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SSOCANET - Empowering VANETs with Salp Swarm Optimization-Enhanced Clustering Algorithm

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Vehicular Ad hoc networks (VANETs) present significant challenges due to the dynamic nature of vehicle movements, leading to a constantly changing vehicular network topology. This instability results in packet loss, network fragmentation, message reliability, and scalability issues. To address these challenges, clustering has emerged as a promising solution to escalate vehicle communication efficiency. However, determining the optimal number of clusters remains a crucial problem. The proposed solution, the Salp Swarm Optimization-Enhanced Clustering Algorithm for VANET (SSOCANET), leverages the foraging behavior of salps to optimize cluster formation based on multiple objectives. SSOCANET achieves an optimal number of clusters by employing carefully designed objective functions, minimizing communication overhead and end-to-end communication latency in a network. The simulation results demonstrate the superior performance of SSOCANET compared to other clustering approaches, offering a robust solution for VANETs.

Keywords: Bio-Inspired Clustering, Salp Swarm Optimization Algorithm, VANETs, Vehicular Clustering.

Introduction:

Vehicular Ad-hoc Networks (VANETs) have a decentralized network topology, where vehicles communicate directly with each other without relying on a central authority. VANETs play a significant role in enabling vehicle-to-vehicle (V2V) communication, fostering enhanced road safety for passengers and comfort for drivers [1][2]. This communication allows vehicles to share critical data like speed, direction, and position, empowering them to anticipate and respond effectively to potential hazards, enhancing transportation safety and efficiency. Moreover, VANETs facilitate the exchange of real-time traffic updates and warnings, empowering drivers to make informed decisions [2]. Furthermore, vehicles can seamlessly communicate and share data by leveraging advanced transceivers and Wireless Access Vehicular Environments (WAVE) technology, revolutionizing the future of smart and intelligent transportation systems [3][4][5][6][7].

However, a dynamic topology maintains the mobility of vehicles leading to frequent disconnections and message loss due to their significant distance from each other, contributing to the increased vehicle malfunctions [8][9][10]. Ensuring reliable communication between vehicles and addressing scalability is a significant challenge for communication protocols. The potential solutions lie in the scalability of VANET through the implementation of clustering [11][12][13]. Clustering refers to the grouping of nodes that share similar characteristics, forming a network of vehicles is regarded as a collection of small groups or clusters, each comprising of Cluster Head (CH) and another vehicle known as the Cluster Member (CM). CHs play a crucial role in the cluster's formation and communication with members, effectively managing limited wireless resources and overseeing vehicles on the road.

The primary challenge for researchers is to form and determine the optimal number(s) of vehicular clusters. The increased number of clusters in a specific vehicular environment can lead to an increase in the overall communication delay [14][15][16]. This study centers on vehicular clustering as a combinatorial optimization problem to address this issue. Moreover, network-based meta-heuristic clustering algorithms have been suggested. The objective is to improve the formation of vehicle groups by simulating the hunting strategies of gray wolves' techniques, as discussed in a study [17]. A MOPSO-based technique is also utilized for VANET operational efficacy [18]. The Comprehensive Learning Particle Swarm Optimization (CLPSO) algorithm is suggested to minimize the number of CHs, thereby, enhancing the efficacy of the weighted clustering algorithm. The Grey Wolf Optimization (GWO) clustering algorithms were proposed by Fahad et al. [19] and Liang, Jing J., et al.[20]. This study demonstrates the application of the Salp Swarm Algorithm (SSA) in determining the optimal number of clusters for Vehicular communication. The Salp Swarm Algorithm is derived from the foraging behavior of the Salp chain, which seeks out optimal sources of food. In the SSA, each salp functions as a search agent to find an optimal set of Cluster Heads. The proposed algorithm is being compared to benchmark algorithms, namely GWOCNET (Grey wolf optimization clustering algorithm) [19], MOPSO [18], and CLPSO-based clustering algorithm proposed in a study [17] and [20]. The proposed algorithm outperforms another clustering algorithm in terms of identifying the optimal number of clusters. Despite the availability of multiple clustering algorithms for vehicular networks aimed to enhance network efficiency by minimizing end-to-end delay and reducing network overhead, there remains room for enhancing the network's performance by acquiring the necessary optimal clusters for a specific vehicular network. The contributions of this paper are the following:

- A vehicular clustering algorithm based on Salp Swarm Optimization (SSOCANET) is proposed to reduce the number of clusters.
- Salp swarm optimization is mathematically modeled for combinatorial optimization problems.

- A comparative analysis has been performed to confirm the usefulness of the proposed algorithm in terms of end-to-end delay and network overhead.

Study Objectives:

The proposed mechanism aims to develop the optimal number of clusters using identified objective functions. This novel work enhances inter-vehicular communication efficacy by reducing overhead and end-to-end delay in the network caused by a large number of clusters.

Literature Review:

Meta-heuristics algorithms represent a class of optimization algorithms, specifically designed to solve a wide range of optimization problems, including medical health treatment, engineering design, and economics. These problems often exhibit intricate, non-linear, and multi-modal, involving conflicting objectives, posing significant challenges in finding optimal or near-optimal solutions. Meta-heuristic algorithms are autonomous, making them versatile tools that can be utilized for a wide range of research problems. Diversification and intensification are the key elements of meta-heuristic algorithms, necessitating the employment of randomized operators to generate a wide range of solutions and explore global space search. The intensification capitalizes on the regions identified during the diversification phase [21][22][23].

Fahad, M., et al. (2018) [19], introduced GWO clustering algorithms to enhance the formation of groups of vehicles by mimicking the hunting tactics employed by gray wolves. The MOPSO algorithm was introduced by A. Hamid et al. [18], which yields multiple solutions via the Pareto optimal front. The primary goals of the MOPSO algorithm include minimizing energy consumption, optimizing transmission range, and managing node mobility to enhance the life span of networks. In the context of the clustering approach, particles assume the role of search agents. CLPSO enhances the efficacy of the weighted clustering algorithm, by considering several parameters, including transmission range, speed, battery power, and distance [17][20].

Aadil, F., et al. (2016) [24] proposed CACONET and highlighted the process of selecting vehicular cluster heads by imitating the food-hunting behavior of ants. Every ant in the Ant Colony Optimization (ACO) algorithm evaluates a potential solution. Within CACONET, every ant generates a route that spans from the initial nest to the designated food location. Each ant's tour comprises vehicular clusters, which are subsequently assessed using the fitness function. ACONET is an expanded iteration of CACONET, which was originally suggested by the same author [25]. Machine learning techniques are also used for routing schemes used in VANETS [26]. Artificial intelligence, machine, and deep learning can further enhance optimization.

From the literature review, it is found that the existing algorithms lack clusters optimization which leads to increased communication overhead and end-to-end delay during communication. To resolve this issue, we introduce a new approach, which employs salp swarm optimization. The following section details the proposed approach.

Materials and Method:

The Proposed Approach:

The Salp Swarm Algorithm (SSA) is a stochastic optimization algorithm that is based on swarm intelligence inspired by nature, introduced by Mirjalili *et al.*, in 2017 [27]. SSA is created through a population-based optimization process that mimics the collective behavior of Salp, a marine organism, in nature. Nevertheless, the majority of the species exhibit similar characteristics and behaviors, including their ability to move, forage for food, and communicate with one another. A salp is a marine organism classified within the family Salpidae, its shape resembles that of jellyfish. Despite the challenges of accessing living environments, various biological researchers argue that the behavior of salp contributes to improved foraging and locomotor performance.

Exploration and Exploitation:

The Salp Swarm algorithm is designed to explore location to find the best possible solutions globally, while also preventing the algorithm from getting stuck in a local optimum. It aims to maximize the probability of detecting the global optimum. The Salp Swarm algorithm locally explores the region to obtain improved solutions by utilizing the resources available through the neighboring solutions [27]. Figure 1 shows individual salp and chain of salp.

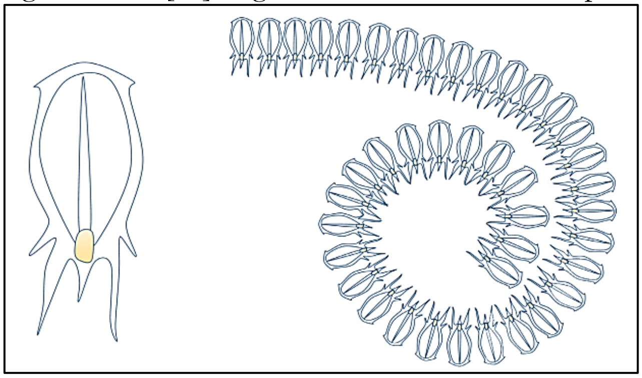

Figure 1: (a) Individual Salp (b) Swarm of Salp (Salp Chain) [27].

Each search agent in the proposed approach maintains data regarding the vehicles belonging to cluster members and cluster head vehicles. This method identifies CH and its neighboring nodes for the selected CH. Each cluster must have only one CH, and a vehicle cannot serve as the Cluster Head for multiple clusters. Every search agent randomly incorporates CHs into their solution. In the optimization of vehicular cluster formation, each search agent in the problem space was randomly initialized to find the optimal solution. Each vehicle was randomly positioned within the search space in terms of grid size. The solution in the cluster matrix was discovered by each search agent through the utilization of Salp swarm behavior. Within the cluster matrix, every search agent picked a vehicle to act as a CH and included it in the cluster matrix for the search area.

Every search agent, such as a salp, located a nearby individual and selected a cluster head. If there were multiple nodes with the highest fitness value, they were included in the cluster matrix. Following the development of the solution, every search agent was assessed based on an objective function, which includes two criteria: i) the delta difference C1, and ii) the distance neighbor C2. The Delta Difference represented the disparity between the optimal capacity of vehicles, which a cluster can efficiently serve during simulation, and the actual number of vehicle(s) present in a particular cluster. The calculation of C1 is outlined as follows:

$$C1 = \sum_{j=1}^{j} |\delta - CMi| \qquad (1)$$

Where δ represents the ideal capacity of vehicles that a j^{th} cluster can efficiently serve, and CM_j denotes the actual number of vehicles obtained in a j^{th} cluster. A minimum value of the delta difference is utilized to minimize the number of clusters. Figure 2 shows the flowchart of the proposed methodology.

Similarly, CHj represents the Cluster Head of Cluster j, and CM_k is a cluster member within the same Cluster j, where L denotes the total number of CH. It is beneficial to choose the search agent with a short range of distance neighbors because minimizing the distance between a CH and its cluster members facilitates efficient message transmission, ensuring highly reliable communication. After evaluation, each search agent updates its position vector toward the best search agent that contains an optimal number of clusters, using the exploitation phase obtained. It is essential to update the agent's position to be near the best superior set of clusters or Cluster Heads (CHs). The update of the search agents' locations is governed by the Vector A coefficient. Diversification behavior is performed in case of A > 1, conversely, intensification behavior is performed in case of A <1 [28].

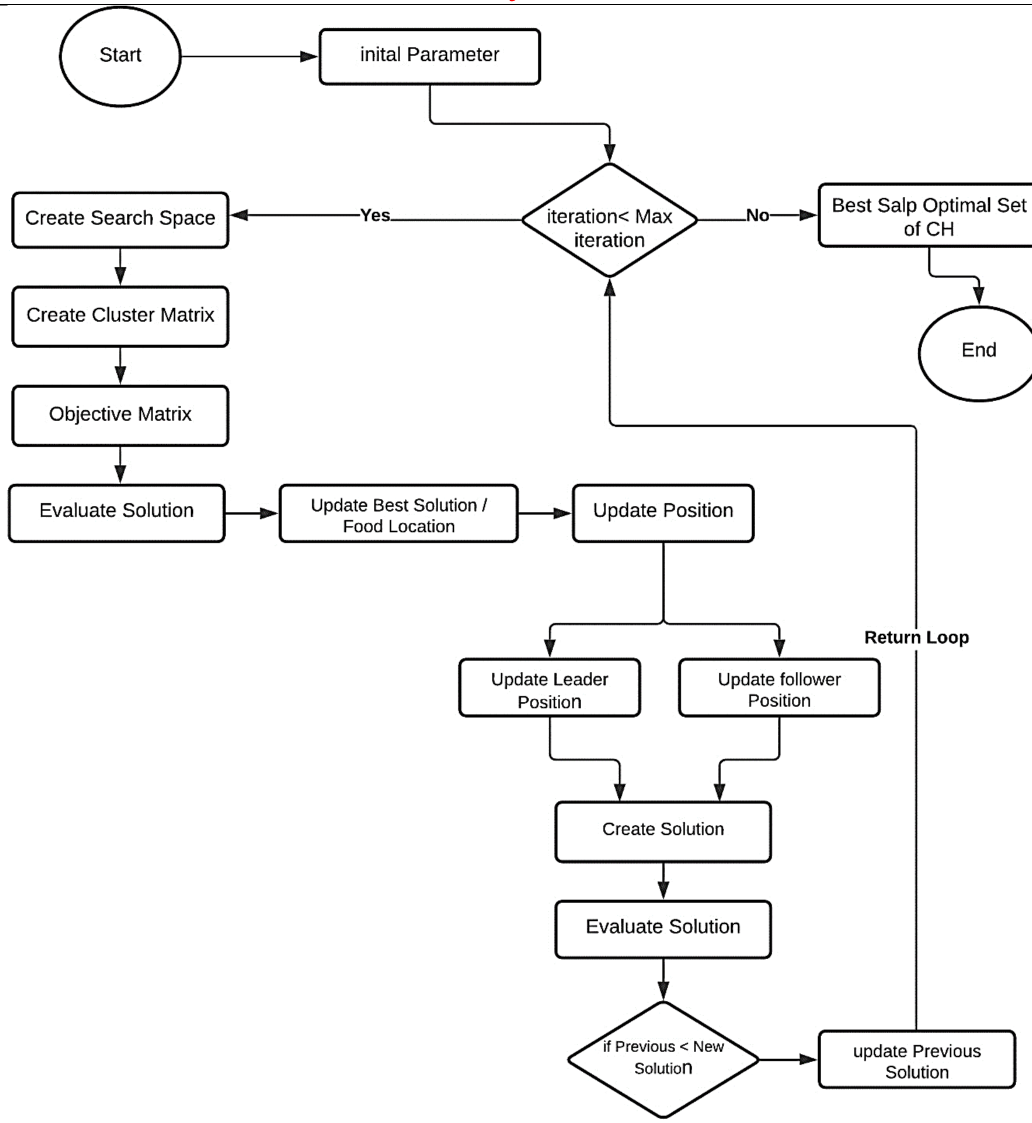

Figure 2: Flowchart of the proposed methodology

The summation of distances between the cluster head and cluster members across all clusters is computed as follows:

$$C2 = \sum_{j=1}^{l} \left[\sum_{k=1}^{CN_k} D\left(CH_j, CM_{k,j}\right)\right] \qquad (2)$$

Behavior of Search Agents:

The swarm of search agents has two categories i.e., the leaders and the followers. The leader is the swarm with the leadership qualities while other search agents follow the leader. The positions of the salps are described in an f-dimension problem space, where f represents a variable specific to the given problem. Therefore, all the salps' positions are stored in a two-dimensional matrix called x. It is presumed that the food source, referred to as f in the search space, is the target of the swarms. Here, x_k^1 denotes the position of the leader (salp) in the kth dimension, fk represents the food source position in the k^{th} dimension, specifying the upper bound of the k^{th} dimension, whereas lb_k indicates the lower bound of the kth dimension. Additionally, h_1, h_2, and h_3 are specified as random numbers.

$$x_k^1 = \begin{cases} f_k + h_1\left((ub_k - lb_k)h_2 + lb_k\right) & h_3 \geq 0 \\ f_k + h_1\left((ub_k - lb_k)h_2 + lb_k\right) & h_3 \geq 0 \end{cases} \qquad (3)$$

Equ:1 shows that leader updates their position concerning a food source.

$$h1=2e-(\frac{4It}{It_{Max}})\,2 \qquad (4)$$

Where It_{Max} and It represents maximum and current iteration respectively, h_1 and h_2 are random numbers in the range [0,1]. The direction of the next position is defined using the equation below.

$$x_k^j = \frac{1}{2}\eta t^2 + \beta_0 t \qquad (5)$$

$\eta = \frac{\beta_{final}}{\beta_0}$ where $\beta = \frac{x-x_0}{t}$ is time to iterations in optimization, inconsistency between iterations is equal to 1. Considering that $\beta_0 = 0$, The equation is figured out for this issue.

$$x_k^j = \frac{1}{2}(x_k^j + x_k^{j-1}) \qquad (6)$$

Where $j \geq 2$ and x_k^j the show is the position of jth follower of Salp in kth dimension. The results are simulations and discussed in the following section. The following Figure 2 shows the flowchart of the proposed methodology.

Result and Discussion:

The proposed approach is compared with similar approaches, i.e., CLPSO [17] and MOPSO [29], and GWOCNET [19]. The results are generated using the simulation parameters listed in Table 1. The results showed that the proposed clustering approach outperformed the other clustering algorithms. It is because high convergence rate and proper equilibrium between exploration and exploitation faced by the Salp Swarm Algorithm.

Table 1: Simulation Parameters

Parameters	Value
Nodes	30-60
Grid Size	1x1 Km
Delta	10
Max Iteration	150
Number of search agents	100
Transmission Range	100m-600m

Count of CHs Versus Transmission Range:

To generate results, the transmission range is varied from 100 to 600m, and the number of nodes increases from 30 to 60. Four distinct solutions are generated, and multiple experiments are conducted on a 1 km × 1 km road network. The proposed algorithm aims to minimize the count of CHs for an optimized solution across each transmission range, ensuring complete network coverage with an optimal number of vehicular clusters.

The proposed solution consistently produces minimal clusters for every transmission range within the 1 km × 1 km grid, effectively covering the entire network. The optimization methodologies utilized in SSOCANET for cluster creation outperformed those of CLPSO, MOPSO, and GWOCNET, resulting in superior cluster formation results. Table 2 provides definitions and explanations of optimization algorithms and networking concepts.

Figure 3 depicts the number of cluster heads with transmission range.

Table 2: Definitions and Explanations of Optimization Algorithms and Networking Concepts

Term	Definition	Explanation
MOPSO (Multi-Objective Particle Swarm Optimization)	An optimization algorithm that extends Particle Swarm Optimization (PSO) to handle multiple objectives.	In traditional PSO, particles (potential solutions) move through the search space to find the best solution to a single problem. MOPSO adapts this by considering several objectives simultaneously, helping to find a set of

Term	Definition	Explanation
		optimal solutions that balance different goals.
GWO (Grey Wolf Optimizer)	A nature-inspired optimization algorithm based on the social hierarchy and hunting behavior of grey wolves.	This algorithm mimics the leadership structure of grey wolves, where alpha, beta, delta, and omega wolves guide the search process. The pack's collective intelligence is used to find optimal solutions to complex problems.
CLPSO (Comprehensive Learning Particle Swarm Optimization)	A variant of the PSO algorithm that enhances particle learning and diversity.	In CLPSO, each particle learns from the experiences of multiple other particles, not just the best-performing ones. This comprehensive learning strategy helps prevent premature convergence and improves the search for optimal solutions.
VANETs (Vehicular Ad Hoc Networks)	A type of mobile ad hoc network specifically designed for vehicles.	These networks enable vehicles to communicate with each other and with roadside infrastructure. VANETs support applications for traffic management, safety, and infotainment by allowing real-time data exchange and cooperative vehicle behavior.

Count of CHs Versus Number of Vehicles:

In this setup, we assessed the experiments by investigating the correlation between the count of CHs and the number of cars. The transmission range remains constant at 100m within a grid size spanning 1x1 km. We experimented by varying the number of cars from 30 to 60. Furthermore, we repeated the same experiment using transmission ranges of 200m, 300m, and 400m. We evaluated the effectiveness of the SSOCANET algorithm in minimizing end-to-end delays compared to similar approaches. The results of these comparative analyses are detailed in subsections and depicted in Figure 4, Figure 5, and Figure 6, respectively.

End-to-End Delay:

This setup investigated the proposed algorithm in terms of the end-to-end delay of the using number of cars set to 30 and 40 within a grid size of 1x1 km. End-to-end delay refers to the delay from the source cluster to the destination cluster. The results showed that SSOCANET exhibited lower end-to-end delay, compared with benchmarked cluster algorithms. This decrease in delay can be attributed to SSOCANET's capability to generate fewer cluster heads, leading to minimized end-to-end delay.

Communication Overhead:

In simulations, the communication overhead was calculated for network nodes ranging from 30 and 40 within a simulation area of 1x1 km. Communication overhead encompasses the overhead generated by the formation and dissolution of cluster heads within their respective clusters, as well as the creation and transmission of packets, which collectively contribute to communication overhead on the network. The level of communication overhead is directly correlated with the count of CHs, implying that a smaller number of clusters results in reduced communication overhead on the network and vice versa. The results show that SSOCANET exhibited lower communication overhead on the network compared to benchmark solutions. This reduction can be attributed to SSOCANET's ability to generate fewer clusters during simulation, thereby minimizing communication overhead on the network.

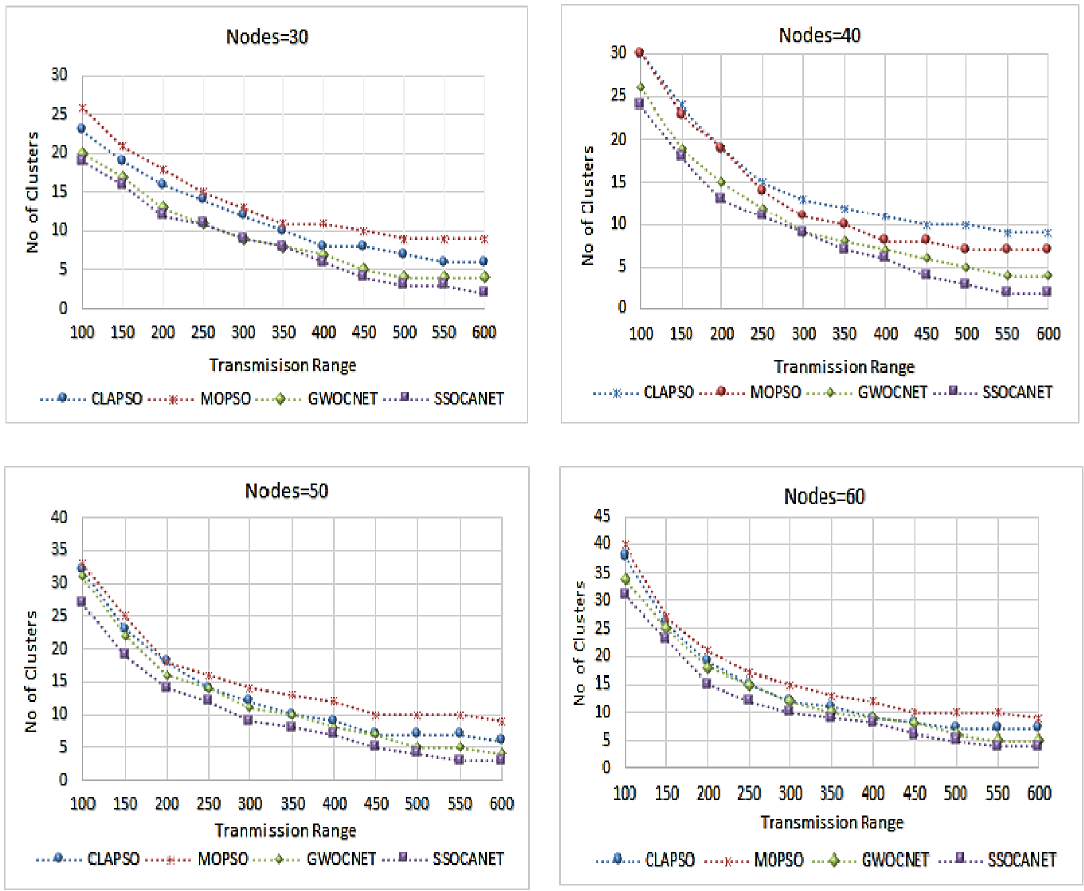

Figure 3: Number of CH's Vs Transmission Range

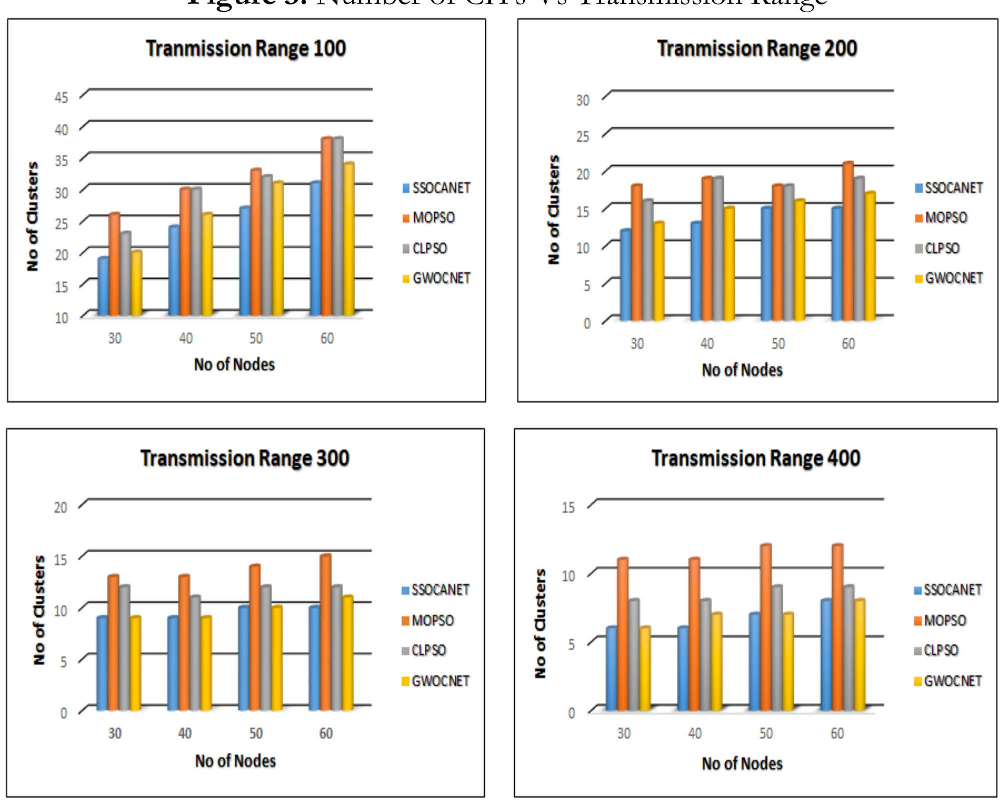

Figure 4: Number of CHs VS Network Nodes

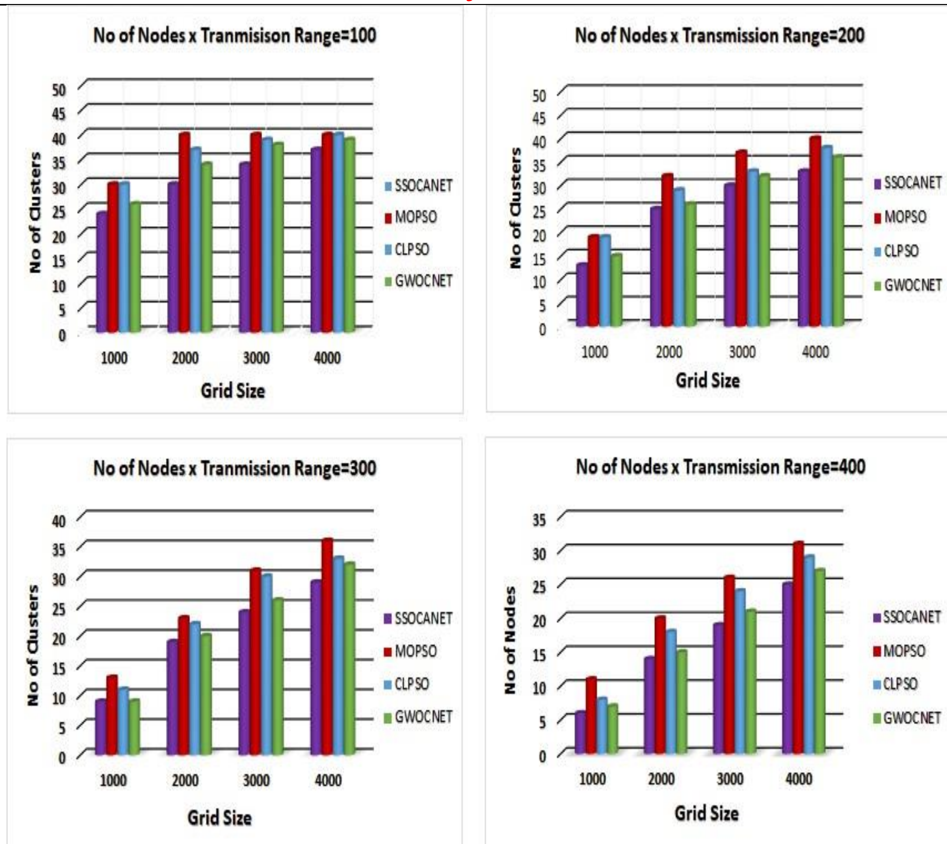

Figure 5: grid size verses Vs count of CHs.

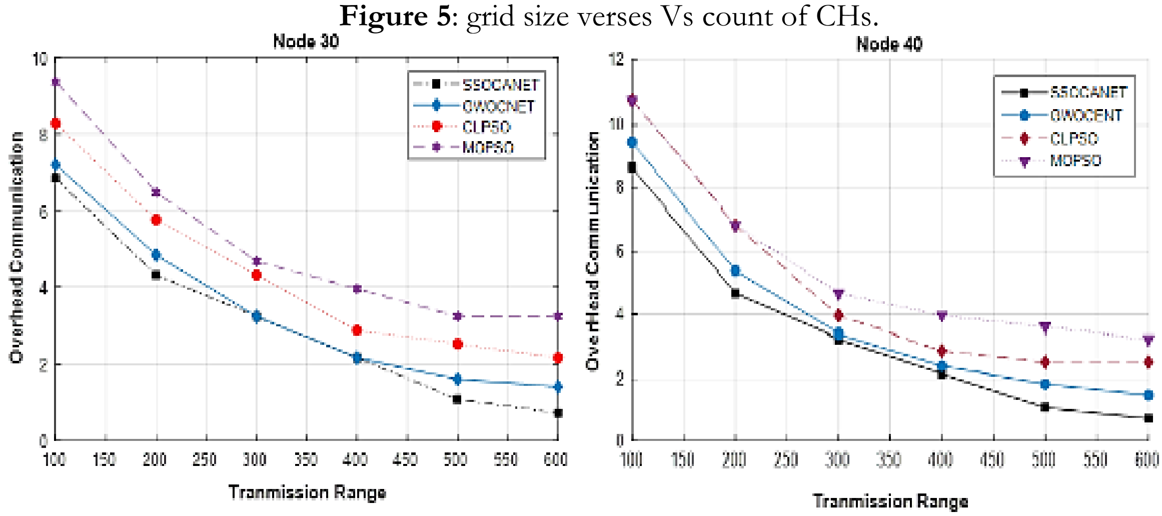

Figure 6: Transmission Range vs. Communication Overhead.

Discussion:

The proposed approach leverages the Salp Swarm Algorithm (SSA) to optimize vehicular cluster formation in VANETs, demonstrating significant improvements in various performance metrics compared to existing algorithms like CLPSO, MOPSO, and GWOCNET. SSA is inspired by the swarming behavior of salps, marine organisms that exhibit efficient collective movement and foraging strategies. The algorithm balances exploration, searching globally for potential solutions, and exploitation, refining locally to improve existing solutions, thereby preventing entrapment in local optima and enhancing the probability of finding the global optimum.

In the SSA-based approach, each search agent randomly selects Cluster Heads (CHs) and evaluates them based on an objective function that includes the delta difference (C1) and the distance neighbor (C2). The delta difference measures the disparity between the optimal and actual number of vehicles a cluster can efficiently serve, aiming to minimize the number of clusters. The distance neighbor criterion measures the total distance between CHs and their cluster members, aiming to minimize communication delays and enhance message transmission reliability.

Comparative performance evaluations against CLPSO, MOPSO, and GWOCNET, using defined simulation parameters, revealed that SSOCANET consistently produced fewer clusters across various transmission ranges and numbers of vehicles, indicating a more efficient clustering process. The SSA-based approach exhibited lower end-to-end delays compared to the benchmark algorithms, primarily due to the optimized cluster formation, which reduces the number of hops required for data transmission between clusters. Additionally, SSOCANET demonstrated lower communication overhead, attributed to its ability to generate fewer clusters, thereby reducing the overhead from cluster formation, maintenance, and data packet transmissions.

The simulation results highlighted in the figures show the superiority of SSOCANET in terms of the number of cluster heads (CHs) versus transmission range and the number of network nodes. These results illustrate the efficiency and scalability of the SSA-based approach under varying network conditions. In conclusion, the application of the Salp Swarm Algorithm in vehicular clustering within VANETs presents a significant advancement over traditional optimization algorithms. SSOCANET's ability to maintain a high convergence rate and balance between exploration and exploitation results in optimized cluster formation, reduced end-to-end delay, and minimized communication overhead, thereby enhancing the overall performance and reliability of VANETs and making SSOCANET a promising solution for efficient vehicular network management.

Conclusion:

This research introduced a salp swarm optimization-based clustering approach for VANETs, comprising four key steps. Initially, the algorithm randomly positions vehicles and search agents within the search space. Subsequently, each search agent generates a clustered matrix to facilitate solution creation, with cluster heads randomly distributed within this matrix. The third step involves evaluating solutions using the objective function, which incorporates delta difference and distance neighbor metrics. Finally, in the fourth step, each search agent updates its position through a combination of exploration and exploitation. Comparative analysis with the benchmark optimization algorithm approaches, including GWOCENET, MOPSO, and CLPSO, revealed that the proposed solution effectively optimized the formation of vehicular clusters and mitigated end-to-end communication delays. This underscores the efficacy of the salp swarm optimization-based clustering mechanism in enhancing the performance of VANETs.

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Author Contributions:

Zeeshan Hidayat conducted the experimental segment of this study. Zulfiqar Ali drafted the manuscript and evaluated the results. Shahab Haider contributed to algorithm design and simulations. Iftikhar Alam organized the results, conducted the literature review, and analyzed the results. Asad Ali performed proofreading of the paper.

Conflict of Interest: The authors declared no conflict of interest.

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