligent route clustering [20]. The system's whole fleet of vehicles is organized into various clusters. Each cluster assigns one node the duty of gathering data from every node in that particular cluster and transmitting it to other clusters or sinks. CH [21], the primary node with responsibilities, is referred to in this way. CHs are chosen using some metrics [22]. CH is applied to reduce the number of direct communication lines between sensing nodes and the data sink [17]. In a study [23] a methodology, ANT Colony Optimization, is employed that aims to minimize the number of shortest routes to the sink. Previous iterations of this method relied on the assumption that all sensory units needed to be in close proximity to the sink in order to communicate. Author in [19] presented a sophisticated routing optimization method for ITS. This approach leverages swarm intelligence and integrates the principles of ANT Colony Optimization (ACO) to improve the effectiveness of routing in the network. High mobility causes scalability problems due to the frequent topology changes. A clustering [24] approach based on Grey Wolf Optimization is presented in [9]. Two strategies—single-hop and multi-hop communication are employed in literature. In the first method, Data packets are sent directly from each device to the target location. While a subsequent strategy optimizes multi-hop communication in ITS by including clustering technology [25]. P-WOA, a probability-based whale optimization algorithm for cluster-based routing, surpassing ALO and GWO with a 75% improvement in cluster efficiency [26]. The Moth Flame Based Clustering method (CAMONET) is introduced in [27] which aims to enhance network stability by applying the Moth Flame Optimization (MFO) technique, with an emphasis on the cluster lifetime and the optimal number of CH. On the other hand, because of the unique characteristics of ITS, A set of guidelines created for WSN along with MANETs Are less executed in the case of ITS. Due to their specific requirements, Because nodes and their specifications, like as memory along with power utilization, vary widely in ITS, there are difficulties with issues like Quality of Service (QoS), among others [28]. The authors in [29] proposed the lion optimization algorithm (LOA) for the optimization of vehicular ad hoc networks (VANETs). This is a modified LOA QoS-based routing algorithm employed for pathfinding in VANETs. This harnesses the key attributes of a lion within a group and leverages the progression from nearby to a more powerful entities to enhance the navigation capabilities of Quality of Service (QoS) in vehicles. The authors in [30] presents a new approach to optimize the routing in Internet of Vehicles (IoV) networks. It utilizes the Harris Hawks' Optimization technique to effectively handle cluster stability and the dynamic changes in network topology. A comparative examination reveals this approach outperforms existing strategies in terms of cluster optimization, stability, Packet Delivery Ratio, bandwidth consumption, and latency. In [8] a cluster optimization technique for VANETs is introduced, utilizing whale optimization to fine-tune various parameters including communication range, number of nodes, network size, and load-balancing outcomes. This optimization process leads to an optimal number of clusters, effectively distributing network resources and prolonging the network's lifespan.

III. METHODOLOGY

This section focuses on clustering and selecting CHs in vehicular scenarios, employing an optimization algorithm inspired by crayfish behavior. The process initiates with the exploration phase, where vehicles on the highway share their data. Following this, the clustering procedure (exploitation phase) selects a CH based on each vehicle's fitness functions. This deploys intelligent clustering for VANET networks, utilizing a nature-inspired population-based approach. In Figure 2, exhibits the proposed COANET flow diagram. The steps of the suggested algorithm are outlined below. Typically, routing protocols focus on essential communication parameters. For instance, temperature-based protocols prioritize lowering node temperatures, considering hotspots, avoiding body motion, and optimizing energy usage. Similar to other routing systems, VANET often overlooks or minimizes important parameters in favor of a single one. Recognizing the significance of various aspects in VANET communication, there is a critical need for improved routing protocols. In order to make the VANET more effective, adaptable, and solvable, the developed framework employs an intelligent The

clustering mechanism to enhance the network's data packet routing. As the theory behind evolutionary algorithms goes, in any given population, only the most fit individuals will survive. A maximized function is employed to produce a number of possible answers. This maximal function, which is an abstract metric or threshold, produces a more meaningful result. In order

to find an even better solution, this fitness metric is used to choose the best candidate solution. These possible answers are the result of a number of processes, including as recombination and mutation. Recombination employs two potential solutions to produce a new solution (the offspring) by means of an operator, in contrast to mutation, which employs a single candidate solution. The process is carried out until a satisfactory solution shows up. Following this process often brings closer to the optimal work flow of evolutionary algorithms shown in Figure 2, where the components that must be included when constructing evolutionary algorithms.

1. Initialization: Create a starting population of prospective resolutions for the problem.
2. Evaluation Function: A fitness function, acting as the foundation for enhancements, is identified. It establishes a threshold value that solutions must achieve to be deemed acceptable.
3. Population: It encompasses every conceivable response.
4. Selection: Determine alternatives that could form the foundation or origin for the ensuing iteration.
5. Variation Operator: Two variation operators, mutations, and recombination are employed to choose new solutions from the current ones.
6. Survivor Selection Strategy: In the subsequent evolutionary round, parents, acting as capable children, provide optimal solutions. The current generation's offspring become maximizing functions for future solutions as they reach maturity for evaluation.

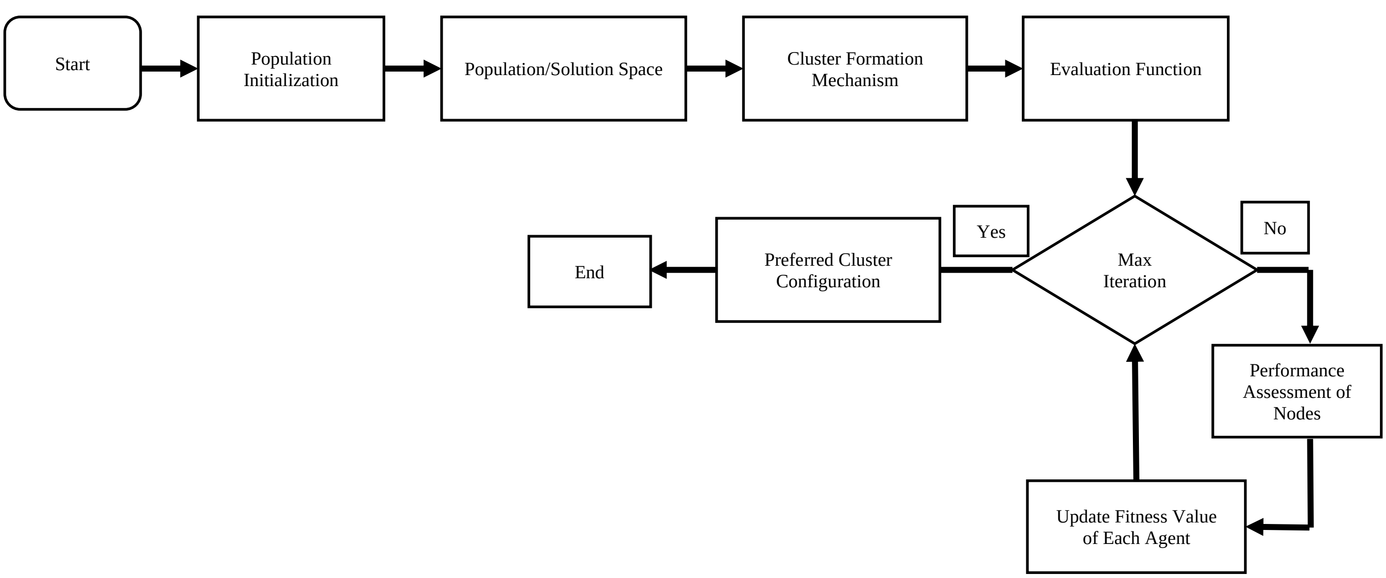

Figure 2: Proposed COANET Methodology

A. CRAYFISH OPTIMIZATION ALGORITHM

The crayfish, with its hard shell resembling a shrimp, falls under the classifications of arthropod, crustacea, or decapod. it exhibits night appearances and cave-digging tendencies. Thriving in various environments, over 600 crayfish species are identified with the ability to dig. These caves, essential for protection and various activities, differ in shape and function depending on the species. Crayfish, weighing 40-60 g after six months, show varied development rates influenced by environmental temperature. The ideal temperature for crayfish is 25° C, as temperatures below 25° C could impact r feeding and growth. Extremely high temperatures may force crayfish onto land, leading to oxygen deprivation. In terms of feeding habits, crayfish use their claws for capturing and dissecting large prey, while smaller prey is directly gripped and nibbled. These behaviors contribute to their survival and ecological role in freshwater environments. Crayfish often use their claws to grab big prey, and then they rip it apart with their second and third walking feet, which they then use to grasp and chew. On the other hand, for smaller prey, they use the same feet to directly grip and nibble [31], as seen in Figure 3.

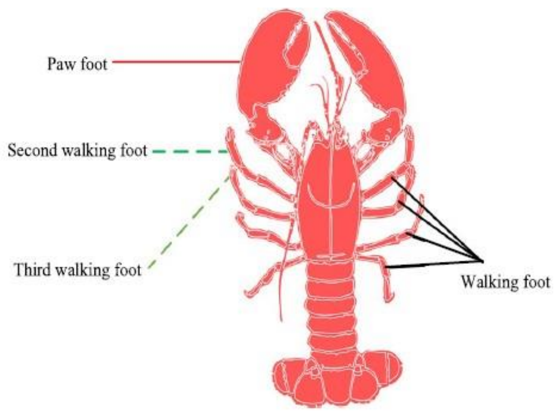

Figure 3: Structure diagram of crayfish [31]

B. SOURCE OF INSPIRATION

COA takes its inspiration from the crayfish's foraging, vacation during the summer, and competitive nature. In COA, the foraging and competition stages are considered exploitation, whereas the summer resort stage is considered exploration. At the beginning of the method, the crayfish colony Y is defined to represent the features of swarm intelligence optimization. The solution is shown by the *i*th crayfish's location, Y_i = { $Y_{i,1}$, $Y_{i,1}$, $Y_{i,1}$... $Y_{i,dim}$}, Where dim is the characteristic quantity of the optimization problem, sometimes called dimension, and Y_i is the set of all possible values from 1 to dim. Y_i utilizes the fitness value, or the function f (·), to find a solution. Temperature, a random constant representing the ambient temperature, controls the COA exploration and exploitation processes. Once the mercury rises beyond a certain point, COA will transition into its summer resort or competitive phase. Revise the updated solution during the summer resort stage based on the individual's position Y_i and the cave's position Y_{CH}. When the weather is right, COA will start to hunt for food. the solution acquired by the optimum solution, are used to determine the food size. When the meal is ready, crayfish use their position to find new solutions. Y_i, a constant dietary intake p, and an updated food position $Y_{No\ of\ vehicles}$. When the meal is too big, crayfish will rip it up with their claw foot, then consume it alternately with their second and third walking feet. To mimic the crayfish's alternate eating habit, we utilized the sine and cosine equations. A crayfish's food consumption may be regulated. Consumption of food follows a positive distribution as a function of temperature [31].

C. INITIALIZATION

In the context of VANETs, every vehicle is depicted as a matrix with dimensions of 1x dim in a multi-dimensional optimization scenario. each column within the matrix indicates a solution to a specific problem. Within Vehicular Ad Hoc Networks (VANETs), a set of variables ($Y_{i,1}$, $Y_{i,2}$, ..., $Y_{i,dim}$) is subject to constraints, with each Yi variable confined within predetermined upper and lower limits. The initialization process entails the random generation of a set of potential solutions Y within the given solution space. All vehicles represent candidate solutions within a solution space, where the vehicle set Y is determined by the population size (N) and dimension (dim). The initialization is represented by eq 1.

$$Y = [Y_1, Y_2, \ldots, Y_N] = \begin{bmatrix} Y_{1,1} & \cdots & Y_{1,j} & \cdots & Y_{1,dim} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ Y_{i,1} & \cdots & Y_{i,j} & \cdots & Y_{i,dim} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ Y_{N,1} & \cdots & Y_{N,j} & \cdots & Y_{N,dim} \end{bmatrix}, \quad (1)$$

In eq 1, Y represents the initial position of the vehicles, N stands for the total number of vehicles, and dim corresponds to the dimension of all vehicles on the highway. Each $Y_{i,j}$ signifies the position of vehicle i along the jth dimension, with its value obtained from eq 2.

$$Y_{i,j} = lb_j + (ub_j - lb_j) \text{ x rand} \quad (2)$$

where lb_j stands for the jth dimension's lower limit ub_j is the maximum value that can be represented by the jth dimension, whereas rand is a random integer.

D. ENERGY LEVEL AND SEARCHING OF VEHICLES

The change of energy will affect the behavior of vehicles to make clusters with the vehicles of different energy levels. The different energy levels will make CH to enter different stages. The Energy level of the vehicle is given in eq 3. The CH will select a summer vacation stage when the Energy level exceeds 30. In terms of suitable energy, the CH will conduct foraging stage. The CH is affected by energy of the surrounding vehicles. The CH performs well between the 15, 30 and 25 energy level where they can exploit the other vehicles. When energy levels are between 20 and 30, CHs will engage in vigorous foraging activities. ITS specifies an energy level range of 30–35.

$$E = \text{rand x } 15 + 20, \quad (3)$$

where E represents the energy of the vehicles where the CH is located. Mathematical Model of a searching of vehicles p,

$$p = C_1 \text{ x } \left(\frac{1}{\sqrt{2 \, x \, \pi \, x \, \sigma}} \text{ x exp } \left(-\frac{(E-\mu)^2}{2\sigma^2}\right)\right) \quad (4)$$

CH's optimal energy level is denoted by μ, whereas σ and C_1 are utilized for vehicle searches at various energy levels.

E. SUMMER RESORT STAGE(EXPLORATION)

When Energy of the vehicles is greater than 30 the energy is at an excessive level, at this time the vehicles possess sufficient energy to escape from a CH and the CH will choose summer vacation. CH exploring for vehicles is a random event. When randomness is less than 0.5 it means that there is no other vehicle for CH to explore. At this stage the CH will enter the summer resort stage using eq 5.

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + \text{rand x } (Y_{CH} - Y_{i,j}^{t}) \quad (5)$$

Each $Y_{i,j}$ signifies the position of vehicle i along the jth dimension, t is the current iteration number, and t + 1 is the iteration number for the following generation. Y_{CH} showcases the optimal position attained through the cumulative iterations and the current vehicle's optimal position. At the summer resort stage, the goal of CH is to explore the surrounding vehicles. Which represents the optimal solution. This brings vehicles closer to the optimal solution and enhances the exploitation ability of COA.

F. COMPETITION STAGE(EXPLOITATION)

When the Energy level of the vehicles is above 30 and the randomness value is equal to or greater than 0.5, it indicates that other vehicles are also showing interest in becoming a CH. The CH will enter a competition stage as shown in eq 6.

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} - Y_{z,j}^{t} + Y_{CH} \quad (6)$$

During the Competition stage, vehicles engage in competitive interactions, and vehicle Y_i repositions themselves in response to the position Y_z of another vehicle. By modifying the location, the exploratory range of the CH is enlarged, hence improving the algorithm's exploratory capability.

G. FORAGING STAGE(EXPLOITATION)

When the Energy of the vehicles is below or equal to 30. at this time the vehicles possess low energy, Currently, the vehicle will exhibit movement in the direction of the CH. Upon locating the vehicles with such appropriate energy levels, the CH will assess the dimensions of the positions of the vehicles. The CH is based on the magnitude of the Number of vehicles. If T (Number of vehicles) is more than $(C_3 + 1)/2$, where C_3 is the Vehicle factor, representing the largest no of vehicles, and the value is constant 3. To model the alternating procedure, a blend of the sine and cosine functions is employed to replicate the oscillating sequence. the CH will use eq 7 to first select the nearest vehicles and then attack on them.

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + Y_{No\ of\ Vehicles} \text{ x } p \text{ x } (\cos(\text{x } \pi \text{ x rand}) - \sin(2\text{x } \pi \text{ x rand})) \quad (7)$$

p represents the searching of vehicles. When T is less than or equal to (C3 + 1)/2, the CH will simply attack on the other vehicles. The eq 8 is given as followings:

$$Y_{i,j}^{t+1} = (Y_{i,j}^{t} - Y_{No\ of\ vehicles}) \text{ x } p + p \text{ x rand x } Y_{i,j}^{t} \quad (8)$$

To improve the algorithm's resource use and ensure its high convergence capacity, CH will systematically approach the most favorable solution throughout the foraging stage. $Y_{No\ of\ vehicles}$ represents optimal solution. The mathematical modeling and simulation for the devised COANET-based approach are presented in pseudo-code format, as detailed in Table 1.

Table 1. Pseudocode of developed COANET

PSEUDOCODE OF DEVELOPED COANET

1: Set up the starting points for all the vehicles, including their speeds, positions, and directions.
2: Create a network design with a grid of interconnected nodes and vertices; assign a unique identifier to each vertex.
3: Computation of the distance between vehicles, standardization, and linking these distances in a mesh network structure
4: Start a new population of randomly selected vehicles
5: Determine the vehicles fitness values.
6: Y* = the finest search agent (Cluster Head)
While (current iteration< maximum number of iterations)
Defining E as Energy of vehicle by eq 3
E = rand x 15 + 20, (3)
IF E>30
If rand<0.5 The positioned vehicle's location should be updated by eq 5
$Y_{i,j}^{t+1} = Y_{i,j}^{t} + \text{rand x } (Y_{CH} - Y_{i,j}^{t})$ (5)
Else position of the vehicle should be updated location by eq 6
$Y_{i,j}^{t+1} = Y_{i,j}^{t} - Y_{z,j}^{t} + Y_{CH}$ (6)
End
Else The searching of vehicles p is obtained by eq 4
$p = C_1 \text{ x } (\frac{1}{\sqrt{2 \text{ x } \pi \text{ x } \sigma}} \text{ x exp } (-\frac{(E-\mu)^2}{2\sigma^2}))$ (4)
IF E ≤ 30
& $T > (C_3 + 1)/2$
Then the currently positioned vehicle's location should be updated by eq 7
$Y_{i,j}^{t+1} = Y_{i,j}^{t} + Y_{No\ of\ Vehicles} \text{ x } p \text{ x } (\cos(\text{x } \pi \text{ x rand}) - \sin(2\text{x } \pi \text{ x rand}))$ (7)
Else position of the vehicle should be updated location by eq 8
$Y_{i,j}^{t+1} = (Y_{i,j}^{t} - Y_{No\ of\ vehicles}) \text{ x } p + p \text{ x } rand \text{ x } Y_{i,j}^{t}$ (8)
End
End
7: Verify and update any search agents that explore beyond the search region
8: Determine each vehicle's fitness level
9: Update Y* if there is a better solution
Current iteration = current iteration+1
10: **end while**
11: return Y*

IV. RESULTS AND DISCUSION

This section showcases the simulation outcomes obtained by taking several network parameters, including communication range, number of vehicles, network size, and load balancing factor. The acquired findings were then compared to those of existing benchmark methods, namely WOACNET and HHO. The proposed approaches and methodologies were executed commissioning GPU settings (Octave Library) and the Google Colab simulation configuration. Factors such as grid size, transmission range, and node count are included in the findings that correspond to the techniques below.

For several grid sizes, modeling and simulations were conducted. Both WOACNET and HHO were used to compare with COANET. Clusters were formed synthetically with transmission ranges of 100m to 1000m and a grid size of 1km x 1km, 2km x 2km, 3km x 3km and 4km x 4km. The simulation parameters are shown in a table 2.

Table 2. Simulation Parameters

Parameters	Values
Population Size	120
Maximum Iterations	350
Inertia Weight W	0.694
Lower Bound (lb)	0
Upper Bound (ub)	100
Search plane	2D
Communication Range	100m-1000m
Mobility Model	Freeway mobility model
Simulation Runs	10
W_1 (weight of first objective function) (Multi-objective)	0.5
W_2 (weight of second objective function) (Multi-objective)	0.5
Nodes	40–70

Experiments were carried out with 50 nodes across grid sizes of 1km x 1km, 2km x 2km, 3km x 3km and 4km x 4km varying the transmission range from 100m to 1000m. The proposed method, COANET, demonstrated superior optimization compared to WOACNET and HHO, yield an optimal number of clusters shown in Figure 4. The findings demonstrate cost-effectiveness for different transmission ranges.

Figure 5 illustrates that experiments were conducted with 70 nodes across grid sizes of 1km x 1km, 2km x 2km, 3km x 3km, and 4km x 4km, where the transmission range was set from 100m to 1000m. The proposed method, COANET, exhibited superior optimization compared to WOACNET and HHO, yielding an optimal number of clusters. The findings indicate that the suggested COANET is the most practical communication algorithm. Experiments show that expanding the Transmission range reduces the number of clusters. The number of clusters parameters exhibits an inverse correlation with the communication range, Decreasing the communication range results in an increase in the overall number of clusters within the network, and conversely, expanding the communication range leads to a reduction in the total clusters. The number of clusters affects network resources. In contrast to earlier methods, the newly developed COANET surpasses them under the specified conditions outlined in Figure 5. The outcomes clearly indicate that the optimized COANET approach improves routing through efficient clustering, resulting in a reduction in the number of hopes for network communication. Consequently, this minimizes packet delays and routing costs, leading to reduced resource requirements for a smaller number of clusters.

Figure 4. Transmission Range vs No of clusters for 50 Nodes in 1x1km, 2x2km, 3x3km, 4x4km Grid size

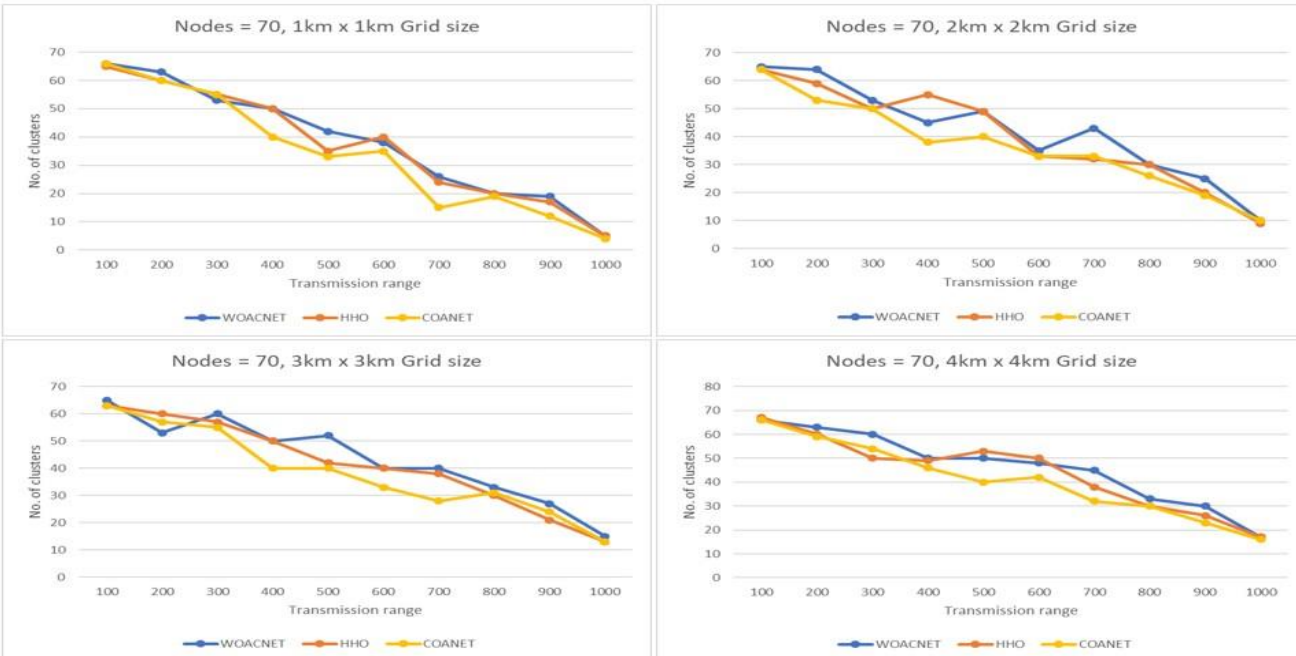

Figure 5. Transmission Range vs No of clusters for 70 Nodes in 1x1km, 2x2km, 3x3km, 4x4km Grid size

V. CONCLUSION

This paper introduces an innovative approach to cluster optimization for resource efficiency. The study employs a clustering optimization technique inspired by the behavior of crayfish in nature. The efficacy of this approach is assessed and examined utilizing both contemporary and cutting-edge methodologies. In terms of the number of CHs, the developed method COANET outperforms the existing algorithms, such as WOACNET, and HHO when communication ranges, network size, and the number of vehicles is varied. Furthermore, the suggested technique decreases the overall costs of the network by minimizing CHs to nearly optimal levels and enhancing cluster stability. Additionally, the application of the proposed clustering in VANETs has the potential to enhance routing scalability and reliability. This was achieved by grouping vehicles, forming a hierarchical network grounded on geographical and velocity distribution. In future, experimentation on extending the developed method within dynamic vehicular environments is progress.

VI. REFERENCES

[1] F. Cheng *et al.*, "UAV trajectory optimization for data offloading at the edge of multiple cells," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 6732-6736, 2018.

[2] X. Shen, G. Wu, R. Wang, H. Chen, H. Li, and J. Shi, "A self-adapted across neighborhood search algorithm with variable reduction strategy for solving non-convex static and dynamic economic dispatch problems," *IEEE Access*, vol. 6, pp. 41314-41324, 2018.

[3] D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: an overview," *Soft computing*, vol. 22, pp. 387-408, 2018.

[4] S. Mirjalili and S. Mirjalili, "Genetic algorithm," *Evolutionary Algorithms and Neural Networks: Theory and Applications*, pp. 43-55, 2019.

[5] M. Dorigo and T. Stützle, *Ant colony optimization: overview and recent advances*. Springer, 2019.

[6] B. Ji *et al.*, "Survey of Secure Communications of Internet of Things with Artificial Intelligence," *IEEE Internet of Things Magazine*, vol. 5, no. 3, pp. 92-99, 2022.

[7] A. Haydari and Y. Yılmaz, "Deep reinforcement learning for intelligent transportation systems: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 1, pp. 11-32, 2020.

[8] G. Husnain and S. Anwar, "An intelligent cluster optimization algorithm based on Whale Optimization Algorithm for VANETs (WOACNET)," *PLoS One*, vol. 16, no. 4, p. e0250271, 2021.

[9] M. Khan *et al.*, "Grey wolf optimization based clustering algorithm for vehicular ad-hoc networks," *Computers & Electrical Engineering*, vol. 70, 02/01 2018.

[10] A. Ali, F. Aadil, M. F. Khan, M. Maqsood, and S. Lim, "Harris Hawks Optimization-Based Clustering

Algorithm for Vehicular Ad-Hoc Networks," *IEEE Transactions on Intelligent Transportation Systems,* 2023.

[11] C. J. Joshua and V. Varadarajan, "An optimization framework for routing protocols in VANETs: A multi-objective firefly algorithm approach," *Wireless Networks,* vol. 27, no. 8, pp. 5567-5576, 2021.

[12] Z. Al Aghbari, A. M. Khedr, W. Osamy, I. Arif, and D. P. Agrawal, "Routing in wireless sensor networks using optimization techniques: A survey," *Wireless Personal Communications,* vol. 111, pp. 2407-2434, 2020.

[13] S. Mirjalili, S. Saremi, S. M. Mirjalili, and L. d. S. Coelho, "Multi-objective grey wolf optimizer: A novel algorithm for multi-criterion optimization," *Expert Systems with Applications,* vol. 47, pp. 106-119, 2016/04/01/ 2016.

[14] A. Raza, M. F. Khan, M. Maqsood, B. Haider, and F. Aadil, "Adaptive k-means clustering for Flying Ad-hoc Networks," *KSII Transactions on Internet & Information Systems,* vol. 14, no. 6, 2020.

[15] Y. Wang, X. Fu, Y. Yang, and O. Postolache, "Analysis on cascading robustness of energy-balanced scale-free wireless sensor networks," *AEU-International Journal of Electronics and Communications,* vol. 140, p. 153933, 2021.

[16] X. Bao, H. Li, G. Zhao, L. Chang, J. Zhou, and Y. Li, "Efficient clustering V2V routing based on PSO in VANETs," *Measurement,* vol. 152, p. 107306, 2020/02/01/ 2020.

[17] G. Husnain, S. Anwar, and F. Shahzad, "Performance evaluation of CLPSO and MOPSO routing algorithms for optimized clustering in Vehicular Ad hoc Networks," in *2017 14th International Bhurban Conference on Applied Sciences and Technology (IBCAST),* 2017: IEEE, pp. 772-778.

[18] H. Li, J. Zhang, X. Sun, J. Niu, and X. Zhao, "A survey of vehicle group behaviors simulation under a connected vehicle environment," *Physica A: Statistical Mechanics and its Applications,* vol. 603, p. 127816, 2022/10/01/ 2022.

[19] F. Aadil, K. B. Bajwa, S. Khan, N. M. Chaudary, and A. Akram, "CACONET: Ant Colony Optimization (ACO) Based Clustering Algorithm for VANET," *PLOS ONE,* vol. 11, no. 5, p. e0154080, 2016.

[20] G. Husnain *et al.*, "An Intelligent Harris Hawks Optimization Based Cluster Optimization Scheme for VANETs," *Journal of Sensors,* vol. 2022, p. 6790082, 2022/10/07 2022.

[21] U. Maan and Y. Chaba, "Accurate cluster head selection technique for software defined network in 5G VANET," *Wireless personal communications,* vol. 118, no. 2, pp. 1271-1293, 2021.

[22] M. Ren, J. Zhang, L. Khoukhi, H. Labiod, and V. Vèque, "A review of clustering algorithms in VANETs," *Annals of Telecommunications,* pp. 1-23, 2021.

[23] F. Aadil, S. Khan, K. B. Bajwa, M. F. Khan, and A. Ali, "Intelligent clustering in vehicular ad hoc networks," *KSII Transactions on Internet and Information Systems (TIIS),* vol. 10, no. 8, pp. 3512-3528, 2016.

[24] B. Alaya and L. Sellami, "Clustering method and symmetric/asymmetric cryptography scheme adapted to securing urban VANET networks," *Journal of Information Security and Applications,* vol. 58, p. 102779, 2021.

[25] L. Chan, K. Gomez Chavez, H. Rudolph, and A. Hourani, "Hierarchical routing protocols for wireless sensor network: A compressive survey," *Wireless Networks,* vol. 26, pp. 3291-3314, 2020.

[26] 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.

[27] Y. A. Shah, H. A. Habib, F. Aadil, M. F. Khan, M. Maqsood, and T. Nawaz, "CAMONET: Moth-flame optimization (MFO) based clustering algorithm for VANETs," *IEEE Access,* vol. 6, pp. 48611-48624, 2018.

[28] B. Abidi, A. Jilbab, and E. H. Mohamed, "Wireless body area networks: a comprehensive survey," *Journal of medical engineering & technology,* vol. 44, no. 3, pp. 97-107, 2020.

[29] M. B. Wagh and N. Gomathi, "Route discovery for vehicular ad hoc networks using modified lion algorithm," *Alexandria engineering journal,* vol. 57, no. 4, pp. 3075-3087, 2018.

[30] G. Husnain, S. Anwar, and F. Shahzad, "An Enhanced AI-Enabled Routing Optimization Algorithm for Internet of Vehicles (IoV)," *Wireless Personal Communications,* vol. 130, no. 4, pp. 2623-2643, 2023.

[31] H. Jia, H. Rao, C. Wen, and S. Mirjalili, "Crayfish optimization algorithm," *Artificial Intelligence Review,* vol. 56, no. Suppl 2, pp. 1919-1979, 2023.

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