EJAIoV: Enhanced Jaya Algorithm-Based Clustering for Internet of Vehicles Using Q-Learning and Adaptive Search Strategies

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***Abstract*—The Internet of Vehicles (IoV) is an indispensable part of contemporary Intelligent Transportation Systems (ITS), providing efficient vehicle-to-everything (V2X) communication. Nevertheless, high mobility and consequent topological changes in IoV networks create overwhelming difficulties in establishing and maintaining stable and effective communication. In this work, we introduce the Enhanced Jaya Algorithm for IoV (EJAIoV), an optimized clustering algorithm using optimization to develop stable and long-term clusters in IoV scenarios. EJAIoV uses efficient random initialization with three scrambling strategies to produce diverse, high-quality solutions. Q-learning selection between three neighborhood operators enhances local search effectiveness by incorporating a segmented operator. In addition, an adaptive search balance strategy adjusts solution updating dynamically to avoid premature convergence and optimize the exploration procedure. Simulation experiments show that EJAIoV outperforms existing clustering algorithms, achieving up to 31.5% improvement in cluster lifetime and 28.2% reduction in the number of clusters across various node densities and grid sizes.**

Keywords*—Internet of vehicles; clustering; Jaya algorithm; Q-learning; optimization

I. INTRODUCTION

A. Background

The Internet of Vehicles (IoV) is an important advancement of Vehicular Ad hoc Networks (VANETs), unifying vehicles, infrastructure, cloud services, and users into an integrated communication and data exchange system [1]. As an intrinsic part of Intelligent Transportation Systems (ITS), the IoV enables vehicle-to-everything (V2X) to support real-time traffic control, accident prevention, and self-driving cars [2].

Taking advantage of emerging wireless technologies, cloud computing, and the Internet of Things (IoT), IoV is significant for roadside safety enhancement, traffic congestion alleviation, and smart energy use [3]. Cloud platform support allows IoV to be easily deployed on a mass level and offers data-assisted services and decision support to urban mobility systems [4]. As ITS evolves, efficient and stable communication in IoV environments becomes vital to ensuring uninterrupted data transmission among high-mobility nodes [5]. Similar to recent efforts in industrial automation using hybrid AI models for real-time defect detection [6], IoV environments demand intelligent, adaptive solutions for dynamic clustering under mobility constraints.

Although IoV offers revolutionary transformation prospects, it is beset with critical technical issues related to maintaining stable communication under highly dynamic conditions. Due to the very nature of vehicular networks in terms of high mobility among nodes, dynamically updating topologies, and variable traffic density, real-time and stable data transmission becomes difficult [7, 8]. Transient disconnection and link failures cause disruptions to communication continuity, which poses significant issues to safety-critical services [9].

Furthermore, dynamic vehicular movement necessitates the quick adaptation of networks to prevent delay and packet losses [10]. Clustering is one commonly used paradigm to address such issues by partitioning the vehicles into clusters and assigning differentiated Cluster Heads (CHs), which carry out the forward and backward communication among and within the clusters [11]. However, under high mobility, stable cluster maintenance and minimizing reassignment of the CHs prove to be demanding without seriously degrading the performance and latency of the network.

B. Literature Review

Multiple clustering algorithms have been proposed to enhance communication efficacy within IoV by selecting the most appropriate CHs based on several measures, such as node degree, mobility patterns, and distance measures. Traditional metaheuristics- and heuristics-based frameworks have demonstrated differential success rates. However, current methods ignore vehicle mobility or fail to adapt dynamically to high mobility among nodes. Such inattention causes more instability in the clusters, heavy re-elections of the CHs, and high control overhead expense.

In addition, most algorithms suffer from premature convergence and exploration limitations with the solution set, thus suboptimal cluster formations. Therefore, there is a critical need to develop smart and adaptive clustering, which means it excels in global search and local exploitation in an IoV environment. The global shift toward intelligent, technology-driven infrastructure further emphasizes the need for adaptive and scalable solutions in dynamic systems such as IoV [12]. The widespread application of machine learning in fields such as business forecasting, transportation, and economic modeling [13] highlights its suitability for real-time, data-driven decision-making in IoV clustering.

Sharif, et al. [14] presented an experience-based CH selection mechanism using an Actor-Critic Deep Reinforcement Learning (AC-DRL). AC-DLR uses reinforcement learning to adaptively manage IoV clustering in noisy and highly dynamic environments. Jamalzadeh, et al. [15] EC-MOPSO, an edge computing-enabled cluster-based routing approach that uses Multi-objective Particle Swarm Optimization (MOPSO).

Salim, et al. [16] presented IoVSSA based on Sparrow Search Algorithm that uses mobility metrics and distances among clusters to optimize fewer and more stable clusters. Shen, et al. [17] introduced Software-Defined Networking (SDN) and Double Deep Q-Network (DDQN) to develop a cloud-edge collaborative resource provisioning framework.

Yuan, et al. [18] suggested an enhanced DBSCAN clustering algorithm integrated with Digital Twins (DTs) and a deep reinforcement learning-based offloading decision scheme (DDQN and dueling DQN). Zhang, et al. [19] combined Simulated Annealing (SA) and NSGA-II algorithms to optimize task offloading within IoV. Ajaz, et al. [20] proposed a Cluster-based Lion Optimization Routing Protocol (CLORP), which improves AODV with the lion algorithm to select CHs and gateway nodes.

Despite recent advances, existing IoV clustering methods exhibit significant limitations in high-mobility scenarios, as highlighted in Table I. Many algorithms fail to adapt to frequent topology changes, leading to unstable clusters and excessive CH reassignments that degrade network performance and increase control overhead. Traditional optimization-based approaches often suffer from premature convergence and inadequate local search capabilities, preventing them from finding robust cluster configurations in dynamic environments.

Reinforcement learning-based techniques, while promising, frequently overlook the need for adaptive exploration-exploitation strategies tuned to mobility-induced fluctuations. Therefore, there is a clear need for a clustering solution that is explicitly designed to operate effectively under high-speed, constantly evolving conditions. Our proposed EJAIoV framework addresses this gap by integrating an enhanced Jaya algorithm with Q-learning-driven local search and adaptive balancing strategies to maintain stability, reduce overhead, and ensure communication resilience in highly mobile IoV networks.

C. Contribution

To overcome the shortcomings mentioned above, this work introduces the Enhanced Jaya Algorithm (EJaya), an efficient metaheuristic optimization algorithm well suited to the dynamism associated with IoV clustering problems. The parsimonious and straightforward Jaya algorithm has been used to solve many complex optimization problems with great success [21].

EJaya takes advantage of this by adding several enhancements intended to yield better performance: random initialization with three scrambling techniques to diversify the solution set, segmented operators to enhance convergence rate, Q-learning-based operator selection for the neighborhood to support local search capacity, and adaptive search balanced approach to avoid premature convergence. Collectively, these features make EJaya well-suited to strike an effective balance between exploration and exploitation to solve the NP-hard clustering problem in high-mobility vehicle networks.

TABLE I. AN OVERVIEW OF RELATED WORKS

Reference	Optimization technique	Achievement	Weakness
[14]	Actor-critic deep reinforcement learning	Improved SLA satisfaction (28%) and throughput (35%) over static and DQN methods	Requires extensive training data; performance depends on reward design
[15]	Multi-objective particle swarm optimization	Reduced latency, fewer hops, and improved packet delivery rate	Scalability can be an issue; mobility modeling is limited
[16]	Sparrow search algorithm	Fewer and more stable clusters with longer lifetimes	Lacks adaptive learning; may struggle with rapidly changing topologies
[17]	Double deep Q network with software-defined networking	Reduced latency by up to 34.8% and increased edge provider profits by 33.3%	Initial clustering is static; computation overhead for DDQN is high
[18]	Enhanced DBSCAN + DRL	Improved clustering under high speed, reduced latency, and better offloading decisions	High complexity; requires robust digital twin modeling
[19]	Particle swarm optimization, simulated annealing, and NSGA-II	Lower system costs by balancing delay and energy consumption	Complexity of multi-objective tuning; simulated annealing increases computation time
[20]	Lion optimization algorithm	Enhanced routing efficiency and reduced control message overhead	AODV dependency limits adaptability; mobility handling is a basic

This study presents an innovative IoV clustering framework called EJAIoV and takes advantage of the advanced optimization power of EJaya to build stable mobility-aware clusters. The algorithm incorporates mobility and distance into a multi-objective fitness function to ensure that chosen CHs are associated with low relative velocity and high link stability. Adaptive learning and search mechanisms incorporated into the algorithm enable the algorithm to adapt well to sudden topological changes, maintain communication effectiveness, and decrease CH reassignments.

The remainder of this paper is organized as follows: Section II presents the system model and formally defines the clustering problem in the context of dynamic IoV environments. Section III details the proposed EJAIoV algorithm. Section IV discusses simulation results, evaluating EJAIoV's performance against state-of-the-art algorithms under various mobility and network conditions. Finally, Section V concludes the study and outlines potential directions for future research.

II. System Model and Problem Definition

As shown in Fig. 1, an IoV setup generally is composed of five main components: RSUs, On-Board Units (OBUs), Cloud Center (CC), Transportation Control Center (TCC), and the Internet. OBUs are vehicle devices utilizing Wireless Access in Vehicular Environments (WAVE) to offer secure and reliable communication. RSUs deployed on the roadside offer vehicle communication so that OBUs can send and receive traffic-related information with the RSUs and the surrounding infrastructure within the communication range.

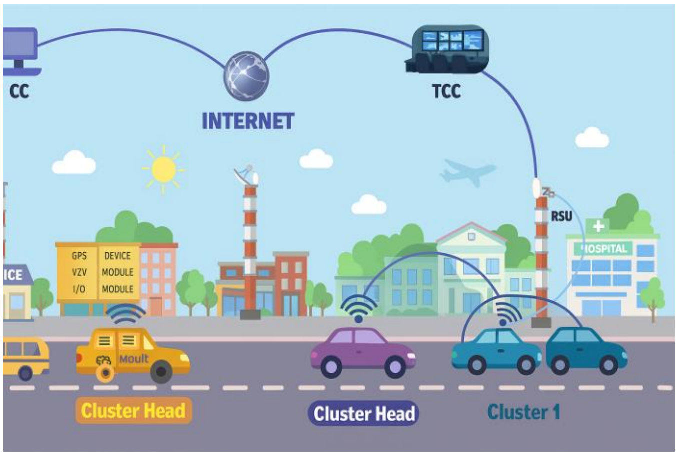


Fig. 1. Vehicular communication framework.

The role of the TCC is to supervise and manage the deployed RSUs, and the CC is the centralized virtual hub used to hold data, resources, and software critical to car control. The framework supports more advanced messaging to reach more cars and infrastructure through the Internet and provides significantly enhanced data-gathering capabilities.

Structure of the IoV topology is represented by an undirected graph $G = (N, L)$, with N stands for vehicles (nodes) and L signifies communication links (edges). Two vehicles n_i and n_j, can communicate with one another if the distance $D(n_i, n_j)$ is not more than the smaller of its transmission ranges Tr_i and Tr_j. The identification of the vehicles is unique and paired with OBUs with GPS receivers and wireless transceivers to track the positions in real-time and to compute the relative distances and speeds among the vehicles. RSUs with a transmission radius of 1.5 km are positioned around 3 km apart to provide extensive coverage and centralized cluster control. The system model parameters can be expressed as follows:

Vehicle neighbors: Directly connected (one-hop neighbors) vehicles are represented as follows:

$$VN_i = \{n_j \in N \mid (n_i, n_j) \in L\} \tag{1}$$

Vehicle degree: This metric quantifies the number of one-hop neighbors connected to the vehicle n_i, mathematically expressed using Eq. (2).

$$VD_i = |VN_i| \tag{2}$$

Mobility factor: In clustering, this parameter is defined by the following sub-parameters:

Neighbor count: This degree is equivalent to the vehicle degree.

$$NC_i = VD_i \tag{3}$$

Average relative velocity: The average relative speed between vehicle n_i and its neighbors, calculated using Eq. 4.

$$ARV_i = \frac{1}{NC_i} \sum_{j=1, j \neq i}^{NC_i} |v_i - v_j| \tag{4}$$

Vehicles with lower ARV values indicate higher stability.

Average neighbor distance: This parameter represents the mean Euclidean distance between the vehicle n_i and its neighbors.

$$AND_i = \frac{1}{NC_i} \sum_{j=1, j \neq i}^{NC_i} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{5}$$

Where (x_i, y_i) and (x_j, y_j) denote the positions of vehicles n_i and its neighbor n_j, respectively. Vehicles with smaller AND are more centrally positioned within their clusters.

Link stability: This parameter indicates the consistency of the connection between the vehicle n_i and its neighbors based on variations in the average distance over time:

$$LS_i(t) = |AND_i(t_1) - AND_i(t_2)| \tag{6}$$

Where $y = t_2 - t_1$.

Considering the above sub-parameters, the mobility factor for vehicle n_i is formulated as:

$$MF_i = \frac{LS_i(t)}{NC_i} + \sqrt{\ln\left(1 - \frac{ARV_i}{v_{max}}\right)^2 + \frac{AND_i}{D_{max,i}}} \tag{7}$$

The mobility factor for vehicle i aggregates three key indicators: average relative velocity (ARV_i), average neighbor distance (AND_i), and link stability ($LS_i(t)$). These are normalized by the product of the maximum observed neighbor distance (D_{max}) and the road's speed (v_{max}), ensuring that mobility values are scale-independent and comparable across different traffic conditions. Lower MF_i values indicate vehicles with greater local stability, making them stronger candidates for cluster heads in high-mobility environments.

These parameters and metrics are essential for accurately characterizing network mobility and stability, thus directly informing the clustering algorithm's effectiveness in dynamic IoV environments.

III. Proposed Method

EJAIoV generalizes the traditional Jaya optimization algorithm for mobility-aware and stable clustering in extremely dynamic vehicular environments. Acknowledging the shortcomings of traditional clustering techniques, EJAIoV incorporates new strategies such as diversity-enhanced initialization, direction-aware solution updates, a reinforcement learning-enabled local search method, and adaptation-enabled exploration-exploitation adjustment. Additionally, EJAIoV includes domain-based mobility and topological attributes in a multi-objective clustering fitness model for tackling specific needs in IoV communication.

A. Solution Representation

In EJAIoV, every possible solution to the clustering problem exists as a one-dimensional vector. The vector describes a full clustering state for all vehicles in the IoV network. It is represented by:

$$S = (s_1, s_2, \dots, s_N) \tag{8}$$

Where S is a candidate solution in the search space and s_i is the cluster identifier assigned to the i^{th} vehicle. s_i is an integer in the range $[1, C_{max}]$, indicating to which cluster vehicle i belongs. N is the number of vehicles (nodes) participating in the IoV network. C_{max} is the predefined maximum number of clusters allowed in the solution space.

This coding assigns each vehicle to a particular cluster, satisfying the condition of mutually exclusive clusters in IoV environments. Cluster-ID acts as a label for clustering vehicles with similar mobility patterns or topological proximity. Every solution vector represents a point in the multidimensional solution space, where each dimension represents a cluster decision for one vehicle. The EJAIoV algorithm optimizes the vector over time toward the most suitable clustering configuration that maximizes intra-cluster communication efficiency, link stability, and mobility awareness. This representation is compact, flexible, and suitable for EJaya's search operations, such as scrambling, updating solutions, and locally guided Q-learning exploration. It also enables straightforward calculation of a cluster's fitness value because each s_i explicitly states cluster membership is necessary for calculating metrics such as intra-cluster distance and mobility value.

B. Initial Population Construction

The quality of metaheuristic algorithms such as EJAIoV depends on initial population diversity and quality. For a wide scope of problem space exploration, EJAIoV utilizes a hybrid population initialization method that blends random generation, linear spreading, and scrambling operators. The initial population generation and diversification mechanisms are described in the following section. The initial construction of each solution vector assigns a random cluster ID for each vehicle as follows:

$$s_i \in \{1,2, \dots, C_{max}\}, \qquad \forall i \in \{1,2, \dots, N\} \tag{9}$$

This provides equal opportunity for any vehicle to be placed in any cluster at initialization, providing randomness for initial exploration. *To* add systematic variation throughout the population and prevent premature convergence based on overly random patterns, a portion of the population is initialized using a linear spreading method.

$$s_i = s_{min} + \left(\frac{i - N/2}{(N-1) - N/2}\right) \times (s_{max} - s_{min}) \tag{10}$$

Where s_{min} stands for minimum cluster-ID and s_{max} denotes maximum cluster ID.

To increase the diversity of the initial population, three specialized scrambling operators, namely exchange, reverse, and insert, are used by EJAIoV, each having a distinct role in exploring the solution space. Exchange scrambling creates two random positions in a solution vector, promoting local cluster assignment adjustments. Reverse scrambling chooses a subsequence (often from a randomly selected index up to the end) and inverses the sequence, admitting moderate-level structural change and local minima avoidance. Insert scrambling introduces diversity from outside by generating a new random cluster insertion of the same at a random position and removing the last element to maintain vector length. Fig. 2 depicts these operators.

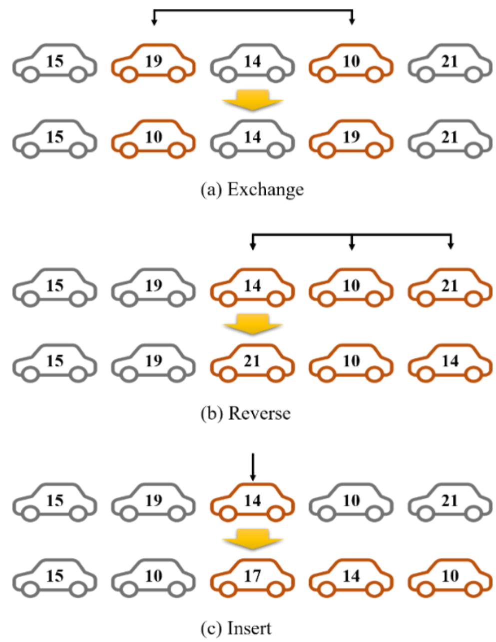


Fig. 2. Scrambling operators in EJAIoV for enhancing population diversity.

C. Best-Worst Guided Solution Update

The key mechanism of the EJAIoV algorithm is efficiently updating solutions by pushing them toward promising regions of the search space. For this purpose, EJAIoV employs a directional updating approach based on the original Jaya algorithm. More precisely, with each iterative update, each solution in the population improves by moving towards the best-performing solution and away from the worst-performing one. The best-worst update rule mathematically represents this mechanism. Each component of a solution vector is updated as follows:

$$s_i^{new} = s_i + r_1.\left(s_i^{best} - |s_i|\right) - r_2.\left(s_i^{worst} - |s_i|\right) \tag{11}$$

After computing the updated solution vector, its fitness is evaluated using the multi-objective function. If the updated solution achieves a better fitness score than the original S, it replaces the current solution in the population. Otherwise, the original solution is retained. This selective replacement policy ensures elitism by preserving high-quality solutions, prevents regression in solution quality over iterations, and gradually refines clustering configurations toward optimality.

D. Q-Learning-Guided Local Search

A local search approach based on reinforcement learning is incorporated to further enhance the precision of EJAIoV, especially for refining clustering configurations in subsequent iterations. Specifically, EJAIoV uses the model-free reinforcement learning algorithm Q-learning for intelligent choice and neighborhood operator application that facilitates improved local exploitation. This renders the algorithm adaptive and self-enhancing, necessary for handling the dynamic characteristics of IoV networks.

As illustrated in Fig. 3, the candidate solution is treated as an agent acting on the environment. There are four phases of learning: state (Current clustering configuration), action (Either one of the three local operators used for perturbing the solution), reward (A real value indicating whether the action resulted in an improved solution), and Q-value (Estimated value for applying action a from state s. The algorithm continually updates its Q-values through trial-and-error interaction with the environment for learning the most useful operator for a particular state of the solution.

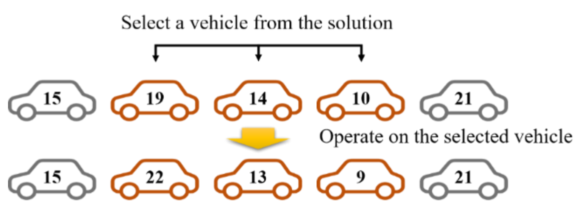


Fig. 3. Segmentation operator.

EJAIoV utilizes three neighborhood operators specific to the domain, as illustrated in Fig. 4, from which the Q-learning agent chooses. The segmentation operator splits the solution into two regions and exchanges them to rearrange cluster assignments. The mutation operator substitutes a random subset of cluster IDs to explore local perturbations. The crossover operator crosses over two parents in the two regions to produce offspring. The operators vary in their level of aggression and granularity, thus catering to a balance between local refinement and structural change of the solution.

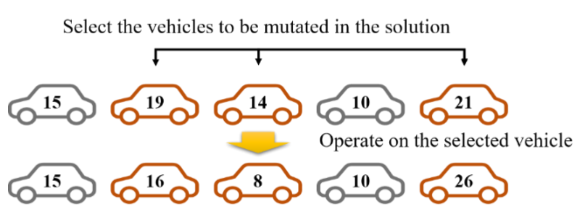


Fig. 4. Mutation operator.

The Bellman update rule governs the learning mechanism of Q-learning:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \tag{12}$$

Where $Q(s,a)$ refers to the current Q-value for applying action a in state s, α is the learning rate controlling how quickly new experiences overwrite old ones, γ is the discount factor that weighs future rewards relative to immediate rewards, s' is the next state (new clustering configuration after applying the action), a' is the next potential action, and r is the immediate reward received after transitioning from s to s' via a.

The reward value is calculated by improving the fitness value of the solution as follows:

$$r = \begin{cases} 0, & if\ fit\ worsens \\ 1, & if\ fit\ remains\ unchanged \\ 2.(old\ fit - new\ fit), & if\ fit\ improves \end{cases} \tag{13}$$

This reward structure encourages the algorithm to explore actions that lead to improvements while penalizing those that degrade solution quality.

As shown in Fig. 5, local search using the Q-learning approach is embedded in the EJAIoV algorithm as a key refinement after the global best-worst update. The incumbent solution is taken as a state. The action (operator) is chosen based on an exploration-exploitation policy (for example, via ε-greedy). The operator is executed to produce a new candidate. Fitness is calculated and reward determined. The Q values are updated. The best solutions are preserved for the next generation.

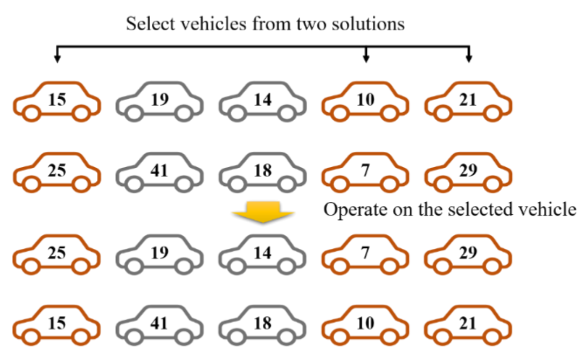


Fig. 5. Crossover operator.

E. Adaptive Search Balance

In dynamic IoV environments, a successful metaheuristic should have a delicate balance between exploration (exploring novel regions of the solution space) and exploitation (iteratively improving already-found good regions). One of the main advances of EJAIoV is its adaptive balance of the search strategy, which evolves gradually from global exploration towards local exploitation with increasing iterations. This mechanism is crucial in preventing premature convergence during initial stages (when the solutions are immature) and facilitating solution refinement in advanced stages (when the algorithm needs to tweak close-to-optimum clusters).

Although no explicit formula is provided in the base framework, the adaptive balance can be mathematically expressed using a time-dependent weighting factor, defined throughout iterations t as follows:

$$\theta(t) = 1 - \frac{t}{T_{max}} \tag{14}$$

This parameter can be used internally to scale or switch between strategies. It may, for instance, scale up and change the frequency or intensity of scrambling operators, bias the probability of choosing aggressive versus mild local search actions, or alter the acceptance criteria for inferior solutions to escape local optima earlier. Let $P_{explore}$ and $P_{exploit}$ be the probabilities of choosing exploration-based or exploitation-based strategies, respectively. These can be controlled as:

$$P_{explore}(t) = \theta(t), \qquad P_{exploit}(t) = 1 - \theta(t) \tag{15}$$

This makes the algorithm self-adaptive to the optimization phase. In early iterations, high exploration ensures broad coverage of the solution space. In later iterations, high exploitation ensures local convergence around optimal solutions.

F. Objective Function

Clustering for effective operations in IoV environments relies on two key objectives: compact cluster maintenance (i.e., intra-cluster distance minimization) and CH stability in the presence of mobility among vehicles. To address these aspects simultaneously, EJAIoV constructs a multi-objective fitness function encompassing both space- and mobility-driven optimization objectives. The global objective function is given by:

$$F = \omega_1 . f_1 + \omega_2 . f_2 \tag{16}$$

In this study, the weights ω_1 and ω_2 are both set to 0.5 to assign equal importance to the two core objectives. This neutral weighting reflects a balanced optimization goal that aims to simultaneously minimize intra-cluster distances and ensure stable cluster head selection, especially under high-mobility IoV conditions. Equal weighting is also common in multi-objective scenarios where no prior bias exists toward either component, and it enables a fair assessment of each objective's influence on the clustering outcome. The first component measures the relative spatial compactness of clusters, formulated as:

$$f_1 = \frac{D_{intra}}{D_{total}} \tag{17}$$

Where D_{intra} refers to the total intra-cluster distance across all clusters and D_{total} is the total communication distance across the entire network, calculated by Eq. (18) and (19), respectively.

$$D_{\text{intra}} = \sum_{j=1}^{|C|} \sum_{k=1}^{|CM_j|} D\left(CH_j, CM_{j,k}\right) \tag{18}$$

$$D_{total} = \sum_{i=1}^{|V|} \sum_{j=1}^{|N_i|} D\left(v_i, N_{i,j}\right) \tag{19}$$

In Eq. (18), $|C|$ is the total number of clusters, CM_j is the CH of the j^{th} cluster, $CM_{j,k}$ is k^{th} member of cluster j, and $\left(CH_j, CM_{j,k}\right)$ is the Euclidean distance between the CH and the member.

In Eq. (19), $|V|$ is the total number of vehicles in the network, v_i is the i^{th} vehicle, N_i is neighbor set of vehicle v_i, $N_{i,j}$ is j^{th} neighbor of vehicle v_i, and $D\left(v_i, N_{i,j}\right)$ is the Euclidean distance between vehicle v_i and its neighbor. A lower value of f_1 indicates that clusters are spatially tight and better organized.

The second objective evaluates the stability of selected CHs based on their relative mobility and local topology as follows:

$$f_2 = \frac{1}{\sum_{t=1}^{|V|} MV_t} \cdot \left(\sum_{i=1}^{|C|} MV_i \right) \tag{20}$$

Where MV_i stands for mobility value of the CH in cluster i, MV_t denotes the mobility value of the t^{th} vehicle. A lower f_2 value means the selected CHs are more stable (less mobile, better connected).

Each vehicle's mobility value is computed using three components: link stability, node degree, and average distance to neighbors, calculated as follows:

$$MV_i = \frac{SL_i}{VNC_i} + \sqrt{\ln\left(1 - \frac{RVA_i}{v_{\max}}\right)^2} + \frac{DA_i}{DA_{\max}} \tag{21}$$

Where SL_i signifies link stability of vehicle i, VNC_i denotes the number of one-hop neighbors of vehicle i, RVA_i is the average relative velocity between vehicle i and its neighbors, $v_{\max}$ is the maximum possible speed in the network, DA_i is the average distance between vehicle i and its neighbors, and $DA_{\max}$ is the maximum observed distance average among all vehicles.

Eq. (21) prioritizes vehicles that maintain stable links, have higher connectivity, move with similar velocity as their neighbors, and stay closer to their local neighborhood. Thus, lower MV_i values are preferred when selecting CHs, as they imply greater stability.

G. Algorithmic Workflow Summary

EJAIoV algorithmic workflow combines all key building blocks into one unified optimization procedure applicable to the time-evolving characteristics of IoV clustering. It starts with a diversified initial population through linear spread and randomness, followed by scrambling operations to include further variation. A fitness function, which evaluates both spatial compactness and stability of mobility, is utilized to evaluate each solution.

The solutions are updated through the convergence of the best and divergence of the worst, thus enabling efficient global search. These solutions are refined through a Q-learning process based on learned reward values for local operator choice in efficient adaptation and exploitation. An adaptive method of search balance is employed that gradually transitions the algorithm from exploration to exploitation with time for greater convergence behavior. The iteration continues until a stopping criterion arises, resulting in a convergent and optimized clustering configuration for application under high-mobility vehicular environments.

IV. Results and Discussion

In this section, we analyze the efficiency of the proposed EJAIoV based on its performance on different parameters like the number of clusters, cluster life, grid size, vehicle density, and transmission range. All simulations were carried out in

MATLAB using the parameters shown in Table II. To validate the robustness and feasibility of EJAIoV, simulations were carried out using 30–60 vehicle nodes on different grid sizes ranging from 1–4 km². Based on several metrics, the abovementioned scenarios have been employed to compare EJAIoV with GWOCNET [22], GOA [23], MFCA [24], and CAVDO [25].

Fig. 6-9 clearly show the interaction between transmission range and number of clusters for different grid sizes and vehicle densities. There is clearly an inverse relationship between transmission range and the number of clusters such that a high communication radius allows every CH to communicate with a large number of neighbors, forming a smaller number of clusters. This behavior occurs for all algorithms, but EJAIoV consistently outperforms baseline approaches by forming fewer clusters in all scenarios.

TABLE II. CONFIGURATION SETTINGS FOR SIMULATION ENVIRONMENT

Parameter	Configured value
Initial population size	100 candidate solutions
Maximum generations	150 iterations
Repetitions per scenario	20 simulation runs
Number of road lanes	6
Mobility model	Freeway traffic mobility
Number of vehicles	30-60
Communication range	100 to 500 meters
Simulation area sizes	1×1 km, 2×2 km, 3×3 km, and 4×4 km
Vehicle speed range	20 to 35 meters per second

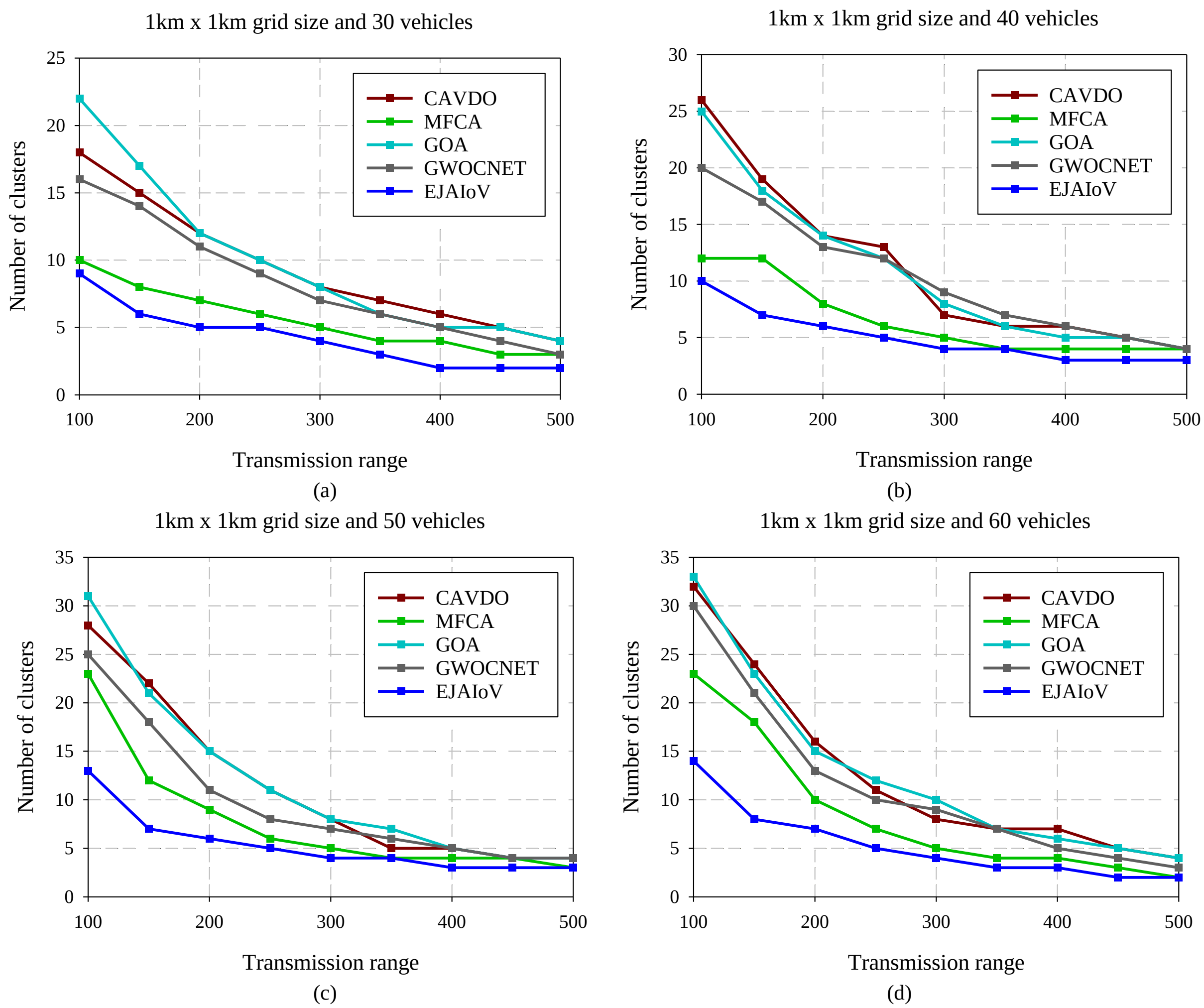


Fig. 6. Clustering performance comparison across different transmission ranges and node densities within a 1×1 km grid: (a) 30 nodes, (b) 40 nodes, (c) 50 nodes, (d) 60 nodes.

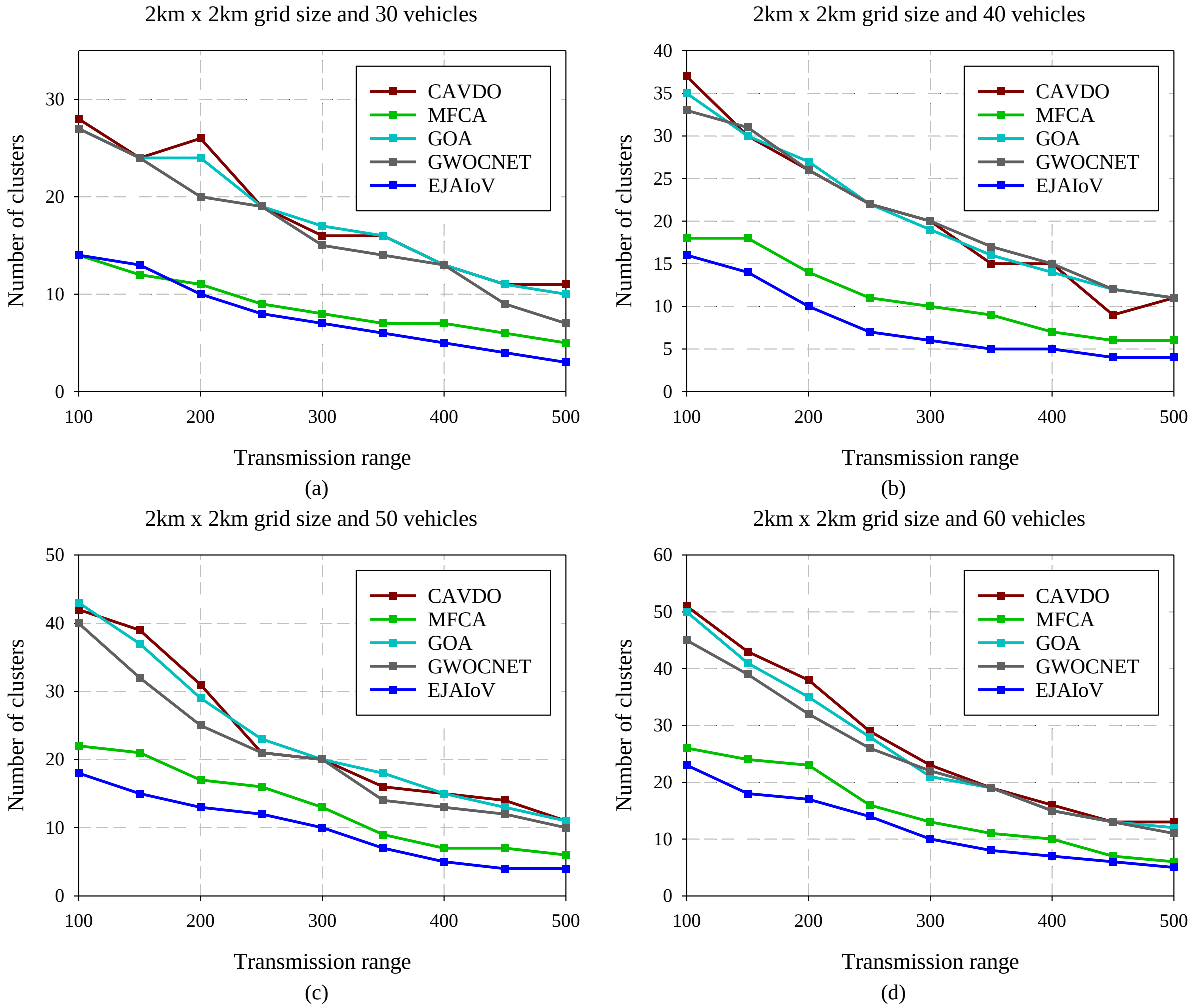
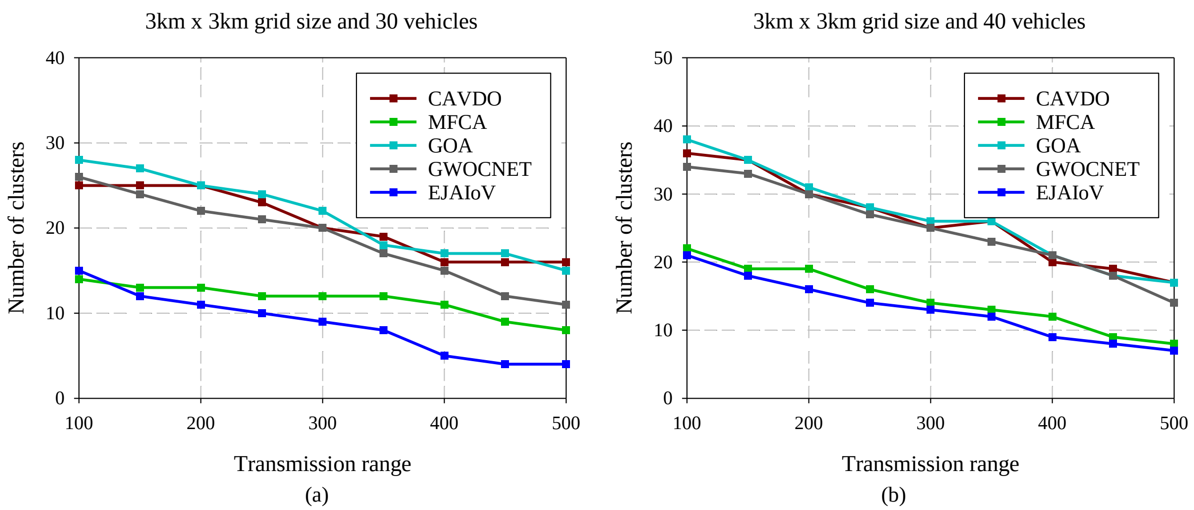
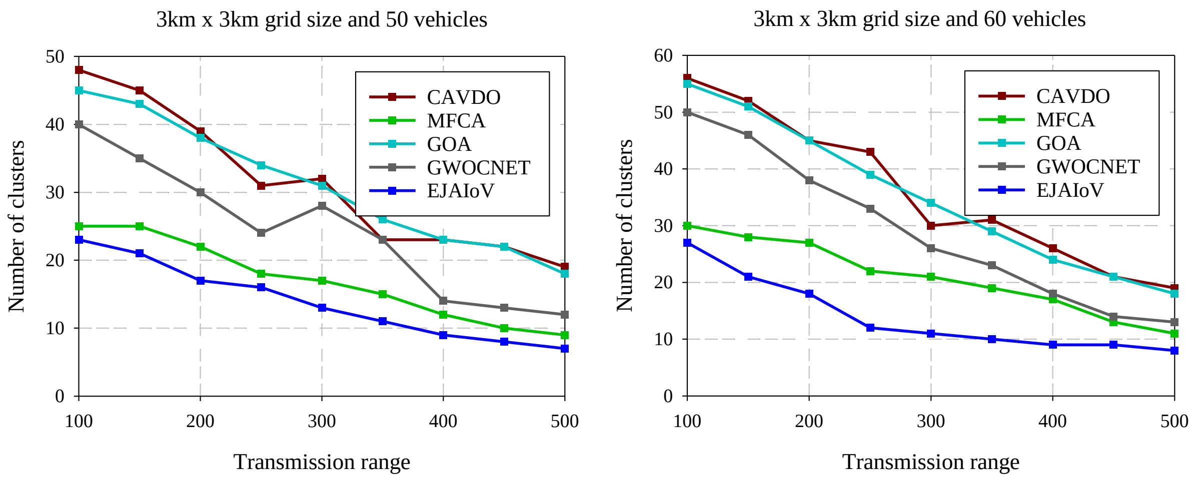


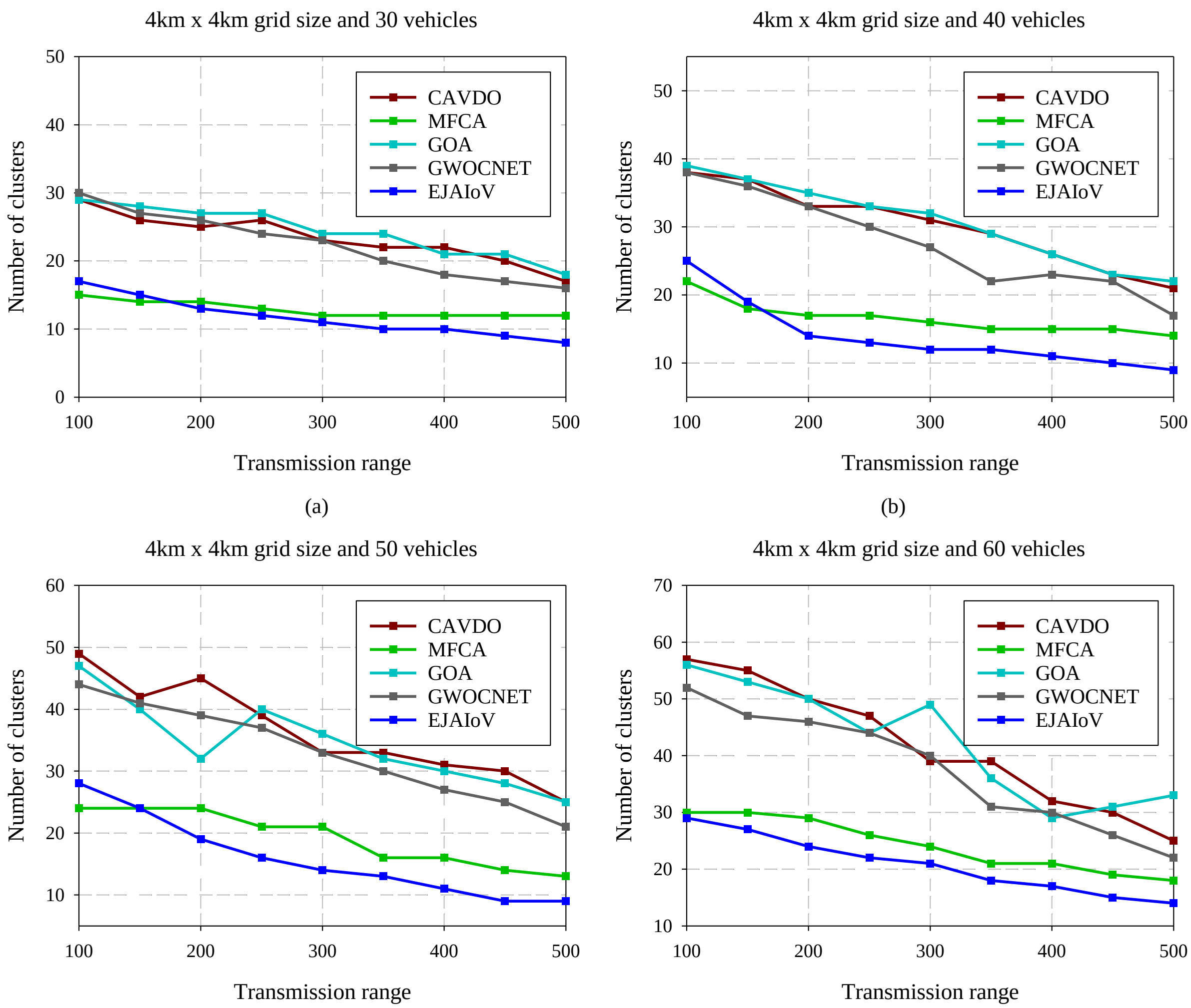
Fig. 7. Clustering performance comparison across different transmission ranges and node densities within a 2×2 km grid: (a) 30 nodes, (b) 40 nodes, (c) 50 nodes, (d) 60 nodes.





(c) (d)

Fig. 8. Clustering performance comparison across different transmission ranges and node densities within a 3×3 km grid: (a) 30 nodes, (b) 40 nodes, (c) 50 nodes, (d) 60 nodes.



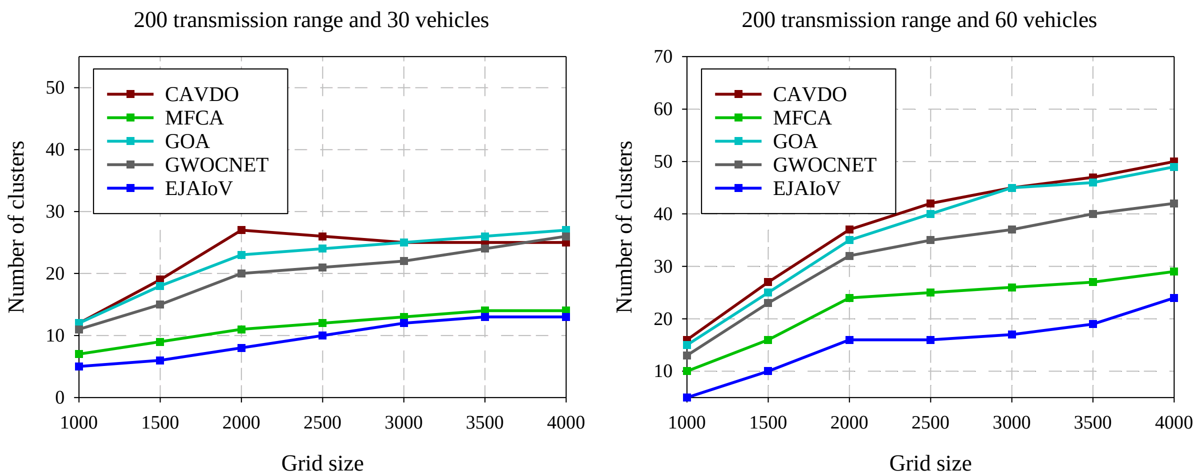
(c) (d)

Fig. 9. Clustering performance comparison across different transmission ranges and node densities within a 4×4 km grid: (a) 30 nodes, (b) 40 nodes, (c) 50 nodes, (d) 60 nodes.

This superior performance can be attributed to EJAIoV's multi-objective fitness function, which balances spatial compactness with mobility-aware stability. By favoring CHs with lower relative speeds and good positional properties, the algorithm constructs clusters that are both topologically efficient and resilient to mobility-induced failures. It is particularly significant that, with both increasing transmission range and node density, the performance difference increases. For example, for a 4×4 km² grid (Fig. 9), with greater inter-vehicle distances and greater mobility effect, EJAIoV performs better with respect to maintaining coherence in clusters than the alternatives. This proves that the proposed approach scales well in large vehicular environments. In addition, consistency with respect to varying vehicular densities demonstrates the resilience of the EJAIoV's adaptive mechanisms, such as operator selection based on Q-learning, which adjusts the exploration-exploitation ratio adaptively according to local topological complexity.

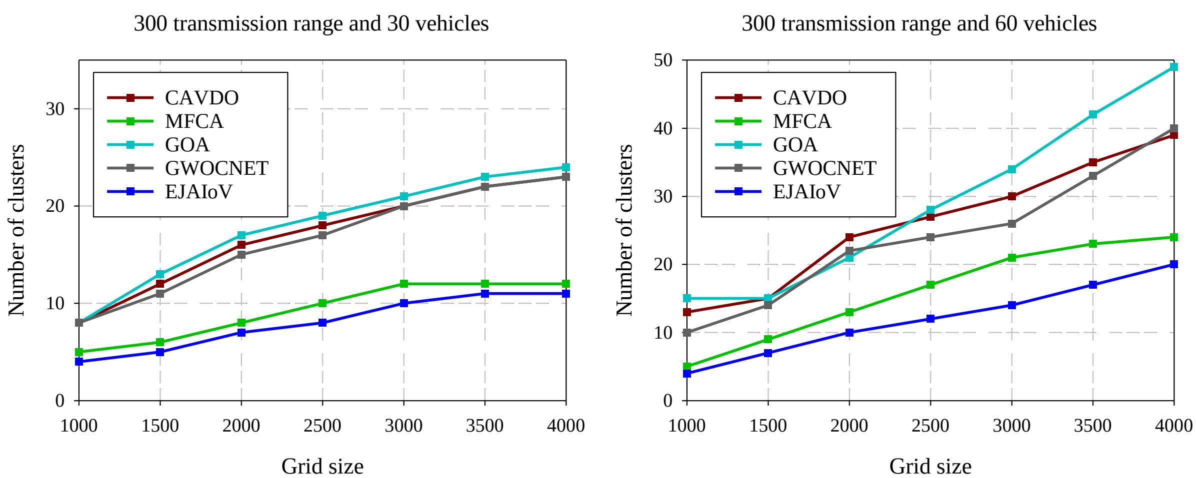
Fig. 10-13 illustrate the effect of increasing grid sizes on the number of clusters produced at constant node densities. Overall, there is a trend that with growth in the simulation area, there is an increase in clusters because there is less connectivity between far-off vehicles, reducing the ability of a CH to have stable links with dispersed nodes. Nevertheless, despite this spatial dispersal, EJAIoV is highly resilient by maintaining a consistent number of clusters across all grid sizes.

Its robustness stems mainly from the algorithm's joint spatial-mobility optimization approach. It is particularly intra-cluster distance minimization that fosters tight clusters, with mobility-aware stability cost that drives the algorithm to choose CHs that are not only close to their members but also show optimal minimal dynamic variance compared to nearby vehicles. Adaptive search balancing ensures solution diversity is sustained through clustering under sparse scenarios and enforces convergence in better spatial configurations.



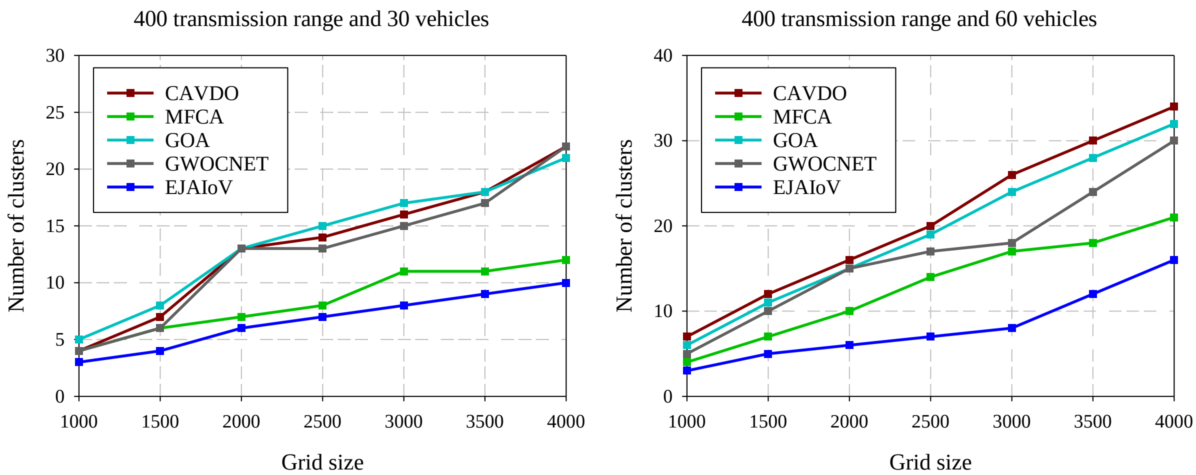
(a) (b)

Fig. 10. Clustering performance comparison across different grid sizes and node densities (200 transmission range): (a) 30 nodes, (b) 60 nodes.



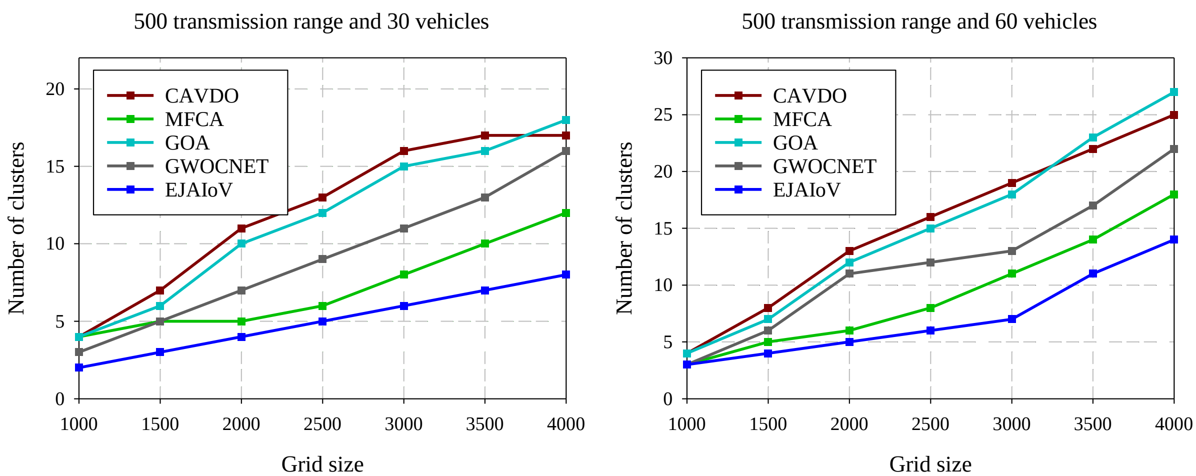
(a) (b)

Fig. 11. Clustering performance comparison across different grid sizes and node densities (300 transmission range) : (a) 30 nodes, (b) 60 nodes.



(a) (b)

Fig. 12. Clustering performance comparison across different grid sizes and node densities (400 transmission range): (a) 30 nodes, (b) 60 nodes.



(a) (b)

Fig. 13. Clustering performance comparison across different grid sizes and node densities (500 transmission range): (a) 30 nodes, (b) 60 nodes.

For example, in Fig. 12 and Fig. 13, with grid sizes extended to 4×4 km², EJAIoV maintains a lower number of clusters with 30 and 60 vehicles, while all other algorithms exhibit an increased rate of clustering fragmentation. This demonstrates that EJAIoV performs better at alleviating sparse topologies issues, with minimal unnecessary CH reassignments and overhead. In short, the observations presented in Fig. 10–13 confirm that EJAIoV supports better spatial scalability and retains effective cluster organization under light-density vehicular scenarios, an important feature in realistic IoV deployments with diverse node distributions and changing network topologies.

Fig. 14 compares clusters over different ranges of transmission, node density, and grid sizes to demonstrate the long-term stability of the proposed EJAIoV algorithm under dynamic IoV conditions. Cluster lifespan is a critical measure indicating the stability and robustness of the clustering approach with respect to vehicular mobility and varying communication ranges. It demonstrates the clustering algorithm's ability to accommodate high vehicular mobility with reduced cluster rebuilding requirements and lower control overhead. Fig. 14(a) to 14(d) present cluster lifetime over different transmission ranges for different grid sizes. Based on the results, with an increase in transmission range, cluster lifetime is prolonged, mostly because of increased communication range. This leads to reduced cluster reassignments. Vehicles with long-range stable links naturally undergo less frequent cluster reformation.

Fig. 14 clearly shows that EJAIoV can sustain stable lifespans in clusters under all scenarios. Compared with some of its competing algorithms, EJAIoV achieves much longer CH lifetimes, especially in high-mobility and large grid environments. This performance reflects the algorithm's strong capability to cope with dynamic variations inherent in IoV networks, particularly considering vehicular movement pattern variability.

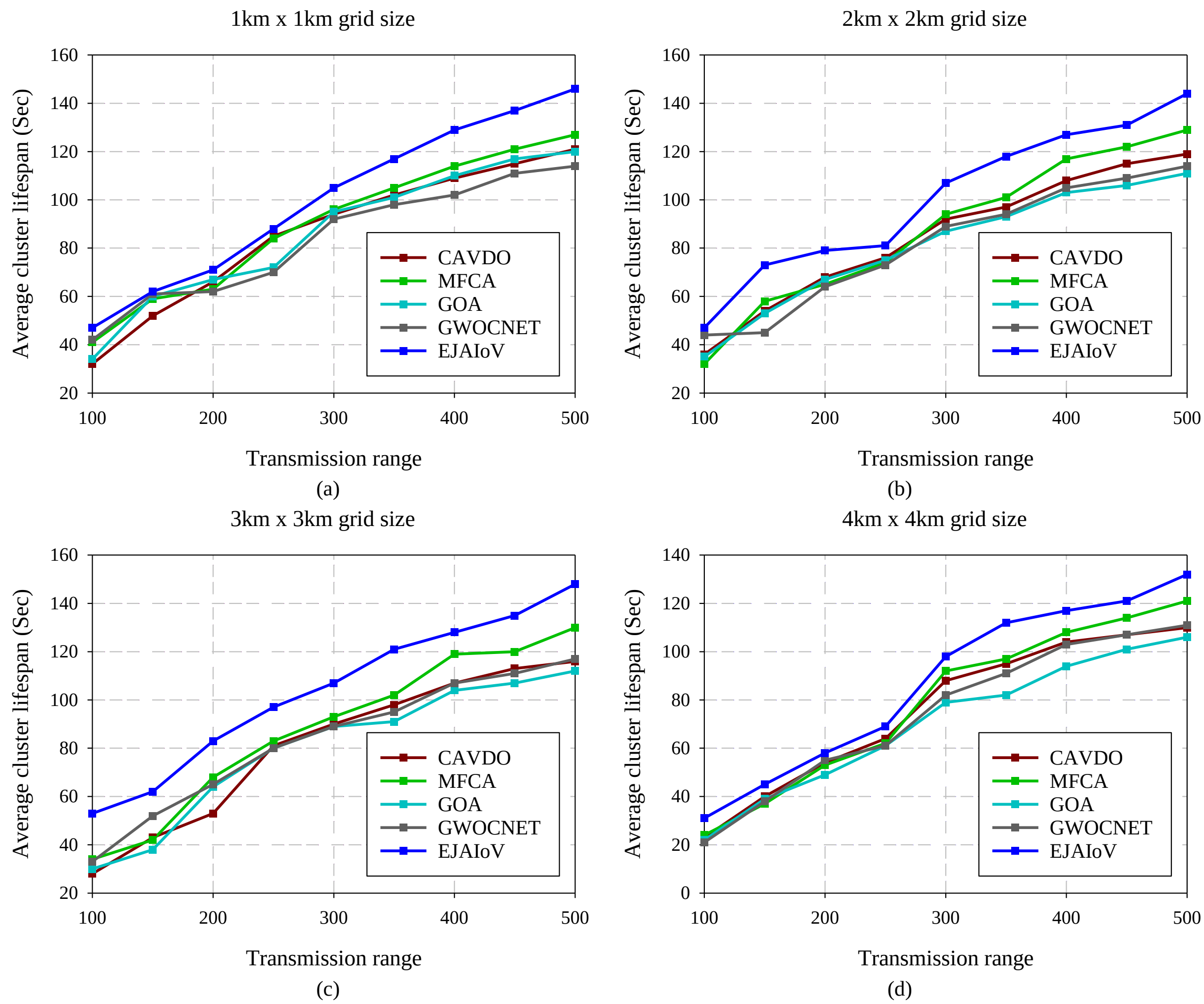


Fig. 14. Cluster lifespan comparison across different transmission ranges and node densities within different grid sizes: (a) 1km x 1km, (b) 2km x 2km, (c) 2km x 2km, (d) 2km x 2km.

Its main driving force for such high performance lies in EJAIoV's paradigm of mobility-aware clustering, which aims to prefer vehicles with smaller relative speeds and improved positional stability. CH reassignments are minimized by opting for steadier, slower CHs with improved connectivity. This minimizes communication interruptions, extending cluster lifetime. This is evident clearly in Fig. 14(a) and 14(b), in which EJAIoV maintains stability in clusters irrespective of large node densities, proving that it could counteract both high-density and high-mobility scenarios.

In addition, the adaptive balance between exploration and exploitation of EJAIoV enables the algorithm to adjust between exploration and exploitation in a dynamic fashion, allowing it to improve clustering based on changing network topology. This is key for sustaining stable clusters over a long time, regardless of varying vehicular speeds and locations. As the number of nodes increases, not only the frequency of CH reassignments decreases, but clusters are also more robust to perturbations, resulting in more resilient clusters.

V. Conclusion

This study introduced EJAIoV, a novel clustering scheme for IoV intended to achieve mobility-aware, communication-efficient, and stable cluster formations in highly dynamic vehicular environments. By incorporating a diversity-improving initialization method, the best-worst directional update method, and a local search module guided by a Q-learning algorithm, EJAIoV optimized global exploration and local exploitation during the optimization task. Moreover, a multi-target fitness function that balances mobility stability and intra-cluster distance recognized strong CHs with higher lifetimes and minimal reconfiguration overhead.

Comprehensive simulations illustrated that EJAIoV outperformed other state-of-the-art techniques like GWOCNET, GOA, MFCA, and CAVDO, to minimize the number of groups, optimize group length, and respond optimally to varying densities and transmission radii. The results revealed that EJAIoV's strength rests on its ability to handle sudden topology change and heavy vehicle mobility, which are key challenges in

IoV clustering. Potential research paths could include real-time traffic data, the algorithm's scalability for a heterogeneous vehicular environment, and the performance assessment with 5G-enabled edge computing environments.

EJAIoV is well-suited for deployment in real-time vehicular networks due to its lightweight design, adaptive learning, and ability to operate under continuously changing topologies. The algorithm can be integrated with edge computing platforms (e.g., roadside units or in-vehicle processors) to make on-the-fly clustering decisions using local traffic and mobility data. Given its reliance on parameters such as relative velocity, neighborhood distance, and link stability, which are readily obtainable from GPS and V2X sensors, EJAIoV can operate effectively with real-world vehicular datasets such as those provided by the VeReMi, SUMO, or TAPASCologne mobility traces. Future work will involve validating EJAIoV against these datasets and deploying the algorithm within a 5G-enabled edge computing framework to assess latency, scalability, and energy impact in real-time communication scenarios.

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