Particle Swarm Optimization based Efficient Cluster Formation in Vehicular Networks

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Abstract. Vehicular ad-hoc networks (VANETs) are extensively utilized for intelligent mobility and roadside advertising. In VANETs, vehicles equipped with wireless sensors function as mobile nodes capable of communication in both infrastructure and ad-hoc modes. Clustering vehicles within VANETs enhances resource utilization, system capacity, and scalability. Our study presents a novel approach to VANET clustering using particle swarm optimization, offering improvements over several existing algorithms. This technique focuses on the creation of clusters that avoid collisions with nearby vehicle nodes. The algorithm determines the optimal number of clusters and selects the cluster head vehicle based on its minimal distance from the respective cluster members.

Keywords: vehicular ad-hoc network · PSO · clustering · cluster head.

1 Introduction

A Vehicular Ad-hoc Network (VANET) is a specialized type of wireless ad-hoc network designed for vehicles. VANETs utilize wireless communication between vehicles and roadside infrastructure to support various applications, including traffic management, road safety, and entertainment [1]. VANETs operate on the principles of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, facilitating real-time information sharing and cooperative decision-making among vehicles [2]. This capability supports various applications, including collision avoidance, traffic congestion reduction, and intelligent transportation systems (ITS) [3]. The VANET architecture is illustrated in Fig. 1.

The primary challenge in VANETs is to efficiently broadcast data to all vehicles within the network region while adapting to the dynamic and unpredictable nature of the vehicular environment. This involves addressing issues such as high mobility, limited bandwidth, and frequent disconnections. Another challenge in VANETs is the formation of clusters for data distribution within the network. This approach allows alerts or signals to be disseminated over a wider range, increasing vehicle awareness of emergencies well in advance [4]. Optimally forming clusters can reduce the overload on Road Side Units (RSUs) during data dissemination, enabling faster availability of data or signals compared to the

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conventional process where RSUs communicate individually with each vehicle. Each cluster will have a cluster head (CH) vehicle responsible for maintaining the cluster at any given time, considering the dynamic nature of the environment due to vehicle movement [5]. The CH must establish a connection with its cluster members (CM) to facilitate data spreading within the VANET.

In recent years, extensive research and development have been conducted in the field of VANETs, leading to numerous solutions for addressing various challenges. Consequently, VANETs have the potential to significantly impact the future of intelligent transportation systems and smart cities.

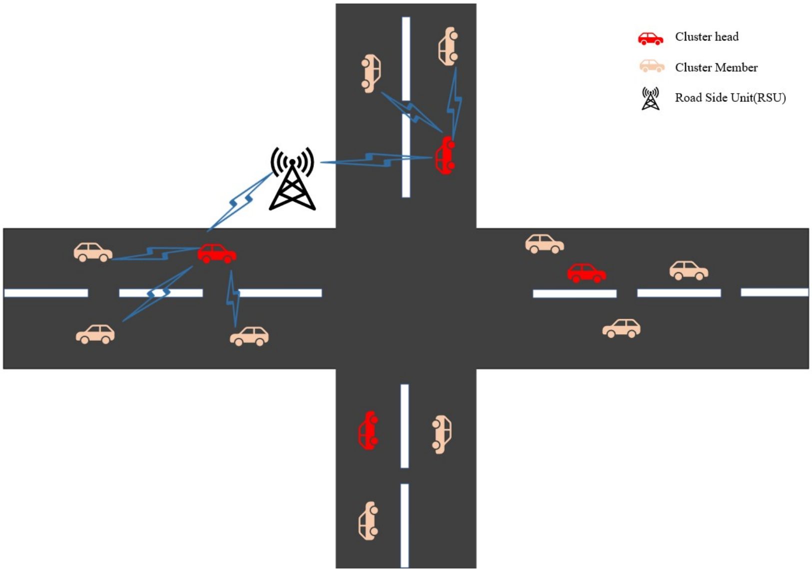


Fig. 1. VANET Architecture.

Our main contribution will be the formulation of the linear programming of the clustering of vehicles, considering the usable parameters. Then a nature-inspired algorithm has been proposed for the formation of fitness functions and producing the clusters in the VANET environment. Then a simulation of the algorithm that has been presented is used to demonstrate how it is superior to some other algorithms that are currently being used.

The remaining paper is organized as follows: The related work is mentioned in Section 2. Section 3 presents the model assumptions and problem formulation. The proposed algorithm is explained in Section 4. The result and analysis are explained in Section 5. Section 6 concludes the paper.

2 Related Work

Several clustering algorithm approaches have been proposed by different authors considering the minimized distance as well as the specific number of cluster formations. Some of the literature review is presented below:

Ant Colony optimization-based routing algorithm for VANET considering reliable low latency in the communication has been proposed by the authors [6]. The multi-lane highway is considered and also the position and velocity of the vehicles, route reliability(RR), and link reliability (LR) are calculated and CH is selected based on RR. Then ACO is used for the formation of an optimal number of clusters in the VANET scenario.

Grey wolf optimization algorithm had been proposed by the author to evaluate the optimal number of clusters in the VANET and CH selection is also implemented. The formation of the clusters of vehicles in this approach is proceeded based on looking into the similar features of the auto-mobiles and those features could be speed, location, and direction [7]. The selected CH will help in maintaining the clusters as well as distribute the data more efficiently.

In [8], authors proposed a Moth-Flame Optimization algorithm to establish clusters in VANET such that the number of clusters formed will be user-specific in the given environment and also the CH selection is carried out based on Euclidean distance between the CH and CM. This approach is only applied to the V2V communication.

Whale optimization algorithm is implemented by the authors that also evaluates the optimal number of cluster formations such that communication will be reliable [9]. The algorithm also signifies the vehicles as CH and CM based on parameters like position, speed, and direction. The ideal number of clusters is user-defined in this proposed algorithm which is decided based on the scalability of VANET in the proposed scenario by the authors.

Multi-hop clustering in the VANET environment is proposed by the authors using the principle of particle swarm optimization (PSO) [10]. The vehicles containing an on-board unit (OBU) will be programmed to send messages to nearby vehicles that are present in the transmission range and the sent message will contain some information like the distance of the vehicle from the other vehicles or the number of hops covered to reach the destination vehicle. Such information helps in selecting the CH vehicles and the CM vehicles for a specific cluster formed. Clustering for other networks can be seen in [11–13].

3 System Model and Problem Formulation

3.1 Model Assumptions

In this paper, we consider the VANET environment based on specific parameters. The environment consists of two two-lane roads with a grid size of G and vehicles with a transmission range of TR. Suppose there are N vehicles present in the scenario, all in motion as depicted in Fig. 2. Additionally, there are K

RSUs in the scenario, connected to the CH vehicles within the network. The designated vehicle as the CH will be responsible for data distribution and cluster maintenance, with each cluster having only one CH. Each CM should participate in only one cluster and must be within the CH's transmission range to ensure reliable data or signal transmission.

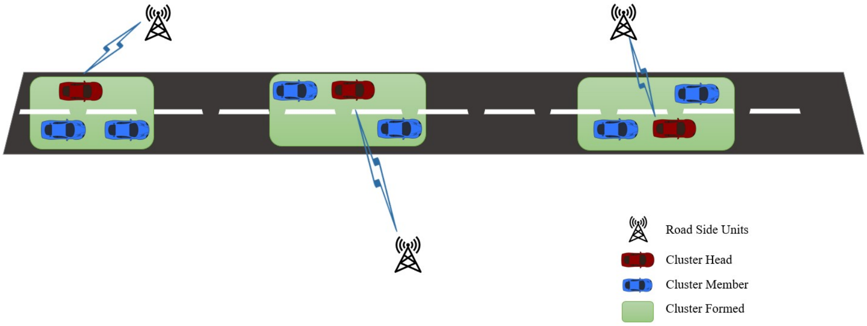


Fig. 2. An example of cluster formation in the VANET environment.

The following notations are used:

- The set of vehicles, $V = \{v_1, v_2, \ldots, v_N\}$
- The set of RSUs, $R = \{R_1, R_2, \ldots, R_K\}$
- Transmission range of vehicles as TR
- Grid size of the environment as G
- Cluster head vehicles are denoted as CH

3.2 Problem Formulation

Definition 1 (Number of clusters formed). *Let s be a boolean variable, which can be defined as follows:*

$$s_i = \begin{cases} 1 & v_i \in CH_i \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Where v_i is defined as a vehicle from the set of vehicle V.

$$Minimize \quad C_{CH} = \sum_{i=1}^{N} s_i \tag{2}$$

where C_{CH} stands for count the number of CH.

Definition 2 (Distance between CH and CM). *We will evaluate the Euclidean distance (ed) between the CH and CM of all the clusters formed as follows:*

$$ed(CH_i, CM_{ij}) = \sqrt{(x_i - x_j) + (y_i - y_j)} \tag{3}$$

where (x_i, y_i) and (x_j, y_j) are the positions of the CH and CM vehicles at a specific time.

$$distCH_i = \sum_{j=1}^{N} \begin{cases} ed(CH_i, CM_{ij}) & ed(CH_i, CM_{ij}) < TR \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Here, the i^{th} cluster head position is represented as CH_i, and the position of j^{th} cluster node in i^{th}cluster is represented as CM_{ij}. $distCH_i$ evaluates the sum of all distances of the CH vehicle from the CM vehicle present in the i^{th} cluster. The sum of all these distances represents the d_{CH} function as defined as follows:

$$Minimize \quad d_{CH} = \sum_{i=1}^{N} distCH_i \tag{5}$$

Here, N denotes the number of clusters formed, and the minimized value of this function is acceptable. Then the formulated Fitness function is given below:

$$F = w_1 \times C_{CH} + w_2 \times d_{CH} \tag{6}$$

where w_1 and w_2 are mentioned as weights for the objective function C_{CH} and d_{CH} respectively. The values of the above weights can be assigned based on the parameters that are specified in Section 3.1 like grid size, number of vehicles, and TR.

4 Proposed Works

4.1 An Overview of Particle Swarm Optimization

Particle Swarm Optimization (PSO) applies nature-inspired principles to tackle optimization problems [14–17]. Inspired by the collective behavior of swarms in nature, such as flocks of birds searching for food and shelter, PSO models each potential solution as a particle. In this analogy, finding food corresponds to discovering the optimal solution [18, 19]. Particles navigate through the search space by adjusting their positions based on the best position they have individually achieved (personal best) and the best position found by any particle in the swarm (global best). This iterative process harnesses velocity to converge towards the optimal solution efficiently.

In the mathematical representation of PSO, parameters involve several particles N, a position vector defined as $\overrightarrow{pos_i} = [\overrightarrow{pos_{1i}}, \overrightarrow{pos_{2i}}, \ldots, \overrightarrow{pos_{Di}}]$ where $1 < i < N$ and D is the dimension of a particle, and this represents a complete solution and another parameter is velocity of the particle such that $V = [v_1, v_2, \ldots, v_n]$ which helps in exploration that defined search space for all the particles.

The final objective of the PSO is to find the best solution in the population which defines the highest or lowest possible value of fitness function as per the need of the problem. At the start of the algorithm, the position is initialized as random values and the velocity of all particles will be equal to zero. in each iteration or generation, Gbest and Pbest values or particles are updated. The velocity is updated [20] using Eq. (7).

$$V_i^{t+1} = \omega \times V_i^t + c_1 \times r_1 \times \left(\overrightarrow{Pbest_i^t} - pos_i^t\right) + c_2 \times r_2 \times \left(\overrightarrow{Gbest_i^t} - pos_i^t\right) \tag{7}$$

where V_i^{t+1} denotes the velocity of i^{th} particle at interval $t+1$. ω stands for inertia weight factor. c_1 and c_2 identifies as acceleration coefficients, r_1 and r_2 are random numbers generated between 0 and 1. V_i^t denotes the velocity of i^{th} particle at interval t.

Algorithm 1 Particle Swarm Optimization Algorithm

Initialise $POP_i(t) = \{pos_{1i}(t), pos_{2i}(t), \ldots, pos_{Ni}(t)\}$
Initialise the $\overrightarrow{Pbest} = \{\overrightarrow{pos_1}, \overrightarrow{pos_2}, \ldots, \overrightarrow{pos_N}\}$
Initialise the $\overrightarrow{Gbest} = \min(\overrightarrow{Pbest_i})$
for $t = 1 : Max_{iter}$ **do**
    for i = 1:N **do**
        Update the velocity.
        Update the position vector.
        if Fitness($\overrightarrow{Pbest_i}$) $>$ Fitness($\overrightarrow{pos_i}$) **then**
            Update $\overrightarrow{Pbest_i} = \overrightarrow{pos_i}$
            if Fitness($\overrightarrow{Gbest}$) $>$ Fitness($\overrightarrow{Pbest_i}$) **then**
                Update $\overrightarrow{Gbest} = \overrightarrow{Pbest_i}$
            end if
        end if
    end for
end for

The basic idea of our proposed algorithm is defined as follows. At the beginning, the application region is prepared by the RSUs which are connected to the internet which will represent our grid size. The vehicles entering the grid formed by the RSUs will be assigned as CH and CM. The vehicles will send or receive the details of distance from each other via RSUs and the clusters will be formed based on the fact that the distance between them will be less than the transmission range of the CH vehicle.

4.2 Particle Representation

We represent the particle in the population as a list of vehicles. The length of each particle will always be equal to the number of vehicles initialized in the scenario. A particle will represent the two values i.e., 0 or 1. Here 0 will represent the vehicle as CM and 1 will represent the vehicle as CH. An example of a particle vector is shown in Fig. 3.

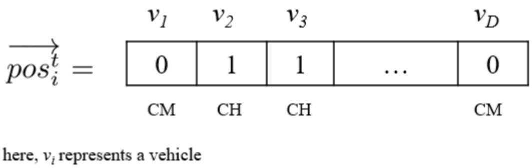


Fig. 3. Particle Representation.

4.3 Fitness Function

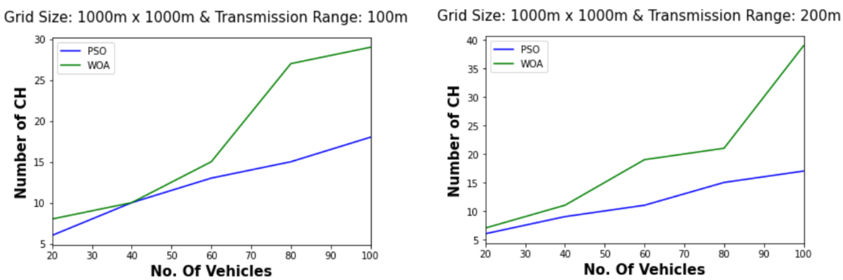
Now, we build a fitness function as the definition provided in Section 3.2. This helps in updating the two vectors ($\overrightarrow{Pbest}$ and $\overrightarrow{Gbest}$). As per the parameters formed in this section, we will calculate the value of the weights w_1 and w_2 mentioned in Eq. (6). The following parameters will be applicable for the evaluation of the weight values:

$$w_1 = \frac{1}{D} \tag{8}$$

$$w_2 = \frac{1}{C_{CH} \times G} \tag{9}$$

Putting the values of the weights in Eq. (6), we will have a finalized fitness function shown in Eq. (10):

$$F = \frac{C_{CH}}{D} + \frac{D_{CH}}{C_{CH} \times G} \tag{10}$$



(a) (b)

Fig. 4. Comparison between PSO and WOA with (a) TR=100m and (b) TR=200m.

5 Result and Analysis

The proposed model of VANET using PSO contains a random allocation of vehicles in a defined grid size G. The PSO algorithm is compared with the whale optimization algorithm (WOA) [9]. The acceleration coefficient is set as $c_1 = 0.42$ and $c_2 = 0.57$. Two random integers r_1 and r_2 are in the range of [0,1). We have implemented both algorithms, i.e., PSO and WOA on the defined parameters as grid size is 1x1km, number of vehicles ranging [20-100], and the transmission range is set as 100-200m as shown in Fig 4(a) and Fig. 4(b) respectively.

6 Conclusion

In this study, we introduce a PSO-based clustering approach for enhancing data dissemination within VANETs. Our method includes the selection of cluster heads, where the particle with the optimal solution is evaluated. Additionally, for fitness assessment, we incorporate the Whale Optimization Algorithm (WOA).

Future research directions involve integrating a quantum-inspired evolutionary algorithm into VANET simulations for comparative analysis with existing algorithms. Furthermore, we plan to refine the objective function to encompass a broader range of parameters.

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