

A Novel Mobility-Aware Clustering Protocol for Internet of Vehicles Using Modified Traffic Jam Optimizer

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Abstract—The Internet of Vehicles (IoV) enables intelligent transportation through large-scale vehicular connectivity, but its high mobility and rapidly changing topology severely degrade communication stability and scalability. Clustering has emerged as an effective solution for reducing channel contention and improving network efficiency; however, existing methods often fail to maintain stable cluster structures under dynamic conditions and suffer from premature convergence in optimization-based approaches. Previous studies have explored swarm intelligence and heuristic optimizers for IoV clustering, yet most of them inadequately capture vehicle mobility dynamics or lack sufficient exploration-exploitation balance in highly constrained environments. To compensate for these limitations, the present study develops a mobility-aware clustering methodology based on the Modified Traffic Jam Optimizer (MTJO). In the proposed scheme, an advanced mobility model that incorporates relative velocity, acceleration, neighborhood density, and link stability is used, along with a multi-objective fitness function that simultaneously optimizes clustering performance, cluster stability, and energy efficiency. The proposed MTJO scheme incorporates adaptive nonlinearity, variable mutations, and mixed search mechanisms to enhance the optimization process for IoV clustering. Simulations show that the proposed scheme significantly improves cluster stability and energy efficiency compared with other schemes.

Keywords—Internet of Vehicles; mobility-aware clustering; traffic jam optimizer; swarm intelligence

I. INTRODUCTION

The rapid development of the Intelligent Transportation System (ITS) has revolutionized traditional transportation infrastructure by turning it into an interconnected, intelligent environment for information sharing, self-governing decision-making, and improved traffic management [1], [2]. Many technologies have been developed for ITS; among them, the Internet of Vehicles (IoV) has become increasingly popular for improving vehicular ad hoc networks by enabling communication among vehicles, roadside facilities, and cloud and edge computing resources [3]. While IoV offers many future benefits, the high dynamism of vehicles poses major challenges that have been identified as barriers to implementing IoV technology. The topology of such a network changes continuously due to the varying speeds, positions, and directions of the vehicles, making communication unreliable [4]. As more vehicles become connected, scalability becomes a major challenge due to congestion on the wireless channel [5].

To overcome such issues, clustering has proven to be a highly effective solution for making vehicular networks more scalable and efficient in communication. In the clustered IoV network architecture, vehicles are grouped into clusters with a Cluster Head (CH) and several Cluster Members (CMs) [6]. The CH serves as the coordinator for intra-cluster communication, information aggregation, and communication with other clusters and the infrastructure [7]. The clustering technique reduces the number of competing nodes, thereby making channel access and communication more efficient by reducing signaling overhead [8]. Besides, stable clusters contribute to improved packet delivery ratio. Despite many clustering techniques introduced in the literature, some issues remain unresolved. Many clustering techniques have adopted static evaluation criteria that do not adequately account for dynamic changes in vehicle mobility. CH election mechanisms based on distance criteria usually focus on geographic position while neglecting other mobility parameters, such as velocity, acceleration, and link stability. In addition, many clustering techniques that rely on optimization processes lack sufficient exploration mechanisms, leading them to get stuck in local optima.

Emerging advancements in swarm intelligence have revealed the potential of these algorithms to address complex optimization problems involving nonlinearity, uncertainty, and high-dimensional search spaces. The Traffic Jam Optimizer (TJO) has received considerable attention owing to the exploration-exploitation trade-off achieved by its mechanism modeled after traffic flow behavior [9]. However, the conventional TJO algorithm still suffers from drawbacks stemming from its reliance on predetermined search strategies and limited adaptability across optimization phases. Modified Traffic Jam Optimizer (MTJO) algorithm, which utilizes non-linear parameter tuning, differential mutation, and dynamic hybrid search techniques, has been adopted for this study. Further, mobility-based information has also been considered in the clustering optimization process to improve cluster robustness, communication efficiency, and energy consumption in dynamically evolving IoV network environments. The major contributions of this paper are as follows:

- A mobility-aware clustering framework is developed to improve clustering stability under dynamic IoV conditions.
- A mobility model integrating relative velocity, accel-

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eration, neighborhood density, and link stability is introduced for vehicle assessment.

- A multi-objective formulation is developed to optimize cluster compactness, stability, and energy efficiency.
- MTJO incorporates adaptive nonlinearity, mutation, and hybrid search mechanisms to improve the optimization process.

The structure of the paper is given as follows: Section II provides an overview of related work on IoV clustering. The system model, the mobility model, and the problem statement are described in Section III. The proposed mobility-based clustering algorithm is introduced in Section IV. The results and comparative analysis of the proposed algorithm are presented in Section V. Finally, Section VI draws the conclusion of the paper.

II. LITERATURE REVIEW

Clustering in the dynamic topology and mobility of IoV networks has been a focus of extensive research to enhance the communication capabilities of such networked systems. However, over the last few years, the field of metaheuristics has attracted considerable interest among researchers due to the ability of these algorithms to solve multi-objective optimization problems in clustering and CH selection. JAYACIoV is a new clustering-based technique presented by Dalbah, et al. [10], formed by integrating the JAYA algorithm with K-means clustering concepts. The Enhanced Sparrow Search Algorithm for Internet of Vehicles (ESSAIoV) was proposed by Khedr, et al. [11]. HHOCNET is a clustering technique proposed by Ali, et al. [12]. IMFOCA-IoV was proposed by Rani and Sharma [13] as an intelligent clustering algorithm based on Moth-Flame Optimization (MFO) for IoV networks.

IoVSSA Salim, et al. [14] is a clustering method that uses the Sparrow Search Algorithm (SSA) to perform clustering in IoV. The algorithm, which is known as the Crayfish Optimization Algorithm (COA), has been used by Husnain, et al. [15] to develop a bio-inspired routing optimization algorithm named COANET. The Collaborative Region-Aware Feature-Driven Dynamic Caching (CRFDC) scheme, which is based on collaboration among edge caches through regional-feature awareness and vehicle clustering, was introduced by Chen, et al. [16] for IoV. Ajmani, et al. [17] introduced a method based on Ant Colony Optimization (ACO) for clustering combined with a vehicular identity-based MAC protocol to spread cooperative awareness messages in extremely dense IoV environments. The clustered federated learning architecture for secure communication in the IoV was proposed by Dhanare [18].

Although significant progress has been achieved in applying metaheuristic optimization techniques to IoV clustering, several limitations remain unresolved, as summarized in Table I. Many existing methods rely on simplified mobility representations that mainly consider distance or speed, which may not accurately reflect the dynamic behavior of vehicles. To address this limitation, the proposed framework incorporates relative velocity, acceleration, neighborhood density, and link stability into the mobility assessment process. Furthermore, several optimization-based clustering approaches may suffer

from insufficient exploration–exploitation balance, resulting in unstable clustering decisions in highly dynamic environments. Therefore, MTJO integrates adaptive nonlinearity, differential mutation, and hybrid guidance mechanisms to improve the search process. In addition, while some existing studies focus on routing, caching, or security-related objectives, this work emphasizes stable cluster formation by jointly considering cluster compactness, mobility stability, and energy efficiency through a multi-objective formulation. These observations motivate the development of the proposed mobility-aware MTJO clustering framework for dynamic IoV environments.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. Network Architecture

This study considers a highway-based IoV environment supported by Cellular Vehicle-to-Everything (C-V2X) communications, as shown in Fig. 1. The communication framework enables both direct Vehicle-to-Vehicle (V2V) interactions and Vehicle-to-Infrastructure (V2I) connectivity through Roadside Units (RSUs). Let the vehicular network consist of N_v vehicles randomly distributed within the road segment. To improve communication efficiency and reduce channel congestion, the entire network is partitioned into clusters, as defined in Eq. (1).

$$\mathcal{C} = \{1, 2, \dots, C\} \quad (1)$$

In each cluster, the CH performs coordination locally through information gathering, aggregation, and forwarding. The CMs send their information periodically to their associated CHs, who then communicate with other clusters or RSUs in the vicinity. Such a hierarchy-based communication system minimizes transmission redundancy and enhances scalability in vehicular networks under heavy traffic conditions. In each vehicle, there is an On-Board Unit (OBU) and a Global Positioning System (GPS) module that continuously provide information on the vehicle's location and mobility. The representation of the vehicular system is given by the undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{L})$, in which $\mathcal{V}$ stands for the set of vehicles and $\mathcal{L}$ denotes the set of communication links. There is a communication link from vehicle u to vehicle v only if they lie within each other's effective communication range. This condition is expressed as follows:

$$(u, v) \in \mathcal{L} \Leftrightarrow d_{uv} \leq \min(R_u, R_v) \quad (2)$$

where, d_{uv} stands for the Euclidean distance between two vehicles, while R_u and R_v signify their respective transmission ranges

B. Mobility Characterization Model

Since cluster stability is strongly influenced by vehicular mobility, a comprehensive mobility assessment model is developed. The proposed model incorporates local connectivity, relative motion characteristics, and temporal link stability to quantify vehicles' suitability for CH selection. For each vehicle u , the number of neighboring vehicles within its communication range is given by Eq. (3).

$$D_u = |\Omega_u| \quad (3)$$

where, Ω_u denotes the one-hop neighbor set associated with vehicle u . A larger value of D_u generally indicates stronger

TABLE I. AN OVERVIEW OF EXISTING STUDIES

Method	Optimization technique	Mobility awareness	Clustering objective	Main strength	Main limitation
JAYAClov [10]	JAYA & K-means	Partial	Routing-oriented clustering	Strong network optimization capability	Limited mobility modeling
ESSAIOV [11]	GA & SSA	Yes	Stable CH selection and minimum clusters	Long cluster lifetime	Risk of premature convergence
HHOCNET [12]	Harris hawks optimization	Partial	Multi-objective clustering	Reduced CH count and latency	Limited mobility dynamics
IMFOCA-IOV [13]	Moth-flame optimization	Limited	Coverage maximization	Low power consumption	Insufficient link stability consideration
IoVSSA [14]	Sparrow search algorithm	Yes	Stable CH formation	Improved cluster lifetime	Exploration capability may degrade in complex scenarios
COANET [15]	Crayfish optimization algorithm	Partial	Routing optimization	High PDR and energy efficiency	Focuses on routing rather than clustering stability
CRFDC [16]	DRL & dynamic clustering	Yes	Cooperative caching	Reduced latency and overhead	Primarily caching-oriented
ACO clustering [17]	Ant colony optimization	Limited	Collision reduction	Improved MAC performance	Not designed for cluster stability optimization
CFL-based framework [18]	FG-CPO & DRNN	Yes	Secure clustering and routing	High throughput and security	High computational complexity

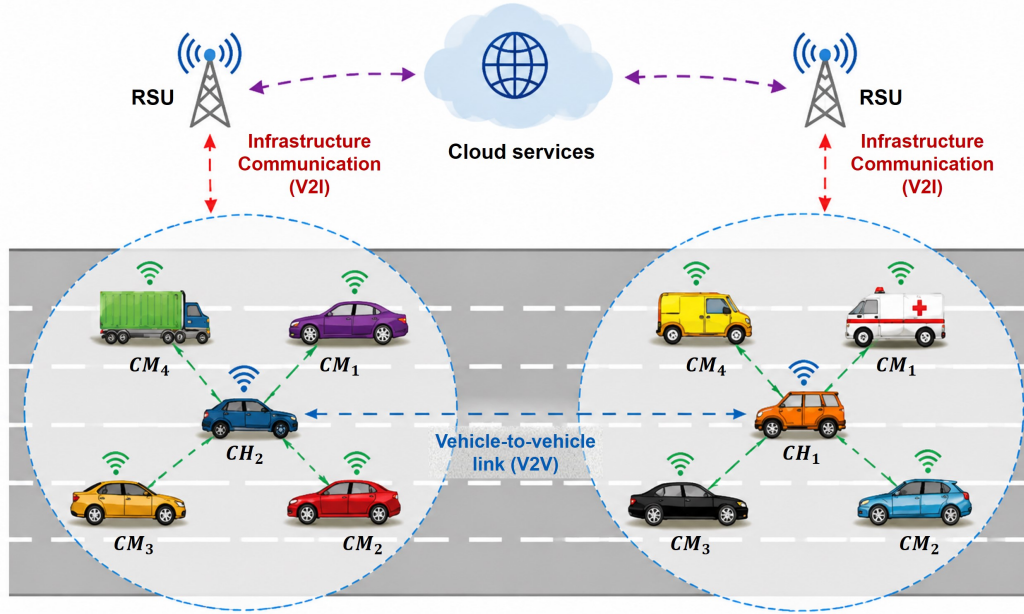


Fig. 1. Network model.

local connectivity and a higher probability of maintaining stable cluster membership. To capture the dynamic behavior of neighboring vehicles, the average relative speed of vehicle u is computed using Eq. (4).

$$\bar{v}_u = \frac{1}{D_u} \sum_{\substack{n=1 \\ n \neq u}}^{D_u} \left| \ln \left(1 - \frac{|s_u - s_{u,n}|}{s_u^{\max}} \right) \right| \quad (4)$$

where, s_u and $s_{u,n}$ represent the velocities of vehicle u and its neighboring vehicle n , respectively, while $s_u^{\max}$ denotes the maximum allowable speed. To ensure the validity of the logarithmic function, the relative velocity difference is normalized within the range of $[0,1)$ before applying the logarithmic transformation. Similarly, the average relative acceleration is

calculated using Eq. (5).

$$\bar{a}_u = \frac{1}{D_u} \sum_{\substack{n=1 \\ n \neq u}}^{D_u} \left| \ln \left(1 - \frac{|g_u - g_{u,n}|}{g_u^{\max}} \right) \right| \quad (5)$$

where, g_u and $g_{u,n}$ denote the accelerations of vehicle u and neighboring vehicle n , respectively, and $g_u^{\max}$ is the maximum acceleration limit. Similar to the relative velocity calculation, the normalized acceleration difference is constrained to avoid invalid logarithmic values. Besides relative motion, communication reliability depends on the spatial consistency between neighboring vehicles. Therefore, the average neighborhood distance of vehicle u is defined as follows:

$$\bar{d}_u = \frac{1}{D_u} \sum_{\substack{n=1 \\ n \neq u}}^{D_u} \sqrt{(X_u - X_n)^2 + (Y_u - Y_n)^2} \quad (6)$$

where, X_u, Y_u and X_n, Y_n denote the coordinates of vehicles u and n , respectively. To quantify temporal communication stability, the variation of average neighborhood distance over time is employed. The link stability indicator is formulated as follows:

$$S_u = |\bar{d}_u(t_b) - \bar{d}_u(t_a)| \quad (7)$$

where, t_a and t_b stand for two consecutive observation instants. Smaller values of S_u indicate more stable communication links and longer expected link durations. To jointly evaluate connectivity, motion dynamics, and link persistence, a comprehensive mobility score is formulated as follows:

$$\Psi_u = \alpha_1 \left(\frac{1}{D_u + \delta} \right) + \alpha_2 (\bar{v}_u \times \bar{a}_u) + \alpha_3 S_u \quad (8)$$

where, α_1, α_2 , and α_3 denote weighting coefficients satisfying $\alpha_1 + \alpha_2 + \alpha_3 = 1$. In this work, mobility behavior is considered the dominant factor affecting cluster stability. Therefore, the weighting coefficients are selected as $\alpha_1 = 0.1$, $\alpha_2 = 0.6$, and $\alpha_3 = 0.3$, assigning the highest importance to relative mobility characteristics, followed by link stability and local connectivity.

C. Energy Consumption Model

Energy efficiency is essential for evaluating cluster-formation performance in IoV scenarios. The energy consumption model adopted in this study follows the first-order radio model introduced in the LEACH protocol by Heinzelman et al. [19]. Energy consumption for communication comprises the transmission energy of CMs and the energy for receiving, aggregating, and forwarding of CHs. The formula for energy consumption for transmitting a b -bit packet at a distance r is expressed as:

$$E^{tx}(b, r) = \begin{cases} bE_c + bE_f r^2, & r < r_0 \\ bE_c + bE_m r^4, & r \geq r_0 \end{cases} \quad (9)$$

where, E_c denotes the circuitry energy consumption, E_f and E_m represent the amplification coefficients for free-space and multipath propagation environments, respectively, and $r_0 = \sqrt{E_f/E_m}$ is the propagation threshold distance. The energy consumed to receive a packet is given by Eq. (10).

$$E^{rx}(b) = bE_c \quad (10)$$

For a CH, the total energy expenditure consists of receiving packets from CMs, performing data aggregation, and transmitting the aggregated information toward the nearest RSU. Accordingly, the CH energy consumption is calculated using Eq. (11).

$$E^{rx}(R_c b) + R_c b E_{agg} + E^{tx}(R_c b, r_{RSU}) \quad (11)$$

where, E_{agg} denotes the aggregation energy coefficient and r_{RSU} represents the distance between the CH and its associated RSU. Assuming a normal CM, energy consumption is solely due to packet transmission to its CH, as expressed in Eq. (12).

$$E^{tx}(b, r_{CH}) \quad (12)$$

where, r_{CH} refers to the distance between the member vehicle and its corresponding CH. Finally, the total network energy

consumption is obtained by summing the energy consumed by all CHs and CMs, expressed as follows:

$$\sum_{c=1}^C E_c^{CH} + \sum_{c=1}^C \left(\sum_{r=1}^{R_c} E_{c,r}^{CM} \right) \quad (13)$$

D. Multi-Objective Clustering Formulation

The clustering task is formulated as a multi-objective optimization problem that simultaneously seeks to improve cluster compactness, mobility stability, and communication energy efficiency. Given the vehicle set $\mathcal{V}$, the objective is to identify an optimal CH configuration that minimizes intra-cluster communication cost while maximizing cluster lifetime and reducing energy consumption. Accordingly, the optimization process aims to determine the CH set that minimizes a weighted fitness function composed of cluster compactness, mobility quality, and network energy expenditure. The resulting optimization problem is subsequently solved using the proposed MTJO, which dynamically searches for the most stable and energy-efficient clustering structure under highly dynamic vehicular environments.

The clustering process in highly dynamic IoV environments can be treated as a multi-criteria optimization task in which several often-conflicting objectives must be optimized simultaneously. Specifically, an effective clustering structure should maintain compact cluster formations, ensure high cluster stability under vehicle mobility, and minimize communication-related energy expenditure. To achieve these objectives, a composite fitness function is developed to evaluate the quality of each candidate clustering solution. The overall objective function is formulated as follows:

$$\phi = \beta_1 G_1 + \beta_2 G_2 + \beta_3 G_3 \quad (14)$$

where, G_1, G_2 and G_3 represent the compactness, mobility-stability, and energy-efficiency criteria, respectively. The coefficients β_1, β_2 and β_3 denote their corresponding importance factors and satisfy $\beta_1 + \beta_2 + \beta_3 = 1$. In this study, the weighting factors are selected as $\beta_1 = 0.3$, $\beta_2 = 0.4$, and $\beta_3 = 0.3$, assigning the highest priority to cluster stability. The first objective evaluates the spatial compactness of the generated clusters. Compact clusters generally lead to shorter communication distances between CHs and CMs, thereby improving communication reliability and reducing transmission costs. The compactness metric is expressed as the proportion between the cumulative distance separating CHs from their associated members and the total neighborhood distance observed throughout the network, expressed as follows:

$$G_1 = \frac{\sum_{c=1}^C \sum_{r=1}^{R_c} \Delta(H_c, U_{c,r})}{\sum_{u=1}^{N_v} \sum_{q=1}^{D_u} \Delta(U_u, U_q)} \quad (15)$$

where, $\Delta(\cdot)$ denotes the Euclidean distance operator, and $U_{c,r}$ denotes the r^{th} member belonging to cluster c . Maintaining stable cluster structures is particularly important in IoV environments due to rapid topology variations. Therefore, the second objective evaluates the collective mobility characteristics of the selected CHs relative to the overall network mobility. The mobility-stability measure is formulated using Eq. (16).

$$G_2 = \frac{\sum_{c=1}^C \Psi_c}{\sum_{u=1}^{N_v} \Psi_u} \quad (16)$$

where, Ψ_c denotes the integrated mobility score of the selected CH in cluster c , while Ψ_u corresponds to the mobility score of vehicle u . In addition to communication stability, reducing energy consumption remains an important design objective, particularly in large-scale vehicular environments. The third objective quantifies the communication energy required by the clustering architecture relative to a non-clustered transmission scheme. The energy-efficiency objective is expressed as follows:

$$G_3 = \frac{\sum_{c=1}^C E_c^{CH} + \sum_{c=1}^C \sum_{r=1}^{R_c} E_{c,r}^{CM}}{\sum_{u=1}^{N_v} E^{tx}(b, r_{u,RSU})} \quad (17)$$

where, E_c^{CH} and $E_{c,r}^{CM}$ represent the energy consumed by CHs and CMs, respectively, while $E^{tx}(b, r_{u,RSU})$ denotes the transmission energy required if every vehicle communicated directly with the nearest RSU without clustering. Based on the three criteria introduced above, the clustering optimization problem can be formulated as Eq. (18), subject to the communication range, cluster membership, connectivity, and CH assignment constraints defined in the network model.

$$\min \phi = \min(\beta_1 G_1 + \beta_2 G_2 + \beta_3 G_3) \quad (18)$$

The optimization framework therefore seeks a clustering configuration that simultaneously minimizes intra-cluster communication distances, selects mobility-stable CHs, and reduces overall communication energy consumption. The resulting multi-objective optimization problem is subsequently solved using the proposed MTJO, which dynamically searches for the globally optimal clustering structure under rapidly changing vehicular network conditions.

IV. PROPOSED MOBILITY-AWARE CLUSTERING FRAMEWORK

The clustering problem in IoV environments is inherently a high-dimensional combinatorial optimization task due to the dynamic mobility of vehicles and the large number of possible CH combinations. To address this challenge, a mobility-aware clustering framework based on the MTJO is proposed. The framework integrates the improved search ability of MTJO with mobility properties, communication cost, and energy consumption into a unified optimization model, which leads to the establishment of concise, stable, and energy-efficient vehicular clusters. The workflow of the proposed MTJO-based mobility-aware clustering mechanism is presented in Fig. 2, and the detailed steps of implementation are provided in Algorithm 1.

In view of the traffic flow concept, MTJO formulates the optimization scheme as the interaction between several agents in a multidimensional search space. Here, each agent is a potential solution to the clustering problem, and the optimization process adapts the population through exploration and exploitation to discover the most appropriate CH configuration. In contrast to traditional clustering algorithms that consider only geographical proximity and/or node degrees, the proposed algorithm explicitly accounts for mobility awareness as part of the optimization process, ensuring greater stability in cluster formation in highly dynamic networks.

Algorithm 1 Proposed MTJO-based mobility-aware clustering

Require: Vehicle set $\mathcal{V}$; mobility information; communication range R ; population size N_p ; maximum iterations $T_{\max}$
Ensure: Optimal CH set $\mathcal{H}^*$ and cluster assignments

- 1: Construct the connectivity graph $\mathcal{G} = (\mathcal{V}, \mathcal{L})$ using $d_{uv} \leq \min(R_u, R_v)$
- 2: **for all** $u \in \mathcal{V}$ **do**
- 3: Determine neighbor set Ω_u and degree D_u
- 4: Compute relative speed $\bar{v}_u$, relative acceleration $\bar{a}_u$, and link stability S_u
- 5: Compute mobility score $\Psi_u = \alpha_1(D_u + \delta)^{-1} + \alpha_2(\bar{v}_u \bar{a}_u) + \alpha_3 S_u$
- 6: **end for**
- 7: Initialize population $\{\mathbf{Y}_n\}_{n=1}^{N_p}$, personal bests $\mathbf{P}_n$, and global best $\mathbf{G}$
- 8: **for** $t = 1$ to $T_{\max}$ **do**
- 9: $\mu \leftarrow t/T_{\max}$
- 10: Compute nonlinear parameters $\kappa(t)$, $\tau(t)$, mutation factor $\Lambda(t)$, and mixing weight $X(t)$
- 11: **for all** $\mathbf{Y}_n$ **do**
- 12: $\mathbf{Y}_n^* \leftarrow (1 - \mu)\mathbf{P}_n + \mu\mathbf{G}$
- 13: Generate exploration solution $\mathbf{Y}_n^E$ using Eq. (24)
- 14: Generate adaptive solution $\mathbf{Y}_n^A$ using Eq. (27)
- 15: Randomly select distinct $\mathbf{Y}_a, \mathbf{Y}_b, \mathbf{Y}_c$
- 16: $\mathbf{Z}_n \leftarrow \mathbf{Y}_a + \Lambda(t)(\mathbf{Y}_b - \mathbf{Y}_c)$
- 17: Obtain trial vector $\mathbf{W}_n$ by crossover
- 18: Generate guided solution $\mathbf{Y}_n^G$ using Eq. (31)
- 19: $\mathbf{Y}_n^{new} \leftarrow X(t)\mathbf{W}_n + [1 - X(t)]\mathbf{Y}_n^G$
- 20: Repair boundary violations in $\mathbf{Y}_n^{new}$
- 21: Decode CH decisions: $H_i \leftarrow \mathbb{I}[\sigma(y_i) > 0.5]$
- 22: Assign each non-CH vehicle to its nearest reachable CH
- 23: Promote uncovered vehicles to CHs and remove empty CHs
- 24: Evaluate $\phi = \beta_1 G_1 + \beta_2 G_2 + \beta_3 G_3$
- 25: Update $\mathbf{P}_n$ and $\mathbf{G}$
- 26: **end for**
- 27: **end for**
- 28: Decode $\mathbf{G}$ as $\mathcal{H}^*$ and final clusters
- 29: **return** $\mathcal{H}^*$ and cluster assignments

A. Fundamentals of the Traffic Jam Optimizer

TJO is a swarm intelligence algorithm that emulates the evolution of traffic jams and the distribution of traffic in transportation networks. TJO interprets the optimization effort as the route-selection decision made by multiple vehicles seeking the most efficient path to a destination. Within the search space, each driver corresponds to a candidate solution. Each driver's movement is influenced by both its own past experiences and the most accurate information available about the community. Consequently, TJO achieves a balance between local exploitation and global exploration by executing sequential phases, including exploration, adaptive regulation, and directed guidance. Assuming a population size of N_p , the population matrix is represented by Eq. (19).

$$\mathbf{Y} = [\mathbf{Y}_1, \mathbf{Y}_2, \dots, \mathbf{Y}_{N_p}]^T \quad (19)$$

where, $\mathbf{Y}_n = [y_{n,1}, y_{n,2}, \dots, y_{n,D}]$ denotes the n^{th} solution vector and D is the search-space dimensionality. The fitness values corresponding to all candidate solutions are stored as follows:

$$\mathbf{\Gamma} = [\Gamma(\mathbf{Y}_1), \Gamma(\mathbf{Y}_2), \dots, \Gamma(\mathbf{Y}_{N_p})]^T \quad (20)$$

where, $\Gamma(\cdot)$ denotes the objective function value associated with each solution.

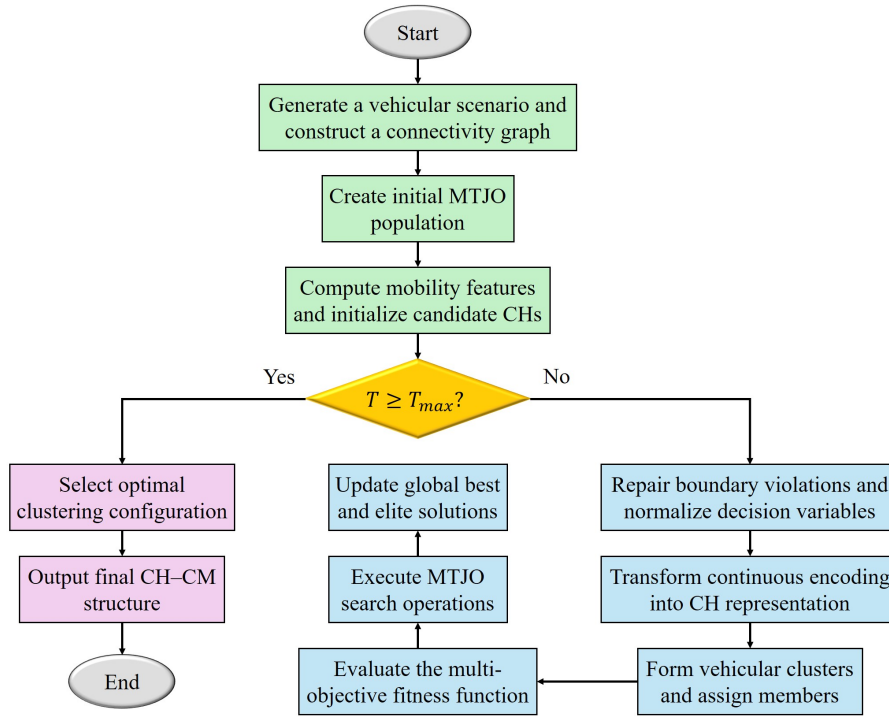


Fig. 2. Workflow of the proposed MTJO-based mobility-aware clustering framework.

B. Exploration Phase

The first search stage focuses on exploring promising regions of the solution space. The normalized iteration ratio is defined by Eq. (21).

$$\mu = \frac{t}{T_{\max}} \quad (21)$$

where, t denotes the present iteration and $T_{\max}$ represents the highest iteration count. The desired search direction is computed using Eq. (22).

$$Y_n^*(t) = (1 - \mu)P_n(t) + \mu G(t) \quad (22)$$

where, P_n represents the personal best solution of the agent n and $G(t)$ denotes the globally best solution. A stochastic movement coefficient is then calculated using Eq. (23).

$$\zeta = \kappa(1 - \mu)e^{-\mu} \sin(\theta_1) \cos(\theta_2) \quad (23)$$

where, κ is a control parameter and $\theta_1, \theta_2 \in [0, 2\pi]$. The exploration update is subsequently performed according to Eq. (24).

$$Y_n^E(t+1) = Y_n^*(t) + \zeta(\rho(U - L) + L) \quad (24)$$

where, ρ is a random vector and L and U stand for the lower and upper search bounds, respectively.

C. Adaptive Regulation Phase

After the initial exploration stage, the population enters a self-adaptive adjustment phase to improve solution quality while preserving population diversity. The original TJO employs a linearly decreasing adjustment coefficient. However, to improve convergence behavior, the proposed MTJO introduces

a nonlinear adaptation mechanism defined by Eq. (25) and (26).

$$\kappa(t) = 1.5(1 - \mu)^2 + 0.5\mu^2 \quad (25)$$

$$\tau(t) = 0.5(1 - \mu)^2 + 1.5\mu^2 \quad (26)$$

Compared with linear scheduling, the nonlinear adaptation mechanism enables stronger exploration in early iterations and smoother exploitation in later stages. The adaptive update strategy is formulated as follows:

$$Y_n^A(t+1) = \begin{cases} Y_n(t) + \kappa(t)e^{-2\mu} \sin(\theta_3)(Y_r(t) - Y_n(t)) \\ \quad \times (1 + 0.5 \sin(2\pi\mu)), & \Omega > 0.5, \\ Y_n(t) + \kappa(t)e^{-2\mu} \sin(\theta_4)(Y_n^*(t) - Y_n(t)) \\ \quad \times (1 + 0.3 \cos(\pi\mu)), & \Omega \leq 0.5. \end{cases} \quad (27)$$

where, Ω is a uniformly distributed random variable and Y_r is a randomly selected solution from the population.

D. Differential Mutation Mechanism

Although TJO exhibits strong search capability, it may still converge prematurely when solving highly nonlinear clustering problems. Therefore, MTJO features a differential mutation operator to enhance population diversity. Three distinct solutions Y_a , Y_b , and Y_c form the mutation vector randomly as follows:

$$Z_n = Y_a + \Lambda(t)(Y_b - Y_c) \quad (28)$$

$$\Lambda(t) = \max(\Lambda_{\min}, \Lambda_0(1 - \mu)) \quad (29)$$

A crossover procedure is subsequently performed to generate a trial solution, represented by Eq. (30).

$$W_{n,d} = \begin{cases} Z_{n,d}, & \text{rand}(0,1) \leq CR(t) \text{ or } d = d_{rand}, \\ Y_{n,d}, & \text{otherwise} \end{cases} \quad (30)$$

where, $CR(t) = CR_0(1 - \mu)$. The mutation and crossover procedures improve the algorithm's ability to escape local optima and explore unexplored regions of the search space.

E. Dynamic Hybrid Guidance Mechanism

The final search phase combines the exploitation capability of the original TJO with the diversification capability introduced by differential mutation. The guidance stage of the original TJO is first expressed as follows:

$$Y_n^G(t+1) = Y_n^*(t) + \tau(t) \sin(\theta_5)(Y_n^*(t) - Y_n(t)) \quad (31)$$

where, $\theta_5 \in [0, 2\pi]$. Subsequently, the mutated solution and guided solution are merged using a dynamic weighting strategy:

$$Y_n^{new}(t+1) = X(t)W_n + (1 - X(t))Y_n^G(t+1) \quad (32)$$

where, the adaptive mixing coefficient is defined by Eq. (33).

$$X(t) = 0.7 - 0.3\mu \quad (33)$$

F. Solution Encoding and Cluster Formation

Each candidate solution is encoded using a real-valued representation. For the p^{th} individual, the encoding vector is expressed as:

$$S_p = [s_{p,1}, s_{p,2}, \dots, s_{p,N_v}] \quad (34)$$

where, each dimension corresponds to one vehicle in the network. To maintain feasible solutions, out-of-bounds values are repaired according to Eq. (35).

$$s_i = \text{rand}(0,1)(U_b - L_b) + L_b \quad (35)$$

where, L_b and U_b stand for the search boundaries. A sigmoid transformation is then employed to convert real-valued solutions into binary CH decisions:

$$H_i = \begin{cases} 1, & \sigma(s_i) > 0.5 \\ 0, & \text{otherwise} \end{cases} \quad (36)$$

where,

$$\sigma(s_i) = \frac{1}{1 + e^{-s_i}} \quad (37)$$

A value of $H_i = 1$ indicates that the vehicle i is designated as a CH. Following CH determination, an ordinary vehicle is associated with the nearby CH located within its communication radius. If a vehicle remains uncovered, it is temporarily promoted to a candidate CH, and the clustering process is repeated. Conversely, CHs without assigned members are removed from the CH set during subsequent iterations. This procedure continues to ensure all vehicles are grouped into appropriate clusters.

All clustering solutions for each candidate are assessed by the multi-objective fitness function given by Eq. (18). At each step, the MTJO algorithm creates a new population through exploration, adaptive control, differential mutation,

and hybridization. All solutions with high fitness are preserved, and those with low fitness values are discarded. The iteration process will stop upon reaching the termination criterion. S_{best} is the clustering configuration of the CHs where the objective function takes its optimum value and where there is an increase in cluster stability, a reduction in communication costs, and energy efficiency of the network.

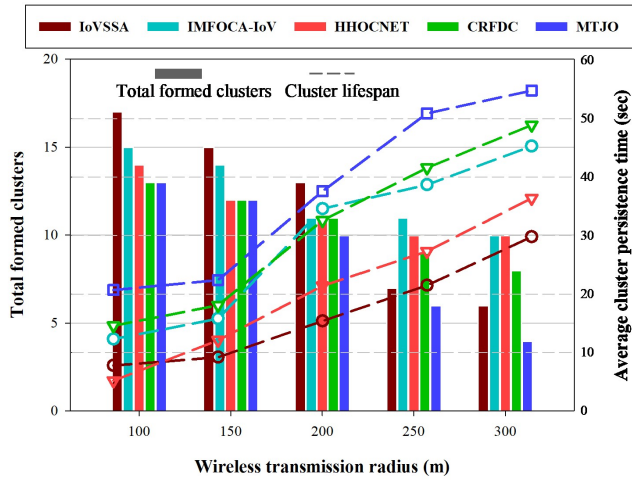
V. RESULTS AND DISCUSSION

The validity of the proposed MTJO-based mobility-aware clustering framework was evaluated through simulations under different vehicular conditions. The evaluation focuses on the effectiveness of the integrated clustering framework, including the mobility-aware fitness formulation and the enhanced optimization mechanisms, compared with representative IoV clustering approaches. To ensure accurate comparisons across all algorithms, the algorithms were implemented under similar simulation conditions. These tests were carried out on a computer with an Intel Core i7 processor and 16 GB of RAM. A highway scenario with a 1km^2 area was considered, where vehicles travel at speeds ranging from 72 to 108 km/h on a six-lane road. The population size and iteration limit during the optimization process were set to 100 and 150, respectively.

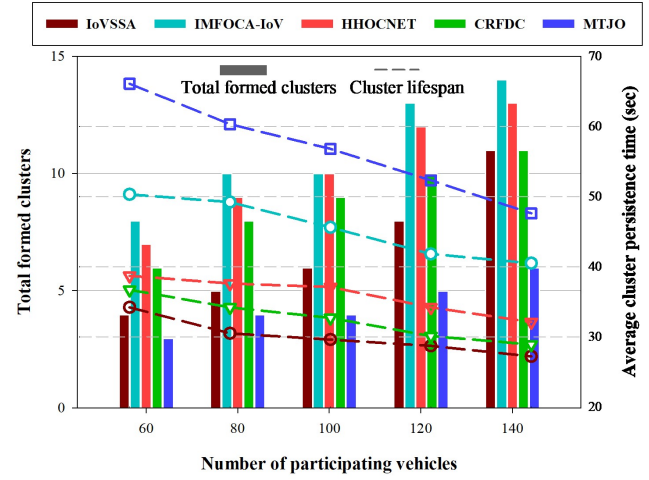
A. Impact of Transmission Range

The first series of experiments explores the impact of the transmission range on clustering performance. As illustrated in Fig. 3, the performance of various clustering algorithms across different communication ranges is analyzed on a 100-node network. In the first evaluation, the impact of the communication radius on clustering behavior and stability is analyzed, whereas in the second, energy efficiency and packet delivery performance are evaluated under similar conditions. The experimental results show that the MTJO-based approach outperforms state-of-the-art approaches across all aspects. This phenomenon is due to the mobility-aware CH selection process in the new framework. Unlike most existing clustering mechanisms that rely largely on distance criteria, the new technique not only depends on neighborhood connectivity and link stability but also considers relative mobility during clustering. This results in the choice of vehicles with stable mobility characteristics as CHs. Moreover, MTJO's improved search capabilities help find globally optimal CH selections, thereby forming larger clusters.

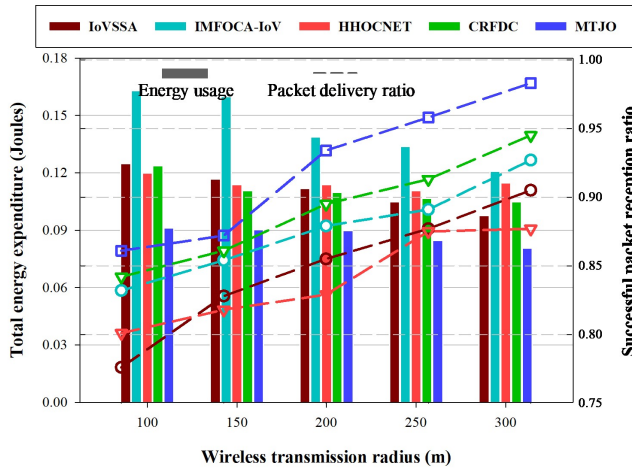
In addition to reducing the number of clusters, the proposed approach ensures a very long lifetime for each formed cluster. An increase in the transmission range would improve connectivity; however, the extent to which this occurs depends heavily on CH effectiveness. Many existing approaches use optimization techniques that select CHs based on geometric properties, which are often unreliable because they do not account for speed variations. On the other hand, the suggested mobility parameter can account for both mobility and communication conditions. Another aspect to consider regarding energy efficiency and PDR is the influence of transmission range. In this case, the proposed technique shows lower energy consumption than other existing techniques across all transmission ranges. As it forms fewer clusters, there are fewer transmissions from CH to RSU, thereby lowering communication costs. Stable



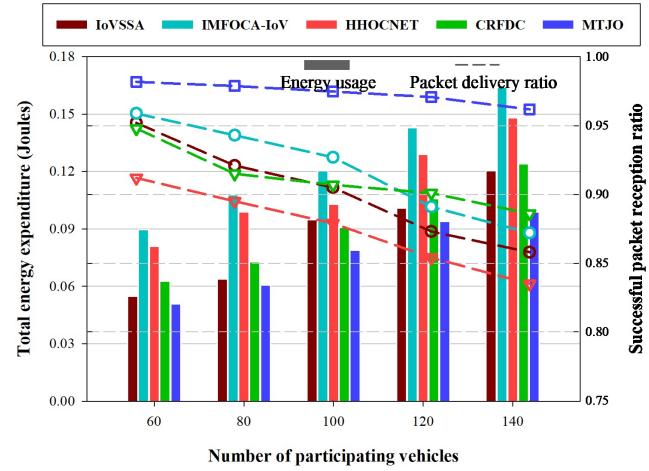
(a) Cluster count vs. cluster lifespan



(a) Cluster count vs. cluster lifespan



(b) Energy usage vs. packet delivery ratio



(b) Energy usage vs. packet delivery ratio

Fig. 3. Performance evaluation of clustering schemes under varying communication coverage distances (100 vehicular nodes).

Fig. 4. Performance evaluation of clustering schemes under varying vehicular density with fixed communication range (300 m).

clusters also involve fewer control message exchanges during cluster formation and maintenance.

B. Impact of Vehicle Density

The second set of experiments is conducted to examine clustering performance across varying numbers of vehicles. Fig. 4 presents the performance results of the various clustering schemes as vehicular density increases, with a fixed transmission range of 300 m. The first experiment measures the scalability and stability of the clustering scheme as vehicle density rises, while the second assesses packet delivery performance and energy efficiency. In such cases, most clustering algorithms exhibit an exponential increase in the number of clusters and a decrease in stability.

Based on the simulation findings, the new MTJO approach generates significantly fewer clusters than the existing benchmark techniques, regardless of network size. This is due to MTJO's effectiveness at balancing exploration and exploita-

tion in optimization. Due to its nonlinear parameter-tuning capability, MTJO is able to explore widely at an early stage and exploit this at later stages. Moreover, the cluster lifetime study supports the reliability of the framework proposed here. The decrease in cluster lifetime for all algorithms as network density increases is significant for MTJO; however, it is far less than for the other algorithms, mainly because of the inclusion of the mobility-aware fitness metric. As a result, vehicles with steady movement and high local connectivity are selected as CHs.

From an energy perspective, increasing vehicle density inevitably raises network energy consumption because more packets must be transmitted and processed. Nevertheless, the proposed framework exhibits the lowest energy consumption among all competing approaches. The reduction in CH replacements and control signaling contributes directly to this improvement. In addition, the differential mutation operator, added to MTJO, increases population diversity and helps prevent early convergence, enabling the algorithm to find

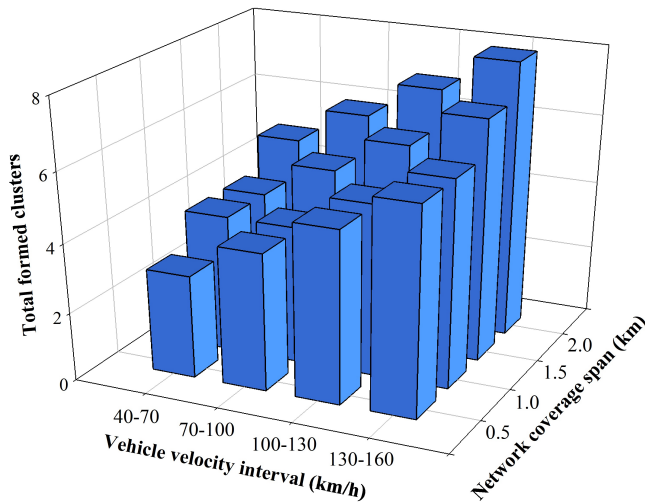


Fig. 5. Variation of clustering behavior under combined vehicular speed dynamics and spatial deployment scale.

energy-efficient clustering schemes even in highly congested environments. The delivery success ratio decreases as the number of vehicles increases due to increased competition between channels and interference. Nevertheless, the suggested method consistently demonstrates high performance in delivery success.

C. Impact of Vehicle Speed

As an additional step to test the resilience of the developed architecture, a series of simulation experiments was conducted in which vehicle speeds were varied while network size and transmission ranges were held constant. Fig. 5 shows the impact of joint variation of vehicle mobility and deployment size on the performance of clustering schemes. The findings clearly show that any increase in vehicle speed degrades clustering performance across all clustering algorithms. As vehicle speed increases, cluster reorganization becomes more frequent, leading to a gradual increase in the number of clusters. However, the proposed MTJO framework exhibits a slower growth rate than competing methods. The reason lies in the mobility model adopted in this work, which explicitly incorporates relative velocity and acceleration into the CH evaluation process. Vehicles exhibiting highly unstable movement patterns are therefore less likely to be selected as CHs, resulting in more robust cluster structures under high-speed mobility conditions.

The cluster lifetime is highly dependent on speed variations. An increased velocity increases the likelihood that links are cut, thereby reducing cluster lifetimes. However, the new methodology ensures the longest cluster lifetime across all considered speeds. The combined mobility index selects vehicles that are mobile relative to the surrounding vehicles. Analysis of energy consumption and packet delivery rate shows that the trends are similar for both. Higher vehicle speeds make routing less stable, leading to additional signaling and retransmission costs. Nonetheless, the proposed model is

shown to be more efficient than the benchmark algorithms in terms of energy consumption and packet delivery rate. This is due to the MTJO algorithm's better capacity for cluster formation, as well as the hybrid search algorithm.

D. Impact of Network Area

The final series of experiments examines the effects of varying the network area size while keeping the number of vehicles constant. Fig. 6 shows the variation in cluster lifetime across different vehicle speeds and network area sizes. An increase in network area means that the vehicles are more dispersed; hence, the nodes are less dense and the distance between vehicles increases. The simulation results have shown that a larger network area leads to more clusters formed by any algorithm. More CHs are needed to preserve network connectivity due to greater vehicle dispersion. Nevertheless, the suggested MTJO-based approach produces fewer clusters than other techniques.

The lifespan of cluster networks decreases with increasing network size due to greater distances between cluster members and their associated CH nodes. The distance between these nodes reduces the communication channel's strength and causes disconnections. But this proposed approach performs better in this situation. The inclusion of the link stability factor in the mobility score ensures that more stable areas get priority. Also, growth in network coverage impacts energy usage and packet delivery. Long-range links require more energy for transmission and are prone to greater packet delivery losses. While all methods show poor performance, our framework still attains the best performance in terms of energy use and packet delivery. This is mainly due to the fitness function, which ensures optimal cluster formation, stability, and communication costs.

E. Discussion of Performance Improvements

The excellent performance of the MTJO-based clustering method is due to the following three reasons. First,

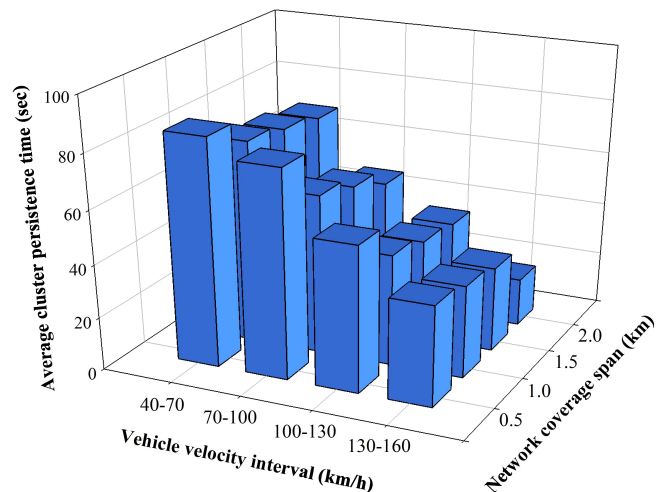


Fig. 6. Influence of vehicular mobility and spatial scale on cluster stability duration.

the connectivity-aware mobility evaluation method provides a more practical depiction of vehicle behavior by considering connectivity, relative speed, acceleration, and link stability. Thus, CHs can be chosen, as they remain stable despite dynamic traffic changes. Second, the MTJO-based approach significantly improves the optimization performance of the basic TJO algorithm. In particular, a nonlinear parameter adaptation technique regulates the balance between exploration and exploitation at each stage of the optimization process, while a differential mutation technique increases population diversity, preventing the algorithm from falling into a local optimum.

Third, the dynamic hybrid approach successfully merges the advantages of guided exploitation with mutation-driven exploration. This combination enhances convergence accuracy while still being able to avoid local optima. Therefore, the proposed method can generate effective, robust, and energy-efficient cluster formations independent of traffic density, transmission range, vehicle speed, and other parameters. These results demonstrate the effectiveness of integrating state-of-the-art swarm-intelligence-based optimization with CH selection considering the vehicles' mobility.

VI. CONCLUSION

The main contribution of this research was the design of a mobility-aware clustering scheme for the IoV, based on a modified version of the TJO algorithm. The use of nonlinear parameter adaptation enables better control of the exploration-exploitation trade-off, while the differential mutation strategy increases population diversity and prevents early convergence. The hybrid search approach helps MTJO avoid getting trapped in local minima. All these enhancements enable the MTJO algorithm to find good CH configurations with improved convergence properties. As far as networking is concerned, the main advantage of the developed mobility-aware clustering scheme is that it accounts for a new set of factors that influence vehicle clustering. In particular, it suggests a new metric for evaluating vehicles that accounts for their relative velocity, acceleration, neighborhood density, and link stability. Simulation results demonstrate the effectiveness of the proposed scheme compared with the best available clustering techniques across varying transmission ranges, number of vehicles, movement speeds, and network sizes. The proposed scheme offers fewer clusters, longer cluster lifetimes, lower energy consumption, and a higher packet delivery ratio. The proposed scheme increases network efficiency and scalability while providing high robustness in dynamic scenarios.

Although the proposed MTJO-based mobility-aware clustering framework achieves improved performance under the considered simulation conditions, some limitations remain. The current evaluation focuses on a highway-based IoV scenario, and the framework's performance under other road structures and urban environments requires further investigation. Moreover, the computational overhead introduced by the enhanced optimization mechanisms of MTJO has not been quantitatively analyzed in comparison with the considered baseline approaches. These aspects will be considered in future studies. For future work, the proposed framework can be further investigated under more diverse vehicular scenarios, including different road structures and traffic conditions. In

addition, further studies can analyze the computational complexity of the optimization process and explore strategies to improve the efficiency of MTJO-based clustering for large-scale IoV networks.

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