

Intelligent User Clustering and Resource Allocation in Fog-Based Vehicular Networks Using a Hybrid Optimization Approach

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Abstract: Due to the rapid proliferation of transportation, the vehicles that are connected to a centralized cloud have led to an exponential increase in data generation and also provide high computational demands in vehicular networks. Traditional methods depend on centralized cloud processing, which introduces significant delays due to the time taken for data transmission. This latency is particularly critical for real-time vehicular applications that demand immediate responses for safety and navigation purposes. Therefore, fog computing has emerged as a promising solution to address latency and bandwidth constraints in cloud computing. By decentralizing computation and bringing resources closer to the end-users, fog computing significantly enhances data processing efficiency. Hence, this article devises an innovative framework, called Fractional House Swallow Optimizer (FHSO), for user clustering and resource allocation in fog-based vehicular networks. At first, a fog-based vehicular network is simulated between cloud data centers and a fog Virtual Machine (VM). This simulation replicates real-world vehicular mobility patterns and communication flows to evaluate performance metrics accurately. Then, user grouping is done by Fuzzy Local Information C-Means (FLICM) Clustering based on Signal-to-Interference-plus-Noise Ratio (SINR) and user distance. After user grouping, resource allocation is performed by the proposed FHSO. FHSO is the combination of the Fractional Concept and House Swallow Optimizer (HSO). For 1000 iterations, FHSO achieved energy efficiency of 80.878 Megabits per Joule (Mbts/Joule), throughput of 95.768 Megabits per Second (Mbps), and subchannel utility of 290.988 bits per second per Hertz (bps/Hz) with 150 vehicles.

Keywords: Internet of Vehicles, Fog Computing, Resource Allocation, Deep Learning, Fractional House Swallow Optimizer.

Nomenclature

Abbreviation	Description
IoT	Internet of Things
IoV	Internet of Vehicles
VFC	Vehicular Fog Computing
RSU	Road Side Unit
V2R	Vehicle-to-RSU
VANET	Vehicular Ad-hoc Network
FLICM	Fuzzy Local Information C-Means
SINR	Signal-to-Interference-plus-Noise Ratio
HSO	House Swallow Optimizer
FHSO	Fractional House Swallow Optimizer
DL	Deep Learning
ML	Machine Learning
NOMA	Non-Orthogonal Multiple Access
SIC	Successive Interference Cancellation
BMAB	Budgeted Multi-Armed Bandits
MEC	Multi-access Edge Computing
DT	Digital Twin
CaaDet	Convolutional Autoencoder-Aided Detection
FBL	Finite Block Length
GWO-MFO	Grey Wolf Optimizer-Moth Flame Optimizer
SBS	Small Base Station
VM	Virtual Machine

1. Introduction

Today, the Internet of Things (IoT) plays an important role in many aspects of daily human life, such as smart homes, automobiles, industry, energy, transportation, and both personal and social health [1], [2] [3]. Its expansion has revolutionized the connectivity between devices, enabling intelligent systems to interact autonomously and contextually. In recent years, the expansion of IoT initiatives and the development of the Internet of Vehicles (IoV) [1]. The IoV integrates vehicle communication systems with IoT infrastructures to facilitate real-time vehicular interactions, thereby enhancing road safety and traffic management. The vehicles connected to the IoV system process real-time data for responding to users, who send requests for accessing data. In-vehicle sensors, wireless communication technologies, and equipment with processing and storage capabilities enable smart vehicles to function as providers for sensing, data storage, computing, information transmission, and transportation services [2], [4] [5] [3]. Vehicles spend significant amounts of time parking vehicles or getting stuck in traffic. This idle time represents an underutilized opportunity to harness the embedded computing capabilities of these vehicles. During this time, resources are largely unused or completely idle. Thus, these idle vehicles are considered fog computing sources to attain highly effective resource usage [3]. By treating parked or slow-moving vehicles as fog nodes, the network can offload data and reduce latency, enhancing overall system responsiveness. However, this approach requires the allocation of orthogonal subchannels to different devices, which leads to suboptimal bandwidth utilization [6]. Non-Orthogonal Multiple Access (NOMA) is a promising solution to improve spectral efficiency. NOMA employs Successive Interference Cancellation (SIC) for sharing subcarriers (SB) to devices [5] [3]. NOMA plays a crucial role in next-generation communication technologies, but is not applied to reconfigurable intelligent surfaces [7], millimeter wave and Terahertz communications, power-line communication [8], IoT [5], and satellite communication [9]. Future work must explore the integration of NOMA with emerging technologies to address the limitations of current vehicular communication systems.

Fog computing has emerged as an advanced development model of cloud computing by transporting computational resources closer to end devices at the network edge. The term “Fog Computing” shows its intermediary position between the “cloud” and “ground”. Fog computing is more decentralized and operates near the user's device, which significantly reduces latency and enhances real-time performance than traditional cloud computing. This proximity to the user enables faster decision-making and responsiveness, which is critical for applications like autonomous driving and traffic control. This architecture provides substantial benefits in terms of cost efficiency, lower latency, and improved reliability, and also addresses some of the common limitations that are faced by IoT services. Fog computing is more effective for time-sensitive and energy-intensive IoT applications [3] [10]. A new paradigm called Vehicular Fog Computing (VFC) has emerged into fog computing. These vehicles act as both data consumers and processing nodes, facilitating dynamic edge intelligence. VFC uses vehicles as mobile infrastructure for both communication and computation. VFC also supports resource-constrained vehicles by providing additional computational resources [6]. This cooperative framework enhances the computational reach of IoV systems, especially in areas with poor or intermittent cloud access. One of the main challenges in fog environments is optimal task distribution among fog nodes, especially for applications that require intensive computation. The VFC framework enhances processing speeds and also reduces task latency [7]. Numerous Machine Learning (ML) and DL algorithms are developed for resource allocation across different domains and datasets. DL-based resource allocation approaches have demonstrated superior performance over traditional signature-based and shallow learning methods. These intelligent models are capable of learning from traffic patterns, user mobility, and resource demands, enabling adaptive resource management. Although these techniques have improved resource management, their accuracy remains limited in complex, real-world network environments [6]. Scalability, convergence time, and adaptability to dynamic conditions remain open challenges in current DL-based solutions.

This paper presents a novel approach, called FHSO, for resource allocation using fog computing. Initially, the fog-based vehicular network is simulated, where the vehicular cluster, fog, and cloud are presented for allocating resources for vehicle users. The simulation incorporates realistic vehicular mobility and network dynamics to validate the proposed model's robustness. After the simulation, user grouping is done between the intermediate users using FLICM clustering. Here, similar users are grouped based on SINR and user distance. Finally, resources are allocated to vehicle users using FHSO, which is the combination of HSO and the Fractional Concept.

The main objective of this article is given as,

- ❖ **Innovative FHSO for Resource Allocation:** This research devises FHSO for resource allocation to vehicle users using fog computing. Here, FHSO is the fusion of HSO and fractional concepts. This hybrid method introduces adaptive exploration strategies that overcome limitations of traditional metaheuristics in dynamic vehicular environments.

The rest of this paper is organized as follows: Section 2 reviews existing literature. Section 3 presents the System Model. Section 4 describes the proposed approach, along with the algorithms and techniques. Section 5 discusses the experimental results and provides comparative analyses. Finally, Section 6 summarizes the key findings and outlines potential directions for future research.

2. Motivation

IoV presents challenges, like difficulty in managing data processing and resource usage due to the rapid expansion of vehicle users. The increasing number of smart vehicles leads to unpredictable network loads, high mobility, and varying service demands, complicating real-time communication and computation. Traditional cloud computing methods, like Google's computing engine, fail to achieve low latency, high bandwidth, and resource allocation. These centralized systems are not well-suited for latency-sensitive vehicular applications such as collision avoidance, route prediction, and automated driving. Thus, to overcome these challenges, IoV moves towards fog computing, which provides high computational storage and network resources to vehicles. Hence, this approach reduces response time and provides efficient resource allocation. Thus, this is a strong motivation to develop FHSO in this research article for achieving resource allocation.

2.1 Literature Survey

In recent advancements, various traditional methods are explored to address the complexities of resource allocation, and they are discussed in the following section.

Husain *et al.* [3] employed Gray Wolf Optimization and Moth-Flame Optimization (GWO-MFO) for resource allocation in fog computing. GWO-MFO attained more effectiveness in dynamic, resource-constrained scenarios by rapidly identifying promising allocation candidates across large multidimensional spaces. However, GWO-MFO was trapped with local optima and also limited its adaptability. Its exploitation capabilities often outweighed exploration, causing stagnation in complex search spaces. Moreover, Jeremiah *et al.* [10] introduced a Multi-access Edge Computing framework integrated with server Digital Twins (MEC-server DT) to enable predictive resource allocation. MEC-server DT approach enhanced load balancing and responsiveness, but MEC-server DT attained high implementation costs, synchronization issues, and scalability concerns. Despite its predictive capabilities, the reliance on consistent digital twin updates introduces bottlenecks in real-time vehicular systems. Shi *et al.* [11] introduced the Finite Block Length (FBL) mechanism for resource allocation using fog computing. FBL mechanism ensured reliability and delivery of critical data in time, especially in vehicular networks. Nevertheless, the FBL mechanism lacked efficiency in handling large volumes of data and required complex mathematical modeling for decision-making. Its application is more suitable for static or semi-dynamic environments, rather than highly mobile vehicular networks. For effective resource allocation, Hosny *et al.* [9] devised Budgeted Multi-Armed Bandits (BMAB). BMAB highly managed resources and adapted to changing environments with minimal prior knowledge. Yet, the BMAB approach suffered from slow convergence and struggled with continuous allocation decisions. Additionally, BMAB's limited memory of past states restricts its ability to optimize in rapidly evolving network topologies. Finally, Yaqoob *et al.* [6] developed a Convolutional Autoencoder-Aided anomaly Detection (CAaDet) framework for resource allocation. CAaDet enhanced system robustness by identifying abnormal resource usage patterns. However, the CAaDet method introduced computational overhead and delayed responsiveness.

2.2 Challenges

The challenges of various existing techniques for resource allocation are given below,

- GWO-MFO [3] balanced latency and energy but faced convergence issues in high-dimensional search spaces. However, GWO-MFO struggled with balancing exploration and exploitation, which led to sub-optimal resource allocation at times. Its tendency to prematurely converge makes it unsuitable for large-scale, highly dynamic vehicular fog systems that require continuous adaptation.
- MEC-server DT [10] enabled fast, rule-based decision-making in edge servers with limited resources. However, MEC-server DT lacked robustness in high-mobility environments.
- BMAB [9] methods performed well in lightweight and decentralized VFC scenarios. However, BMAB faced slow convergence in environments with non-stationary conditions and also limited performance in complex fog networks. Its performance further diminishes in multi-agent settings where resource competition and frequent reallocation are common.
- Traditional resource allocation methods faced significant limitations due to their reliance on static rules and predefined heuristics. Traditional models struggled to adapt to the dynamic and

heterogeneous nature of fog and vehicular networks, which led to inefficient use of resources. Traditional DL techniques were not able to handle the complexity and variability of workloads.

3. System Model

Fig. 1 depicts the system model [12]. The system model comprises three levels, where at the lowest level, the vehicles form a Vehicular Ad-hoc Network (VANET). Then, the next level is fog, where users and the cloud are placed. Finally, the central cloud is the highest level. This hierarchical architecture ensures scalable data processing and minimizes latency by distributing workloads across local, intermediate, and global layers. The explanation of these levels is given below.

(a) Vehicular Cluster: Clustering is the process of grouping similar vehicles. In this vehicular cluster, the cluster controller manages the clusters and also secures cluster information. Here, the Road Side Unit (RSU) selects cluster controllers based on factors such as connectivity and average speed. This local grouping facilitates low-latency communication, efficient load balancing, and reduces redundant data transmission to the fog or cloud layers.

(b) Fog: In the Fog level, the set of fog nodes with the adjacent RSUs form a fog. The local servers, routers, access points, and adjacent RSU are considered as fog nodes and also contain resources, like computing, storage, and network resources. Here, fog is controlled by VANET using RSU, which is known as Vehicle to RSU (V2R) communication. Fog nodes process time-sensitive tasks locally, reducing dependence on remote cloud infrastructure and improving real-time service delivery.

(c) Cloud: The various groups of servers form a cloud with resources, such as storage, computing, and applications. The cloud layer handles computation-intensive tasks, long-term storage, historical data analysis, and global system coordination.

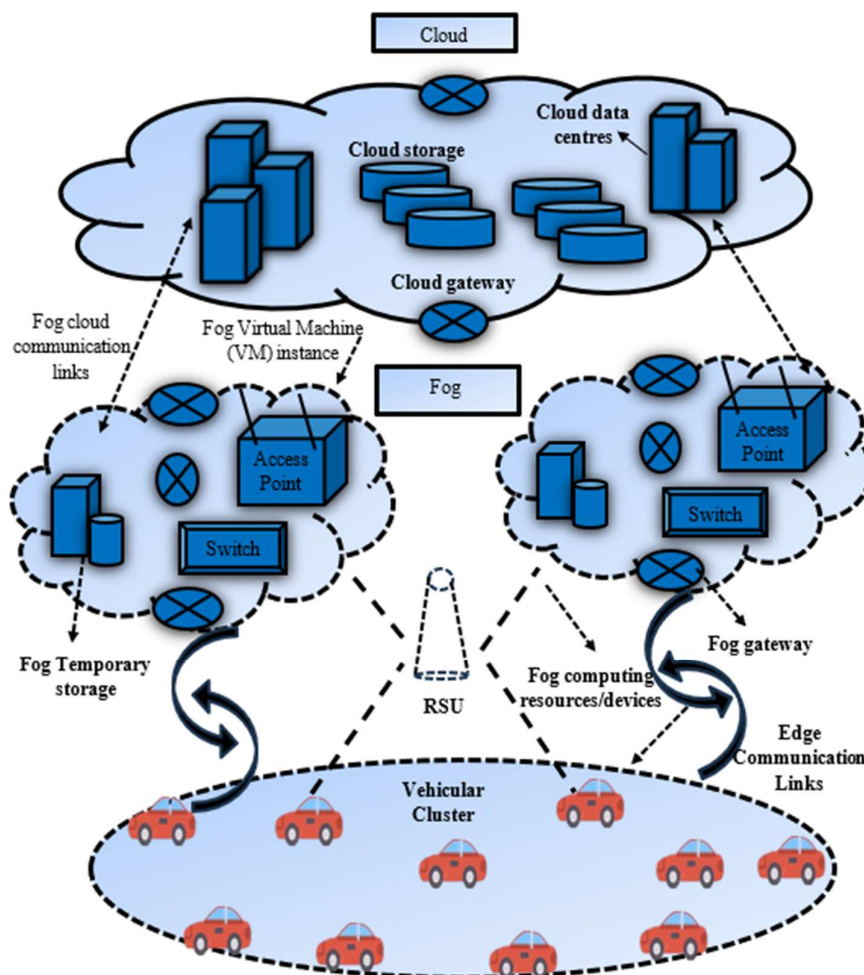


Fig. 1. System Model

4. Proposed Fractional House Swallow Optimizer for Resource Allocation in Fog-based Vehicular Networks.

The main purpose of this research is to develop FHSO for allocating resources effectively using fog computing in vehicular networks. Initially, fog-based vehicular networks [12] are simulated to evaluate data transmission delays, processing workloads, network bandwidth consumption, and latency. This simulation setup replicates realistic vehicular movement patterns and communication delays across urban environments to test the responsiveness of the proposed model. Then, FLICM [13] is utilized for user grouping, where FLICM is used to improve clustering accuracy. Here, vehicles are grouped based on clustering features, like SINR [14] and distance. This clustering reduces communication overhead and enables more targeted and efficient resource allocation by identifying users with similar communication characteristics. Next, resource allocation is performed using FHSO, where FHSO is the combination of HSO [15] and Fractional Concept [16]. In the resource allocation phase, the grouped users require resources from fog nodes. Fig. 2 displays a block diagram of FHSO for resource allocation.

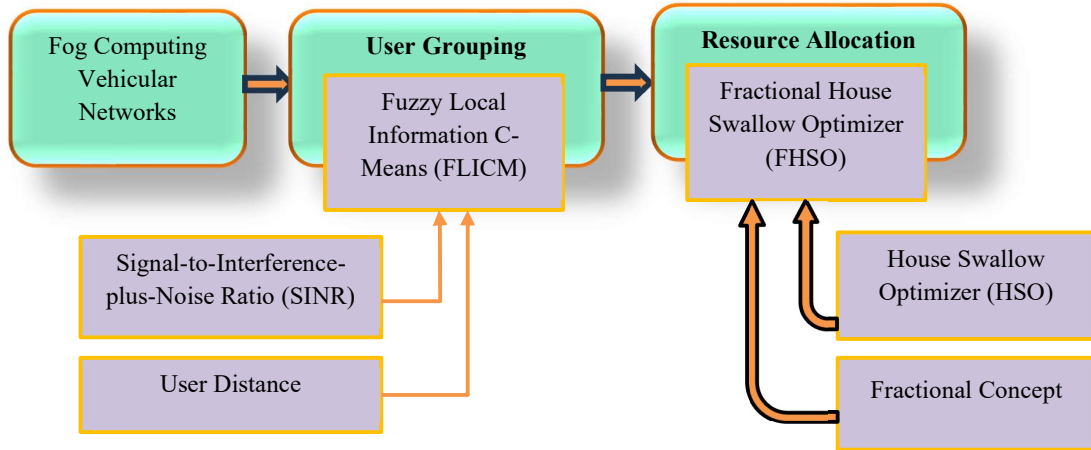


Fig. 2. Block Diagram of FHSO for allocating resources using Fog computing

4.1 User Grouping using Fuzzy Local Information C-Means Clustering

The clustering or grouping of electric vehicle users based on similar characteristics is known as user grouping. In fog computing, user grouping is done to optimize communication between the user and the fog node. Hence, FLICM [13] is utilized for user grouping. Here, the fuzzy factor is used to enhance noise resistance for preserving image details. The fuzzy factor incorporates both spatial and intensity level similarity. In FLICM, empirically chosen parameters are not considered for user grouping. The objective function of FLICM $(F(C, V))$ is given as,

$$F(C, V) = \sum_{m=1}^M \sum_{n=1}^N \alpha_{mn}^p (E(a_m, b_n) + Y_{mn}) \quad (1)$$

here, α_{mn}^p denotes member of the vehicle a_m in the group n , the distance between vehicle m and the group center n is represented as $E(a_m, b_n)$, Y_{mn} indicates a fuzzy spatial factor of the neighbor vehicle b_n , M denotes data points, and N indicates clusters.

Here, user grouping is conducted based on the SINR of the user and user distance, and these parameters are described below,

a) SINR of User: SINR [14] of a user is used to measure the quality of a wireless link, which is experienced by a vehicle user, and it is formulated as,

$$J_l \triangleq \frac{|s_l^H H_l w_l|^2}{\sum_{r \neq l} |s_l^H H_l w_r|^2 + \chi_l^2 \|s_l\|^2} \quad (2)$$

here, J_l defines the SINR of the user l , w_l and w_r indicates the transmit beamforming factor for the user l and r , H_l denotes the channel matrix, s_l^H represents the receive beamforming factor, and χ_l^2 specifies noise variance.

b) User Distance: User distance (L) is the distance between two different vehicle users and it is formulated as,

$$L = \sqrt{\sum_{h=1}^G (E_h^{loc}, E_k^{loc})} \quad (3)$$

here, E_h^{loc} resembles the location of h^{th} user, G resembles the number of vehicle users, and E_k^{loc} defines the location of k^{th} user.

4.2 Resource Allocation based on Proposed Fractional House Swallow Optimizer

In fog-based vehicular networks, resource allocation is the process of distributing resources among users who are connected to fog nodes. Here, the main aim is to minimize total resource usage and to satisfy each user's constraint. Efficient allocation is crucial for meeting latency-sensitive application requirements and ensuring fair access to shared bandwidth. To achieve efficient resource allocation, FHSO is developed in this article. FHSO is the fusion of HSO optimization [15] and the Fractional concept [16]. HSO is used to avoid premature convergence and also maintains diversity in the population for searching wide areas. By mimicking the versatile and adaptive foraging behaviour of house swallows, HSO explores the solution space effectively. The fractional concept is utilized for smooth transitions between exploration and exploitation. The mathematical modeling of FHSO is explained in the following section.

4.2.1 Solution Encoding

The optimal solutions, which are attained from FHSO optimization, are structured in solution encoding. Here, the power allocated for each vehicle user is represented, and for user 10, the allocated power is indicated as R_u . Each solution vector represents a possible configuration of resource assignments, including power levels, subchannel allocation, and bandwidth usage. The solution encoding model is demonstrated in Fig. 3.

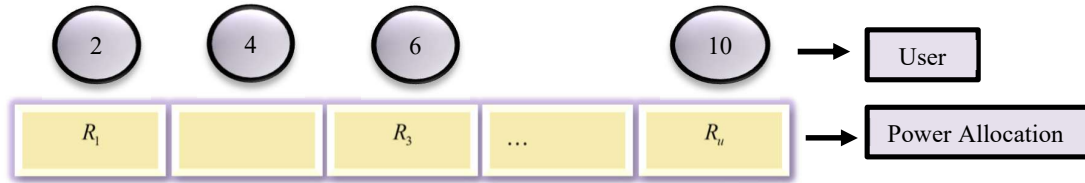


Fig. 3. Solution Encoding

4.2.2 Fitness Function

A fitness function $(I_{\max})$ [17] measures the performance of a candidate solution for a given problem. In fog-based vehicular networks, the fitness function evaluates the efficiency of fog nodes and resources based on capacity, energy efficiency, and utility. The mathematical illustration of the fitness function is demonstrated as,

$$I_{\max} = \frac{1}{3} [U(Y') + S(Y') + T(Y')] \quad (4)$$

here,

$$U(Y') = \sum_{h \in M'} \sum_{p' \in T'} \sum_{w' \in A_{p'}^h} B_{w', p'}^{h'} + \sum_{p' \in T'} \sum_{w' \in A_{p'}} B_{w', p'}$$

where $A_{p'}^{h'}$ specifies users in Small Base Station (SBS) (h') in the subchannel (p'), M' specifies base station, T' denotes sub-channels, $B_{w', p'}^{h'}$ denotes capacity, $U(Y')$ refers to utility function of the user on subchannel in macro and small base station, $S(Y')$ describes capacity, and $T(Y')$ denotes energy efficiency.

4.2.3 Proposed Fractional House Swallow Optimizer for Resource Allocation

Here, resource allocation is performed by the proposed FHSO, which is the integration of the fractional concept [16] and HSO [15]. HSO is developed by inspiring house swallows, which are situated around human-made structures, such as power lines, rooftops, and buildings. House swallows fly along riverbanks and open areas, showing an ecological versatility. This natural behavior reflects a high level of adaptability, which is crucial in dynamically changing vehicular network environments. Usually, house swallows' prey foods are related to agricultural pests, which shows the ecological balance of an environment. Their efficiency in targeting dispersed resources is metaphorically aligned with optimization tasks that involve searching for globally optimal solutions in large, complex spaces. Besides, the nesting behaviors in human-made areas show trust among other species. However, house swallows migrate to search for food and reproduction. During the spring season, males and females together contribute to building nests for the growth of their chicks.

(a) Initialization: Each house swallows are considered a potential solution and also improves at each stage of optimization. Here, the population matrix is represented using this potential solution. Each individual in the population symbolizes a candidate solution vector, encoding resource allocation parameters such as power levels, bandwidth assignments, or subchannel selections. The initial population (P) of house swallows is mathematically formulated as,

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_x \\ \vdots \\ P_Q \end{bmatrix}_{Q \times p} = \begin{bmatrix} v_{1,1} & \cdots & v_{1,z} & \cdots & v_{1,p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ v_{x,1} & \cdots & v_{x,z} & \cdots & v_{x,p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ v_{Q,1} & \cdots & v_{Q,z} & \cdots & v_{Q,p} \end{bmatrix}_{Q \times p} \quad (5)$$

here, P_x denotes the population vector of x^{th} house swallows, $v_{x,z}$ resembles the value of z^{th} the decision variable for the x^{th} individual, Q indicates a total number of solutions, and p represents a number of decision variables.

(b) Fitness function: After initialization of the population matrix, each candidate solution is passed through the fitness function for calculating optimal resource allocation, and the resultant output is stored as a vector of objective function values. The fitness function of each house swallow is estimated using equation (4). This fitness function evaluates the efficiency of each solution based on key performance metrics such as energy efficiency, throughput, and subchannel utility.

(c) Roosting and Hovering Phase: Here, house swallows identify the best-attacking areas for executing the hovering phase. The randomly generated value (y_1) ranges from 0 to 1, which calculates the next phase.

In case if the randomly generated value is less than 0.5, then house swallows follow the roosting and hovering phase. If the generated value is greater than 0.5, then house swallows execute preying behavior. Hovering is the process of flying to attack or nourish insects. To attain a stationary position, house swallows adjust their wings to capture and enhance their prey. Additionally, house swallows modify their location based on prey and other external factors. This phase mimics localized fine-tuning, where candidate solutions adjust their positions based on the best known solutions and the influence of surrounding individuals. The updated position of house swallows ($v_x(j+1)$) is indicated in the expression below,

$$v_x(j+1) = \begin{cases} v_x(j) + (1 + \cos y_2) \times (g_x - v_x(j)) & K_q < K_x \\ v_x(j) + \chi \times D \times (v_{q,x} - v_x(j)) & \text{else} \end{cases} \quad (6)$$

here, g_x denotes best solution for targeting, χ and D indicates Parmeter, and K_{q1} denotes objective function value.

$$P_x = \begin{cases} P_x(j) & K_x(j) < K_x \\ X + W - v_x(j+1) & K_\eta < K_x < K_x(j) \\ P_x & K_x < K_\eta \end{cases} \quad (7)$$

here, X and W indicates upper and lower boundaries, and K_η specifies the objective function. The parameter (D) is mathematically modeled as,

$$D = \left(d - \exp\left(\frac{e-1}{\phi}\right) \right) * \cos(2 * \pi * y_3) \quad (8)$$

where e resembles current iteration, ϕ indicates maximum iteration, and y_3 specifies a random number.

(d) Preying Phase: House swallows perform best flighting behavior in both horizontal and vertical directions. They mostly prefer to eat insects, like flies, moths, mosquitoes, and other agricultural pests. Thus, by preying on those insects, house swallows play a crucial role during the preying phase. The house swallows fly in ascending order based on their heights and also fly nearby to the water's surface. This behavior reflects their ability to adaptively search in multiple dimensions, symbolizing global exploration in the optimization process. These are the predator behaviors of house swallows ($v_x(j+1)$) and it is mathematically elucidated as,

$$v_x(j+1) = g_x - U' * O_{Levy} \times (v_x(j) - g_x) \quad (9)$$

here, U' explicit values that are adapted to iterations, and O_{Levy} resembles levy flight.

The equation (9) is rewritten as,

$$v_x(j+1) = g_x - U' * O_{Levy} \times v_x(j) + U'_1 * O_{Levy} \times g_x \quad (10)$$

Thus, to enhance the predator behavior of house swallows, the Fractional concept [16] is applied in the above equation (9) and it is demonstrated as,

$$B' [v_x(j+1)] = g_x - U' * O_{Levy} \times v_x(j) + U' * O_{Levy} \times g_x \quad (11)$$

$$\begin{bmatrix} v_x(j+1) - tv_x(j) - \frac{1}{2}tv_x(j-1) \\ -\frac{1}{6}(1-t)v_x(j-2) - \frac{1}{24}t(1-t)(2-t)v_x(j-3) \end{bmatrix} = g_x - U' * O_{Levy} \times v_x(j) + U' * O_{Levy} \times g_x \quad (12)$$

$$v_x(j+1) = \begin{bmatrix} [t - U' * O_{Levy}]v_x(j) + \frac{1}{2}tv_x(j-1) + \frac{1}{6}(1-t)v_x(j-2) + \\ \frac{1}{24}t(1-t)(2-t)v_x(j-3) + g_x + U' * O_{Levy} \times g_x \end{bmatrix} \quad (13)$$

The final resultant output of FHSO is represented in equation (13).

$$P_x = \begin{cases} P_x(j) & K_x(j) < K_x \\ P_x & else \end{cases} \quad (14)$$

where, $P_x(j)$ denotes the new position of x^{th} house swallows.

Mathematically, levy flight is demonstrated as,

$$O_{Levy} = Levy(p) \quad (15)$$

The adapted value is demonstrated as,

$$U'_1 = 1 - \frac{e}{\phi} \quad (16)$$

The mathematical illustration $Levy(p)$ is modeled as,

$$Levy(p) = 0.01 \times \frac{c}{|f|^{\frac{1}{\varepsilon}}} \quad (17)$$

where, $c \sim G'(0, \kappa_c^2)$ and $f \sim G'(0, \kappa_f^2)$ are the Gaussian distribution and the explanation of κ_c^2 and κ_f^2 are given as,

$$\kappa_c = \left(\frac{\sin\left(\frac{\pi\varepsilon}{2}\right)\Upsilon(1+\varepsilon)}{2^{\left(\frac{\varepsilon-1}{2}\right)}\Upsilon\left(\frac{1+\varepsilon}{2}\right)\varepsilon} \right)^{\frac{1}{\varepsilon}}, \kappa_f = 1 \quad (18)$$

here, Υ denotes the Gamma function, and ε represents the shape parameter.

(e) Nesting Phase: During the nesting phase, house swallows build a nest similar to half bowl shape on human-made structures. These nests are constructed with small mud balls and are also built nearby to rivers with enough amount of food. This behavior illustrates stability, protection, and resourde consoludation concepts that are vital in the refinement phase of metaheuristic algorithms. These nesting behaviors are mathematically demonstrated as,

$$v_x(j+1) = v_x + U' * \lambda \times (v_x(j) - g_x) \quad (19)$$

here, λ denotes the ability of the house swallow to fly during the nesting period. The new position generated ($P_x(j)$) is demonstrated as,

$$P_x = \begin{cases} P_x(j) & K_x(j) < K_x \\ P_x & else \end{cases} \quad (20)$$

The flight ability (λ) of the house swallows is represented as,

$$\lambda = fly * |v_x - g_x| \quad (21)$$

$$fly = \frac{1}{J' * U'} \quad (22)$$

where J' denotes energy expenditure factor and it is demonstrated as,

$$J' = \psi * \frac{g^2}{C} \quad (23)$$

where, C' denotes parameter and ψ specifies weight.

$$U' = 1 + \frac{e}{\phi} \quad (24)$$

(f) Breeding Phase: In this phase, two different types of reproduction phases are found, where the house swallow lays eggs from April to June and June to July. Here, each nest consists of 4 to 5 eggs, and the incubation phase is around 15 days. During the breeding phase, house swallows frequently fly in and out for searching food for their younger ones. The nest of the swallow is closely linked, which is known as house

swallow colonies. These nests are used for both surveillance and defense mechanisms against predators. This phase symbolizes diversification and population regeneration in the optimization process. The diffusion search method is followed for modeling this breeding behavior of swallow. This approach avoids local optima and also explores wider search space.

$$v_x(j+1) = g_x + (P_{dis} - g_x) * (1 + 2F') \quad (25)$$

here, P_{dis} specifies a rearranged matrix, and F' denotes the set of arrays.

$$P_x = \begin{cases} P_x(j) & K_x(j) < K_x \\ P_x & \text{else} \end{cases} \quad (26)$$

(g) Migration Phase: In the Migration Phase, the house swallow migrates for more suitable wintering habitats. During the spring season, the swallow migrates towards northern areas and also southern areas during the autumn season. This migration takes place by optimal individuals using a V-shaped or straight-line format. The swallow birds follow the leading bird for migration. When the leading bird flaps its wings, the following birds automatically updraft, which saves energy. During this migration phase, a random leading bird is selected among the group, and the fitness function is calculated. If the fitness function of the current leading bird is lower, then the current bird leaves its leading position and joins the group. In this case, if the current leading bird has a higher fitness function than the other members of the group, then it leads to migration behavior. This migratory behavior is modeled in FHSO as a global search strategy, where candidate solutions relocate toward more promising areas in the solution space based on the performance of the current leaders. The mathematical illustration of the migration phase is modeled as,

$$v_x(j+1) = \begin{cases} v_x(j) + S'(0,1) * (v_x - \mu * g_x) & K_q < K_x \\ v_x(j) + S'(0,1) * (g_x - \mu * v_x(j)) & \text{else} \end{cases} \quad (27)$$

here, the control parameter is defined as μ , and S' represents Cauchy mutation.

$$P_x = \begin{cases} P_x(j), & K_x(j) < K_x \\ P_x, & \text{else} \end{cases} \quad (28)$$

$$\mu = 0.05 \times \frac{1 - \ln(e+1)}{\ln(C'+1)} \quad (29)$$

The Cauchy mutation is a continuous probability distribution, which is represented by two parameters. The probability density function is demonstrated as,

$$n'(u', r', s') = \frac{1}{\pi} \frac{r'}{r'^2 + (u' - s')^2}, -\infty < u' < \infty \quad (30)$$

where s' denotes location parameter, r' indicates scale parameter, $r'=1$, and $s'=1$ are probability density function and it is demonstrated as,

$$n'(u', r', s') = \frac{1}{\pi} \frac{r'}{u'^2 + 1}, -\infty < u' < \infty \quad (31)$$

(h) Re-evaluation Phase: The fitness function of each candidate is re-evaluated after each iteration and each phase. The best attained optimal solution is recorded during this phase. This continuous re-evaluation ensures that the algorithm remains responsive to changes in the solution landscape and maintains an up-to-date view of the best-performing candidate.

(i) Termination Phase: The FHSO algorithm is terminated when the iteration exceeds the maximum number of iterations. Finally, the best optimal output is acquired for resource allocation. This solution reflects the best configuration found across all candidate solutions throughout the optimization process, based on the fitness function criteria.

Therefore, FHSO enhances the ability of the algorithm to explore and exploit complex solution spaces, making it efficient for resource allocation tasks in dynamic and constrained environments.

5. Results and Discussions

The results obtained from FHSO are exemplified in the following section which also discusses the efficiency of FHSO in resource allocation with prevailing models. Performance is evaluated across multiple metrics, including energy efficiency, throughput, and subchannel utility, to validate the proposed model's effectiveness under dynamic vehicular network conditions.

5.1 Experimental Setup

The implementation of FHSO is carried out using Python Programming language. The simulation parameters of FHSO are illustrated in Table 1. The vehicular network environment is simulated with realistic traffic mobility patterns, communication models, and fog-cloud deployment scenarios.

Table 1. Simulation Parameters

FHSO	
population size	50
Dimension	100
lower bound	-10
upper bound	10
random values	[0, 1]
random values	[0, 1]
random values	[0, 1]
Beta	[0, 2]
Cauchy mutation	[0, 1]
Set-up Parameters	
Number of vehicles	150
Vehicle speed range	50 km/hrs.
Vehicle density	30 vehicles/km
transmission power	20 dBm
Max cluster size	5

5.2 Performance Metrics

The performance of FHSO is validated based on evaluation metrics, like energy efficiency, Throughput, and subchannel utility. A detailed explanation of these metrics is given in the following section.

(a) Energy Efficiency: Energy efficiency is the ability to use less energy to perform the same task and to produce the same results. In the context of fog-based vehicular networks, it is measured in Megabits per Joule and reflects how effectively the system utilizes energy while maintaining high data transmission rates.

(b) Throughput: Throughput measures the amount of work done by a system over a certain period. Higher throughput indicates improved data handling capacity, reduced congestion, and better service delivery for vehicle users.

(c) Subchannel Utility: The benefit of using a specific subchannel in a wireless communication system is known as subchannel utility. Efficient subchannel utilization ensures that limited bandwidth is allocated judiciously across users, maximizing overall network performance.

5.3 Comparative Approaches

The efficiency of FHSO is evaluated with traditional resource allocation models, such as GWO-MFO [3], MEC-server DT [10], BMAB [9], and CAaDet [6].

5.4 Comparative Analysis

In this section, FHSO is evaluated with existing models for analyzing the performance in resource allocation for 100 vehicles and 150 vehicles.

5.4.1 For 100 Vehicles

Fig. 4 displays the estimation of FHSO for resource allocation with prior models for 100 vehicles based on iteration. In Fig. 4 (a), evaluation based on energy efficiency is conducted using FHSO with existing methodologies. For 1000 iterations, FHSO attained an energy efficiency of 245.990 Mbits/Joule, whereas prevailing models, such as GWO-MFO, MEC-server DT, BMAB, and CAaDet obtained 167.876 Mbits/Joule, 174.990 Mbits/Joule, 186.989 Mbits/Joule, and 221.988 Mbits/Joule. This significant improvement demonstrates FHSO's superior energy-aware decision-making, reducing energy wastage while sustaining performance. Fig. 4 (b) displays the evaluation of FHSO in terms of throughput. The FHSO attained a throughput of 93.768 Mbps with 1000 iterations. Similarly, GWO-MFO attained 81.555 Mbps, MEC-server DT achieved 83.877 Mbps, BMAB obtained 85.878 Mbps, and CAaDet acquired 89.888 Mbps. The high throughput achieved by FHSO indicates its ability to support high-volume data transmission in real-time, which is essential for vehicular applications such as video streaming, emergency notifications, and real-time mapping. Fig. 4 (c) elucidates the evaluation of FHSO based on Subchannel utility. FHSO achieved 260.987 bps/Hz subchannel utility, whereas 198.888 bps/Hz, 222.877 bps/Hz, 231.988 bps/Hz, and 245.888 bps/Hz are attained by GWO-MFO, MEC-server DT, BMAB, and CAaDet. This

metric highlights the spectral efficiency of FHSO, showcasing its ability to maximize bandwidth usage while maintaining quality of service across clustered vehicular nodes.

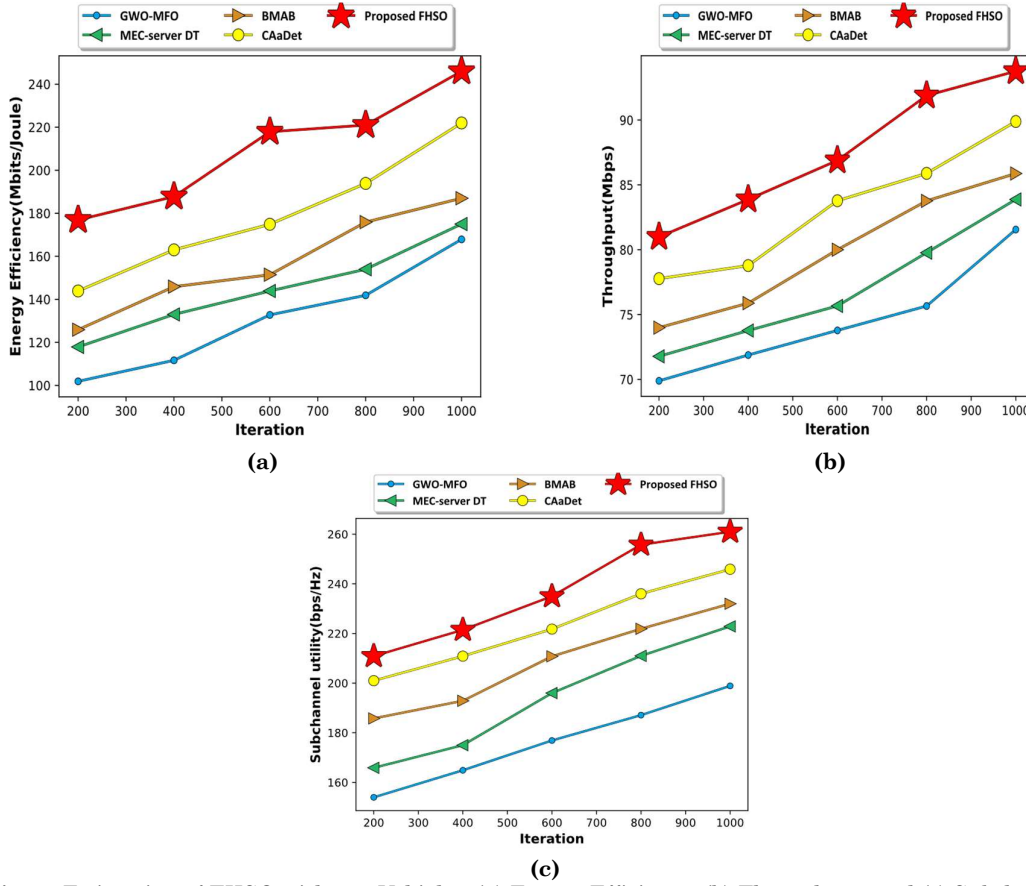


Fig. 4. Estimation of FHSO with 100 Vehicles: (a) Energy Efficiency, (b) Throughput, and (c) Subchannel utility

5.4.2 For 150 Vehicles

Fig. 5 explicit the assessment of FHSO for resource allocation with 150 vehicles based on iteration. Fig. 5 (a) displays validation of FHSO based on energy efficiency. At 1000 iterations, 280.878 Mbits/Joule of energy efficiency is attained by FHSO. The GWO-MFO acquired 215.887 Mbits/Joule, MEC-server DT attained 215.887 Mbits/Joule, BMAB attained 245.988 Mbits/Joule, and CAaDet obtained 262.654 Mbits/Joule of energy efficiency. The results clearly indicate that FHSO maintains high energy performance even with increased network size, highlighting its scalability and robustness in resource-intensive scenarios. Fig. 5 (b) exhibits an assessment of FHSO using throughput. The throughput attained from FHSO is 95.768 Mbps for 1000 iterations. Similarly, prior methods, like GWO-MFO, MEC-server DT, BMAB, and CAaDet obtained 82.879 Mbps, 86.879 Mbps, 88.776 Mbps, and 92.650 Mbps. This throughput gain confirms FHSO's ability to effectively manage higher vehicular density without compromising communication quality or speed. Fig. 5 (c) expounds the estimation of FHSO using the Subchannel utility. FHSO attained subchannel utility of 290.988 bps/Hz, whereas GWO-MFO, MEC-server DT, BMAB, and CAaDet attained 218.987 bps/Hz, 234.766 bps/Hz, 251.677 bps/Hz, and 274.676 bps/Hz. Such improvement in spectral efficiency demonstrates that FHSO ensures optimal utilization of available bandwidth, even under dense vehicular traffic conditions.

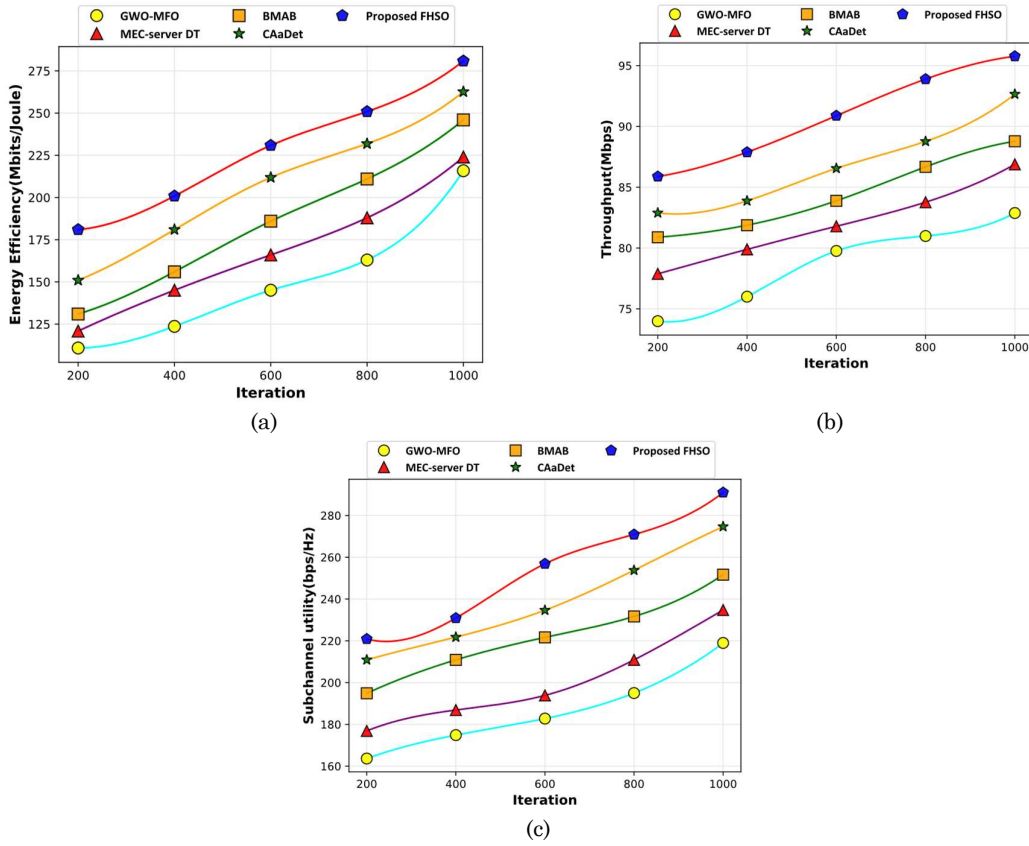


Fig. 5. Validation of FHSO based on 150 Vehicles: (a) Energy Efficiency, (b) Throughput, and (c) Subchannel utility

5.5 Comparative Discussion

Table 2 portrays a comparative discussion of FHSO with existing methods based on iterations. FHSO attained an energy efficiency of 280.878 Mbits/Joule with 1000 iterations. Similarly, state-of-the-art techniques, like GWO-MFO, MEC-server DT, BMAB, and CAaDet acquired energy efficiency of 215.887 Mbits/Joule, 215.887 Mbits/Joule, 245.988 Mbits/Joule, and 262.654 Mbits/Joule. This superior energy efficiency indicates FHSO's ability to reduce energy consumption while maintaining effective communication in vehicular fog networks. FHSO acquired a throughput of 95.768 Mbps using 1000 iterations. The prevailing models, like GWO-MFO achieved 82.879 Mbps, MEC-server DT attained 86.879 Mbps, BMAB obtained 88.776 Mbps, and CAaDet attained 92.650 Mbps. FHSO's higher throughput reflects its superior capability to support high speed data transmission, essential for real-time vehicular services. In the case of subchannel utility metric, FHSO attained 290.988 bps/Hz, while prevailing models, such as GWO-MFO, MEC-server DT, BMAB, and CAaDet achieved 218.987 bps/Hz, 234.766 bps/Hz, 251.677 bps/Hz, and 274.676 bps/Hz. This illustrates FHSO's effectiveness in maximizing spectral efficiency, ensuring optimal use of limited bandwidth in high-density vehicular environments. Due to the combination of HSO and the Fractional concept, FHSO attained better results in terms of all performance metrics. HSO attained less computational overhead when compared to other metaheuristics approaches, whereas the Fractional Concept is used to divide tasks and equally assigns for better load balancing. Hence, FHSO is developed by integrating HSO and fractional concepts.

Table 2. Comparative Discussion

Metrics	Prevailing Models				Proposed FHSO
	GWO-MFO	MEC-server DT	BMAB	CAaDet	
	For 100 Vehicles				
Energy Efficiency (Mbits/Joule)	167.876	174.990	186.989	221.988	245.990
Throughput (Mbps)	81.555	83.877	85.878	89.888	93.768
Subchannel utility (bps/Hz)	198.888	222.877	231.988	245.888	260.987
For 150 Vehicles					
Energy Efficiency (Mbits/Joule)	215.887	223.988	245.988	262.654	280.878
Throughput (Mbps)	82.879	86.879	88.776	92.650	95.768
Subchannel utility (bps/Hz)	218.987	234.766	251.677	274.676	290.988

6. Conclusion

Due to the massive expansion of vehicle users, storage capacity and resource allocation are highly required for flexible services. Traditional methods often lack adaptability and scalability, which limits their effectiveness. Hence, fog computing is the best solution for resource allocation. By decentralizing computational resources to the network edge, fog computing minimizes latency and enhanced real-time responsiveness, which is critical for vehicular applications. Here, an optimization approach, named FHSO is formulated by combining the Fractional concept and the HSO optimization approach for allocating resources. At first, the fog-based vehicular network is simulated for effective data transmission between the fog node and vehicle users in IoV. Then, LICM clustering is utilized for user grouping, where users with similar characteristics are grouped for clustering fog nodes. Here, user grouping is done based on SINR and user distance. At last, the resource allocation is performed by a novel model, called FHSO. The FHSO attained energy efficiency, throughput, and subchannel utility of 80.878 Mbits/Joule, 95.768 Mbps, and 290.988 bps/Hz for 1000 iterations with 150 vehicles. These results clearly demonstrate the effectiveness of the proposed approach in optimizing resource usage while maintaining high network performance under dense vehicular conditions. Future research will explore several promising directions to further enhance resource allocation in fog and vehicular computing systems. Moreover, security and privacy-aware optimization techniques should be developed to protect sensitive data while maintaining efficiency.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

References

- [1] R. P. , R. T. D and . R. V. P, "Internet of Things: Challenges, issues and applications," *J. Circuits, Syst. Comput*, vol. 27, no. 12.
- [2] J. Chen, M. Xu, . W. Xu, D. Li, W. Peng and H. Xu, "A flow feedback traffic prediction based on visual quantified features," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 9, pp. 10067-10075, 2023.
- [3] M. Husain, M. Ahmadi and F. Mardukhi, "A GWO-MFO-based Resource Allocation in Vehicular Fog Computing with Latency Constraints and Energy Reduction," *IEEE Access*, 2024.
- [4] S. Abdelhamid, H. Hassanein and G. Takahara, "Vehicle as a resource (VaaR)," *IEEE Network*, vol. 29, no. 1, pp. 12-17, 2015.
- [5] A. Samir, . M. Elsayed, A. El-Banna, K. Wu and . B. ElHalawany, "Performance of NOMA-Based Dual-Hop Hybrid Powerline Wireless Communication Systems.," *IEEE Trans. Veh. Technol.*, vol. 71, no. 6548-6558, 2022.
- [6] S. Yaqoob, A. Hussain, . F. Subhan, G. Pappalardo and . M. Awais, "Deep learning based anomaly detection for fog-assisted IoVs network," *IEEE Access*, vol. 11, pp. 19024-19038, 2023.

- [7] D. Long, Q. Wu, Q. Fan, P. Fan, Z. Li and J. Fan, "A power allocation scheme for MIMO-NOMA and D2D vehicular edge computing based on decentralized DRL," *Sensors*, vol. 23, no. 3449, p. 7, 2023.
- [8] C. Gamal, K. An, X. Li, V. Menon, G. Ragesh, M. Fouda, and B. ElHalawany, "Performance of Hybrid Satellite-UAV," *In Proceedings of the ICC—IEEE International Conference on Communications*, p. 189–194, 2022.
- [9] R. Hosny, S. Hashima, E. Mohamed, R. Zaki, and B. ElHalawany, "Budgeted bandits for power allocation and trajectory planning in UAV-NOMA aided networks," *Drones*, vol. 7, no. 8, p. 518, 2023.
- [10] S. Jeremiah, D. Camacho, and J. Park, "Maximizing throughput in NOMA-enable industrial IoT networks using digital twin and reinforcement learning," *Journal of Advanced Research*, vol. 66, pp. 59-70, 2024.
- [11] C. Shi, J. Wei, Y. Zhu and A. Schmeink, "Fog Computing Meets URLLC: Energy Minimization of Task Partial Offloading for URLLC Services," *IEEE Access*, 2024.
- [12] A. Sutagundar, A. Attar and D. Hatti, "Resource allocation for fog enhanced vehicular services," *Wireless Personal Communications*, vol. 104, pp. 1473-1491, 2019.
- [13] A. Madhu, A. Kumar and P. Jia, "Exploring fuzzy local spatial information algorithms for remote sensing image classification," *Remote Sensing*, vol. 13, no. 4163, p. 20, 2021.
- [14] Q. Shi, M. Razaviyayn, M. Hong and Z. Luo, "SINR constrained beamforming for a MIMO multi-user downlink system: Algorithms and convergence analysis," *IEEE Transactions on Signal Processing*, vol. 64, no. 11, pp. 2920-2933, 2016.
- [15] J. Dong, L. Wang, S. Qiao, P. Wang, and X. Tan, "House Swallow Optimizer: A new meta-heuristic algorithm and its application for DOA estimation of broadband signal in vector hydrophone array," *IEEE Access*, 2025.
- [16] P. Bhaladhare and D. Jinwala, "A clustering approach for the-diversity model inprivacy preserving data mining using fractional calculus-bacterial foraging optimization algorithm," *Advances in Computer Engineering*, 2014.
- [17] Y. Liu, H. Zhang, K. Long, H. Zhou and V. Leung, "Fog computing vehicular network resource management based on chemical reaction optimization," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 2, pp. 1770-1781, 2021.