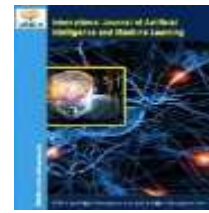




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A Gaussian Map Honey Badger Algorithm (GMHBA) Based Energy Aware Routing and Load Balancing Method in Vehicular Fog Computing

R.Sunitha¹, Dr.B.Sumathi²

¹Ph.D Scholar and Assistant Professor, Department of Artificial Intelligence & Machine Learning, CMS College of Science and Commerce, Coimbatore, Tamilnadu, India

²Head & Associate Professor, Department of Artificial Intelligence & Machine Learning, CMS College of Science and Commerce, Coimbatore, Tamilnadu, India

ABSTRACT

A cluster of vehicles enabled by the Internet of Things (IoT) not only facilitates effective collaboration through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure connectivity, but it also offers a wealth of computational resources. Vehicular (FC) fog computing (VFC), in which automobiles serve as Fog Nodes (FN) and offer cloud-like services to the IoT, makes this possible. To finish the tasks together, it is further connected with the conventional cloud. However, the dynamic nature of the Vehicular Ad-Hoc Network (VANET) makes effective load management in vehicular FC (VFC) difficult. In this research, a Gaussian Map Honey Badger Algorithm (EA-GMHBA) is used to offer an Energy-Aware (EA) approach for load balancing (LB) in fog-based VANET. Two stages are involved in its operation: Initially, it considers the mobility of fog devices when doing clustering using GMHBA. Then, the load is effectively distributed across the vehicle nodes using a capacity-based load-distribution method. A new method called dynamic clustering (DC) is presented, which uses the location, velocity, and path of the vehicles to create clusters that serve as a computer resource pool. A method to find a vehicle's leaving time from the cluster is suggested. This makes it possible to predict where the vehicle will be in the dynamic network in the future. As the network energy consumption (EC) was balanced, the VFC's network utilization improved and the network delay decreased, based on the Network Simulator 2 (NS2) background's simulated findings.

Keywords: Vehicular Fog Computing (VFC), Gaussian Map Honey Badger Algorithm (GMHBA), VANET, Fog computing (FC), Internet of things (IoT), Green Computing (GC), Quality of service (QoS), Energy efficiency (EE), and Load-Balancing (LB)

INTRODUCTION

A IoT Real-Time (RT) applications such as smart buildings, smart transportation, smart healthcare, and military surveillance need high bandwidth (BW) and enough processing power to operate [1]. As a result, managing and storing a lot of data is quite difficult, particularly when it rises locally and momentarily. As a result, it could demand for processing power and storage space from outside sources [2,3]. In addition to delivering information quickly, the data gives end users "tools of wisdom" by offering wise choices, judgement, and analytical predictions that enhance their day-to-day functioning.

A significant amount of processing is needed to enable these operations. IoT devices can't manage this because they frequently have low computing power. For this reason, cloud computing (CC) services are used by IoT applications to carry out computation and storage tasks. Depending on the needs of the user, the processed data is then returned to the nearest IoT device next to the user [4]. FC also uses IoT resources, such as smart hubs, switches, routers, sensors, and cameras, that can meet the needs of RT-critical applications.

Similarly, another crucial part of this middle layer that distinguishes between apps that must be performed on fog or cloud is the fog gateway (FGW). Furthermore, because of the advancements in the FC model, some new uses are being proposed and achieved, like face detection, RT processing, distributed edge computing (EC), and live streaming [5].

One possible option for implementing an intelligent transport system in a city is VANET. Any vehicle with this

modem may act as a repeater for other VANET members due to VANET technology. Vehicles are the nodes of a VANET. VANET is a type of mobile network [6,7]. The purpose of VANETs is to enable communication between vehicles. These nodes must so implement communication radio interfaces, and a specific range spectrum needs to be assigned for VANET Data Transmission (DT). In order to be an essential part of a VANET and communicate efficiently, nodes need certain features to help them acquire information, alert their neighbours, and make decisions by assessing all the data collected.

The low latency requirement for safety and control messages for V2V communication is currently met by Dedicated Short-Range Communications (DSRC)/Wireless Access in Vehicular Environments (WAVE), and Long-Term Evolution (LTE) is utilized for V2I communication. Then, 5G millimetre waveband is being researched for attaining an ultra-low latency for vehicle communication. An On-Board Unit (OBU) is utilized in every vehicle for communicating with the other vehicles during V2V communication, and each vehicle functions as a mobile router.

Due to a high volume of messages being transmitted among the vehicles for V2V communication, VANET has substantial packet loss in the absence of any central infrastructure. The hidden terminal problem, broadcast storm problem, excessive latency for safety message transmission, message security, packet routing, congestion control, quality of service (QoS), and Resource Management (RM) are some of the other problems that affect VANET. A hierarchical structure can be utilized to address these problems. Clustering is the process by which two or more close vehicles that share certain characteristics come together to form a group in a hierarchical structure. Data mining (DM) and machine learning (ML) both make extensive use of the clustering concept.

MANET also makes advantage of clustering. In order to cluster the mobile nodes, MANET was predecessor of VANET. A big network of vehicles is regarded as a network of several smaller networks or clusters in a clustered vehicular environment.

In VANET clustering, a crucial component in the cluster creation process is Cluster Head (CH). There are several approaches to establish a cluster, and it is based on input metrics. A CM vehicle is known as a Cluster Member (CM) vehicle. Some algorithms, known as Cluster Gateways (CG), employ two CM in addition to CH and CM to interact with other clusters on behalf of the CH. Every member of a cluster is referred to as CM until designated as CG. A cluster may have one CH, zero/one/two CG, and any number of CM. CM is a mobile node and CH is a mobile router in VANET clustering.

Metrics including the vehicle's average relative velocity, acceleration, position, direction, degree, density, transmission range, etc. are used to calculate the cluster. Among the participating vehicles, CH is chosen from the ones that are the most stable. As CM, the remaining vehicles enter the cluster. Consequently, there is no need to offer distinct CM selection criteria because CH selection (CHS) is a component of the cluster formation process. Several hierarchical Routing Protocols (RP) and Multi-Hop (MH) are suggested to address the VANET's restricted range communication issue. In order to process and store data during vehicle interaction, the user also requires a platform.

Using a vehicular cloud (VC) model, the vehicles are linked to form a cloudlet. As a result, there is network congestion and under utilization of vehicle resources because there aren't enough cloudlets. Therefore, vehicles are thought to offer cloud-like services as fog devices [8, 9].

A vehicular fog network's dynamic nature makes it more challenging to employ as a distributed system, and it was previously indicated. LB approaches are thought to be an effective way to mitigate the aforementioned issues in order to prevent the bottleneck problem and make efficient use of the available BW. However, it is very difficult to apply scheduling and LB approaches in a dynamic, mobile network such as VANET. The following is a summary of this paper's contributions:

1. To handle IoT requests efficiently, a vehicular fog distributed computing architecture based on GMHBA is presented.
2. A DC method that considers a vehicle's location, velocity, and path is suggested. Additionally, a technique is provided to determine when a vehicle leaves the cluster. In a dynamic context, this feature facilitates the cluster creation.
3. A capacity-based Load-Distribution (LD) method is developed to achieve inter-cluster global LB and local LB between clusters.
4. Examine real automotive network scenarios and put them into practice in a simulated setting to demonstrate the work's effectiveness. Researchers can make use of the plentiful vehicle resources as FN, according to the scenario study. Additionally, the network's performance and energy efficiency (EE) was enhanced by DC and LB.

LITERATURE REVIEW

For delay-aware scheduling, four-tiered architecture and LB in a fog setting has been recommended by Sharma et al. [10]. IoT devices comprise Tier-1, the lowest tier. In the second layer, the router uses the Dual Fuzzy Logic Algorithm (DFLA) to classify the applications (workloads) into two groups: High Priority (HP) and Low Priority (LP). Task size, arrival time, minimum execution time, and maximum completion time are the four input metrics that Fuzzifier takes into account. The third tier, often known as the fog tier, receives a high priority task. An innovative fog structure called Artificial Fractals, which is made up of nodes, it has been used in the third tier.

The K-means++ clustering technique is used to cluster the FN.

The Earliest Deadline First (EDF) task scheduling (TS) method is suggested as a way to schedule work inside the FN. Artificial Neural Networks (ANN) determine how FN is currently used. The request is sent to the cloud tier if an IoT device is unable to obtain the necessary resource. After the recommended task has been verified, the performance is assessed in terms of response time, scheduling time, LB rate, latency, and EC using an RT Video Surveillance/Object Tracking (VSOT) with iFogSim.

A two-level Resource Scheduling (RS) model was presented by Sun et al. [11]. Furthermore, an RS scheme based on the theory of the improved non-dominated sorting genetic algorithm II (NSGA-II) is offered among FN in the same fog cluster. Device diversity is considered by NSGA-II. Two-level RS schemes can efficiently lower service latency and increase task execution stability, according to MATLAB simulation results.

In content delivery fog networks, Shahid et al. [12] suggested a popularity-based caching approach. Two EA mechanisms: content filtration and LB appear in this context. The suggested method uses a random distribution to identify popular content. The suggested method is then divided into three classes. An active FN is chosen based on the number of neighbours, energy level, and operational power once the file popularity has been determined. Additionally, a screening technique is used to cache the popular content on the active node. Additionally, an LB algorithm is suggested to improve the cached fog network's overall system efficiency. In terms of EC and latency, the study of the suggested method shows favourable outcomes. When compared to simple caching systems and no caching, the suggested scheme uses 82.70% and 92.60% less energy. Similar improvements in delay have been observed when employing advance caching as opposed to simple caching and no caching of 85.29% and 67.40%.

An EE Geographic (EEG) Routing Protocol (RP) that prioritizes network throughput (T) and EC of Sensor Nodes (SN) has been suggested by Hammed et al. [13]. Additionally, this approach aids in preventing the network from developing void regions. The suggested methodology effectively balances the EC among SN, hence reducing the Energy Hole Problem (EHP). In contrast to a state-of-the-art (SOTA) geographic RP, the thorough simulations demonstrate that the suggested method maintains EC and packet delivery ratio (PDR) more well.

An effective EA predictive clustering approach for vehicles has been suggested by Bali et al. [14]. For predicting upcoming flexibility and calculating usual deviations of vehicles on the road, effective algorithms are created. Both the number of vehicles in the cluster and the clustering period are estimated by the procedures. Using comprehensive simulations, the performance of the suggested algorithms is examined in relation to the bench-marked system currently in use in the literature by altering the number of vehicles and cluster duration. The results demonstrate that the suggested scheme outperforms the current system in its category.

An EA approach is suggested by Qun and Arefzadeh [15] by integrating a hybrid optimization technique (Ant Colony Optimization and Artificial Bee Colony (ACO-ABC)). This EA approach that is appropriate for LB in fog-based VANET. The results of the simulation in the Network Simulator 2 (NS2) environment demonstrated that the VANET's EC increased with the number of nodes. Additionally, LB using the suggested way has improved when the number of tasks has increased. The suggested hybrid algorithm (ACO-ABC) works better than any other algorithm, according to the simulation tests.

A cluster-enabled capacity-based LB technique has been suggested by Hammed et al. [16] to execute IoT tasks efficiently through Energy and Performance Aware (EPA) vehicular fog distributed computing. A DC technique is introduced that considers the path, speed, and position of vehicles for creating clusters that serve as a computational resource pool. Additionally, a technique for figuring out when the vehicle leaves the cluster is suggested. It makes it possible to forecast where the vehicle will be in the dynamic network in the future. It also provides a capacity-based LD mechanism on the intra-cluster (IC) level of the vehicular fog network with the inter-cluster level to perform LB.

The SOTA NS2 network simulation environment is used to obtain the simulation results. The suggested approach improves network utilization, lowers network latency, and achieves balanced network EC, and it was demonstrated by the outcomes.

Soft computing (SC) algorithms have been introduced by Aravindan and Dhas [17]. The first suggestion is a hybrid clustering algorithm (HCA). The geographic-based and context-based clustering techniques are combined in this HCA. The HCA lowers network traffic and control overhead. The second suggestion for inter-clustering routing is the destination-aware RP. It lowers the E2ED and raises the PDR overall. The performance of the well-known CB techniques and the suggested approach are contrasted. The outcome demonstrates that the suggested strategy performs better than the current strategies.

For urban city scenarios, Ren et al. [18] introduced a clustering strategy based on stability and dynamic mobility. The suggested plan makes use of the relative position, movement direction, and Network Lifetime (NL) estimation of the vehicle. compared the CH duration, CM duration, number of clusters, CH change rate, and number of state changes between the Lowest-ID scheme and the modern and often mentioned clustering technique. The results of the lengthy simulation demonstrated that the suggested system performs better in terms of stability.

PROPOSED METHODOLOGY

Using a GMHBA, an appropriate EA approach for LB in fog-based VANET is presented in this paper. It operates in two stages: It first clusters via GMHBA while taking fog device (FD) mobility into account. Then, the load is effectively distributed across the vehicle nodes using a capacity-based load-distribution method. Fog serves as a mediator between cloud and IoT devices in the suggested method. To meet the needs of RT-critical applications at the network's edge, the fog layer (FL) has FD. When vehicles serve as fog devices, the suggested method takes VFC into account. However, compared to cloud data inputs, vehicle FD have limited communication, computation, and storage capabilities. The DC technique is presented. This DC technique considers the direction, speed, and position of vehicles to create clusters that serve as a computational resource pool. A method for determining a vehicle's departure time from the cluster is suggested. Future location of the vehicle in the dynamic network was enabled by this mechanism.

NETWORK STRUCTURE

Figure 1 illustrates the network structure of the recommended method. Three levels make up the network architecture: the cloud layer, the intermediate vehicle FL, and the bottom layer IoT devices. The FGW node receives data signals from IoT devices in the network on a regular basis. There is a classification process in FGW. The task is effectively categorized as either time-critical or delay-tolerable using this classification process. The accessibility and ability of FD are examined prior to allocating the FL time-sensitive tasks. The FL completes the necessary work and provides the solution to IoT devices after verification. The data is sent to the cloud if it needs to be stored. When offloading tasks to the FL, vehicle mobility and capacity limitations are taken into account. In the next sections, mobility prediction and balanced offloading are explained.

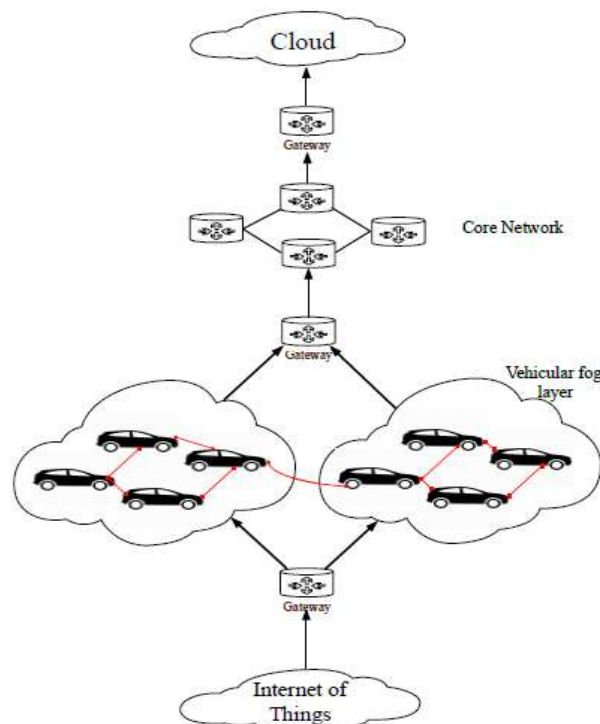


Figure 1. Suggested System's Network Structure

The clusters of vehicles in Figure 1 serve as a source of FC resources.

ROUTING MECHANISM

Vehicle fog devices are supposed to receive tasks from IoT devices that are linked to the upper layer. Many different kinds of sensors are installed in modern vehicles. Contemporary vehicles are equipped with sensor systems that detect movement and measure the distance driven. Each vehicle's radio range encompasses the whole road's width. Every vehicle in the network transmits beaconing messages to allow the vehicles to connect. The time stamp, location coordinates, road condition, and vehicle identification are all included in this message.

Using the beaconing message, vehicles establish a connection with neighbour nodes that fall within their communication range and calculate the approximate distance between them. The term "clusters" is used to describe these collections of linked vehicles.. In order to represent actual mobile scenarios, such as the position, speed, and acceleration of moving devices, the Random Waypoint Model (RWP) creates device mobility [19]. According to the criteria of vehicle proximity and velocity, which are explained in steps 5–10, Algorithm 1

shows how the CH vehicle is chosen. Prior to this, steps 1-4 are used to initialize the amount of FN, FGW, and CH. Steps 7 and 8 determine the minimal Euclidean distance (ED) between FGW and vehicular fog. The steps 9 and 10 in CHS criteria is described as FN should be less than of FGW and evaluates the threshold (T) value. Additionally, the CHS is linked along with nearby nodes to build clusters (steps 13-15). Since the stable vehicle's mobility, the system model turns into vibrant generally. Hence, CM and CHs are changed in particular interval time. Since, this process, the beaconing message's overhead is amplified. Therefore, forecast the upcoming location of vehicles to reduce the beaconing message's overhead. For predicting the upcoming location of the vehicles, the recent location, speed, and path of movement of a vehicle are considered

Algorithm 1. Clustering mobile FD

```

Nodes count in the WSN, and output total cluster count
N ← FN count
A ← FGW
CH ← CHS by EAHBA
method CLUSTERING(N)
for nodes count from n to N do
    ED(A,n)
    Least(distance)
    if(distance <= range) and (time <= T)
        CH ← n
    end for
for nodes count from n to N do
    ED(CH,n)
    if(distance <= range)
        Neighbour(n)
    end for
end method
    
```

GAUSSIAN MAP HONEY BADGER ALGORITHM (GMHBA)

The foraging behaviors of honey badgers (HB) for CHS, which rely on the distance and speed of vehicles. It had an impact on GMHBA. In addition to using its sense of smell, the HB uses digging as a second means of finding its prey. The HB moves swiftly in response to strong fragrances and inversely, because of its olfactory sensitivity [20].

Initialization process: The first CH is determined at this stage by using the upper (HU) and lower (HL) boundaries of the problem space for the energy, distance, proximity, and speed of vehicles. Therefore, in accordance with Equation (1), the initial solutions are stochastic sets [20].

$$H_i = HL + (r_1(1, D) \times (HU - HL)), i = 1, \dots, N. \quad (1)$$

The dimension of the CHS is denoted by D. The total of the possible solutions is denoted by H. The number of solution providers (HB) is N.

Updating positions: At this stage, the candidates' H_{new} coordinates have been updated. In order to use either the honey or the digging stages, a technique may be applied.

Digging phase: The potency of the predator fragrance and the distance between the HB (agent) and the prey (P) affect the movements of the possible CH search during this phase. The polarized circle is where the HB excavates. The stated formula for its motion is as follows:

$$H_{new} = P + Fg \times \beta \times In \times P + Fg \times r_3 \times (P - H_i) \times (\cos 2\pi r_4) \times (1 - \cos 2\pi r_5) \quad (2)$$

Here, the ability of an insect to gather food is measured by β . The maximum value of $\beta=6$, and it was reported by Hashim et al. [20]. The intensity is In , and the random variables $r_3, r_4, \&r_5$ were chosen from a uniform distribution and have a range of 0 to 1. Fg functions as a direction indication for searches and Fg is created in the following way:

$$Fg = \begin{cases} 1 & \text{if } r_6 \leq 0.5 \\ -1 & \text{else} \end{cases} \quad (3)$$

Honey phase: HB use the honey phase to move in relation to the honey lead bird when searching for beehives. CHS uses a vehicle's energy, distance, proximity, and velocity. Hashim et al. [25] determined the honey phase

using the following equation (4)

$$H_{\text{new}} = P + Fg \times r_7 \times \sigma \times (P - H_i) \quad (4)$$

The optimal solution found so far is P. A random number with values ranging from 0 to 1 is called r_7 .

Modeling intensity In:

The way HB perceives insect fragrance determines how it behaves. The following formulation was developed by Hashim et al. [20] for the intensity of each contender's fragrance In_i . The following is a description of the prey:

$$In_i = r_2 \times \frac{(H_i - H_{i+1})^2}{4\pi(P - H_i)} \quad (5)$$

Here, r_2 is a random number between 0 and 1 and P represents the location of the prey.

Modeling the density parameter (sigma): The sigma value is a regulator of transmission between the local search (LS) and global search (GS) stages, according to Hashim et al. [20]. According to the hypothesis put forth by Hashim et al. [20], beta is represented throughout the iterations, as seen here.

$$\sigma = C \times \exp\left(\frac{-IT}{IT_{\text{max}}}\right) \quad (6)$$

Here the current and total number of iterations are denoted by IT and IT_{max} . To enhance the algorithm's basic performance, a constant called C has been calculated based on the Gaussian map. The Gaussian function provides a nonlinear (NL) iterated projection of the real into a real interval.

$$C = 5 * y_{t+1} \quad (7)$$

$$y_{t+1} = \exp(-\alpha y_t^2) + \beta \quad (8)$$

Here, the current iteration is denoted as t. the vectors of the Gaussian map is denoted as y_{t+1} .

Escaping from local solutions: To prevent becoming trapped on local solutions Warning, (Fg) indicate the direction of the search [20].

Minimum of the fitness value (FV): Each method's minimum result as determined by the fitness function (FF) is captured by this metric. It is explained below:

$$\text{Min} = \min_{1 \leq i \leq \text{Nr}} \text{Fit}_b^i \text{ (Energy, distance, proximity of vehicles)} \quad (9)$$

The number of runs is denoted by Nr. The FV is referred to as Fit^i . The best fit at run i is denoted by Fit_b^i .

Algorithm 2. GMHBA procedure

Inputs: Agents size N, number of iterations Iter_{max} , number of FN

Outputs: The optimal CH solutions

Compute the initial set of CH (N) solutions U having dimension d (i.e., number of FN).

Calculate the FF using Equation (9) and corresponding swarm matrix as the best solutions (P).

While ($\text{Iter} \leq \text{Iter}_{\text{max}}$) do

For ($i = 1$ to N) do

Calculate the intensity by Equation (5).

if $r < 0.5$ then

Upgrade the position of H_{new} by Equation (9).

Else

Upgrade the position of H_{new} by Equation (4).

Calculate the novel CH solutions and calculate the Fit_{t+1} and assign $\text{Fit}_{\text{max}_{t+1}}$

if $\text{Fit}_{t+1} \leq \text{Fit}_t$ then

Set $H_i = H_{\text{new}}$ and $\text{Fit}_t = \text{Fit}_{t+1}$

if $\text{Fit}_{\text{max}_{t+1}} \leq \text{Fit}_{\text{max}_t}$ then

Set $H_{\text{best}} = H_{\text{new}}$ and $\text{Fit}_{\text{max}_t} = \text{Fit}_{\text{max}_{t+1}}$.

End if // phase 12

End if // phase 11

End if // phase 6

End for

End while

COOPERATIVE OFFLOADING

IoT requests the necessary services from the fog layer following the route setup stage. As a result, IoT devices within its communication range send requests to the FGW. The CH fog devices receives the tasks from FGW. The task distribution between the clusters and inside the vehicle cluster is the responsibility of this CH fog device. Figure 2 illustrates both within-cluster and among-cluster LB examples in the same context. Congestion is a problem because of the increased demand on the C1. The load is thus redirected to neighbouring cluster C3 by CH1. Moreover, the load is distributed throughout the cluster by CH3. Within the cluster, CH2 divides the load among the idle FN. Achieve a balanced load and a faster network response time as a result.

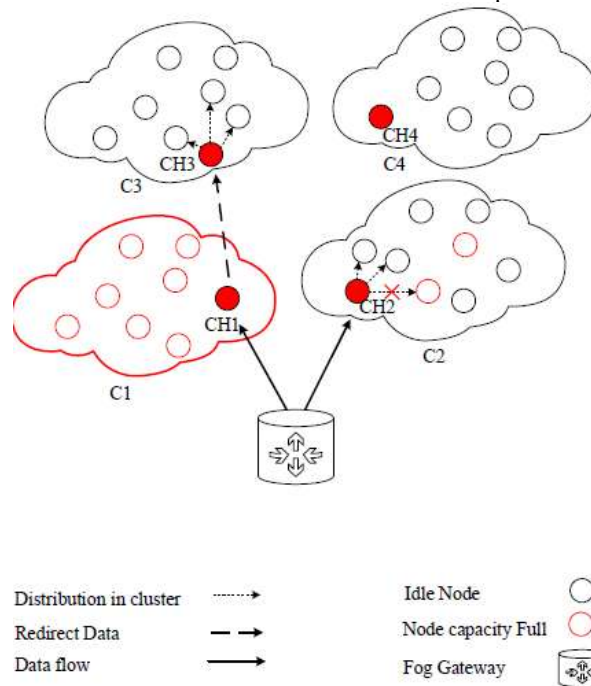


Figure 2. Cooperation Mechanism Among (Vfn) Vehicular Fn

FGW uses beaconing and prediction algorithms to choose the appropriate node as a CH. FGW gathers data on neighboring mobile nodes in this way. The gateway node chooses CH based on the mobile node's velocity being less than or equal to a computed T and proximity (close to the FGW). The task's deadline is taken into account by the T value. A list of nearby nodes that are CM is obtained by the elected CH. The node count and the background of the network may determine the creation of many clusters. However, the data packets (DP) are regarded as dropped if CH leaves the FGW's range before accepting the results.

Task replication guarantees task completion (TC) with a slight increase in TC time, recovers this condition. FGW transfers the responsibility to CH following cluster formation. Other CHs that are outside of FGW's communication range are connected to the elected CH. Based on node capacity, the CH divides tasks between clusters and within a cluster. The node's queue length and FN processing power are included in its capacity. By effectively managing the idle and overloaded fog devices, the LB mechanism in Algorithm 2 lowers network congestion. LB within a cluster is demonstrated in steps 6 through 12 of the suggested algorithm 3.

Additionally, as seen in Algorithm 3 (steps 14–22), IoT requests are sent to nearby clusters if the chosen cluster's capacity is reached. This method affects the fog network's Load-Distribution (LD), EC, E2ED, and Network Lifetime (NL)

Algorithm 3. Effective LD

```

Input: Clusters count, Output: LB nodes
Start  $C \leftarrow$  clusters count
Neighbour ( $C$ )  $\leftarrow$  cluster neighbor
 $CH \leftarrow C$ 
method CLUSTERING( $C$ )
for cluster count from  $c$  to  $C$  do
if ( $capacity(c) \leq capacity.task$ )
for Neighbour  $n_i$  of Neighbour( $c$ ) do
     $CH \leftarrow n_i$ 
if ( $c(n_i) \leq c.task$ )
    assign  $n_i \leftarrow task$ 
    
```

```

End if
end for
else if
    ED(cil, cjl)
    Least(distance)
    if(distance <= range) and (time <= T)
    if (capacity(cil) <= capacity.task)
        repeat phases 1-15
    end if// step 16
    end if// step 17
end for
end

```

Depending on the way resources are used, the network is categorized by the suggested scheme. Likewise, IoT devices transmit sensed data to the FGW during the DT phase. The suggested clustering process is used by the FGW to elect CH and identify essential data. A cluster's remaining computing capacity can be sent to the FGW node by the CH. CH is then given IoT tasks by the gateway node (GWN) according to its computational capacity.

Capacity-Based LD

Achieving the maximum packet delivery ratio (PDR) is a result of capacity-based LD within the flow nodes. Based on the vehicles' vicinity, speed, and path, the DC of mobile FN chooses CH. Additionally, to improve network utilization, the capacity-based LD mechanism effectively distributes the load both inside and between clusters. A FN's processing power, residual energy (RE), and queue length are the metrics used to assess its capacity. The following constitutes a formalized objective function (OF) based on the above listed factors:

$$\text{Max} \sum_{it=1}^{it_{\max}} P_{td}(it) \forall it \in T \quad (11)$$

$$P_{td}(it) = \sum_{P_{td}=1}^{P_{td}(\max)} C \times N_p \forall N_p \in P_{td} \quad (12)$$

$$C = \begin{cases} 1, & \text{if packets sent to destination} \\ 0, & \text{if packets sent to neighbor fog node} \end{cases} \quad (13)$$

$$C_1: E_i \leq E_{\text{initial}} \forall i \in T \quad (14)$$

$$C_2: F_{pr}(i) \geq T_{s_{pr}}(i) \forall i \in T \quad (15)$$

$$C_3: RSE_F \geq E_{tr} \quad (16)$$

$$C_4: RSE_F \geq E_{rc} \quad (17)$$

$$C_5: S_{\text{queue}} \leq T_{\text{queue}} \forall i \in T \quad (18)$$

$$C_6: \text{Min} \sum_{i=1}^{i_{\max}} E \forall i \in T \quad (19)$$

Equation (11) can be used to maximize the network's PDR value. Additionally, the type of DP is explained by equations (12–13). Here, if C is true, N_p is the counter of DP that is increased. The energy of a FN at any given moment is $<$ or $=$ its starting energy, as stated in equation (14). Furthermore, restrictions in equations (15–19) need to be verified for correctly transfer information to the end point. Prior to giving IoT tasks to a FN for full calculation, the suggested work confirms the limitations C2 and C5. Furthermore, the C6 constraint demonstrates a clear correlation between the higher network resource utilization and the minimum EC. The following formula can be used to get the transmit energy E_{tr} :

$$E_{tr} = \frac{T \times p_{\text{size}} \times T_p \times S}{D_{\text{rate}}} \quad (20)$$

Here the packet size is denoted by p_{size} . Transmission power is indicated by T_p . Vehicle speed is indicated by S . The network's data rate is denoted by D_{rate} . Additionally, the following formula can be used to calculate reception energy E_{rc} :

$$E_{rc} = \frac{T \times p_{\text{size}} \times R_p \times S}{D_{\text{rate}}} \quad (21)$$

The LD in the network gets more stable as the simulation time grows, which is significant. The network's PDR rises over time as a result of effective network utilization.

RESULTS AND DISCUSSION

The suggested strategy was assessed, and the SOTA NS2 simulator was used to simulate current techniques. Two network simulation scenarios were examined with respect to the network's load: one with a balanced load and one without. In addition, three traffic scenarios: parked vehicles, vehicles in an urban setting, and vehicles in general, have been considered for simulation. Additionally, the network's simulation time (T) and transmission range (S) are varied during these tests. If the DP is received after the deadline, there is no chance that the packet will reach its destination; if it does, the probability is 1. EC, E2ED, network utilization, PDR, and control packet overhead (CPO) in the network are used to evaluate the methods' results.

Assume a 1000*1000 m2 network with 10 IoT devices and 31 FN. The system and simulation parameters utilized in the experiments are summarized in Table 1. Additionally, the graphical results were obtained by using the spyder anaconda tool. This tool makes use of the matplotlib package. Five runs of the simulation are averaged to determine the results.

Table 1. Simulation Parameter (Sp)And System Parameters

SP (UNITS)	VALUE
Channel	Wireless Channel
Propagation Model	TwoRay Ground
MAC Layer	MAC/802-11
Queue Type	Queue/ Drop Tail/ PriQueue
Mobility Model	Random Waypoint Model
Queue Length	20
VFN count	31
IoT node	10
FGW	1
Interval of VFN in clusters	4-6
Interval of vehicular fog speed (Km/h)	50-90
RP	AODV
Transport Layer Protocol	TCP
Simulation Time (Seconds)	500
Transmission Range(m)	50-300
Initial Energy of mobile FN(j)	50
Receiving Power(W)	1.2
Information Rate (Kbits/seconds)	250
Transmission Power (W)	1.4
Time taken for processing(Seconds)	Object Dimension

RE: The network's residual VFN energy is referred to as RE. Joules (J) are used to measure the energy dissipation.

E2ED: The time it takes for an IoT device to transmit data to the vehicular fog network is known as E2ED. Then get the resulting information. It involves a number of delays, including processing, queuing, and communication. Milliseconds (ms) are the unit of measurement.

Packet Delivery Ratio (PDR): In a vehicular fog network, the percentage of successfully delivered IoT tasks to FD, relative to all tasks produced by IoT devices, is represented by PDR.

Packet Loss Ratio (PLR): It indicates the proportion of tasks from IoT devices in the vehicular fog network that are ineffectively sent to FD.

CPO: It's the proportion of beacon packets to all packets generated in the network altogether.

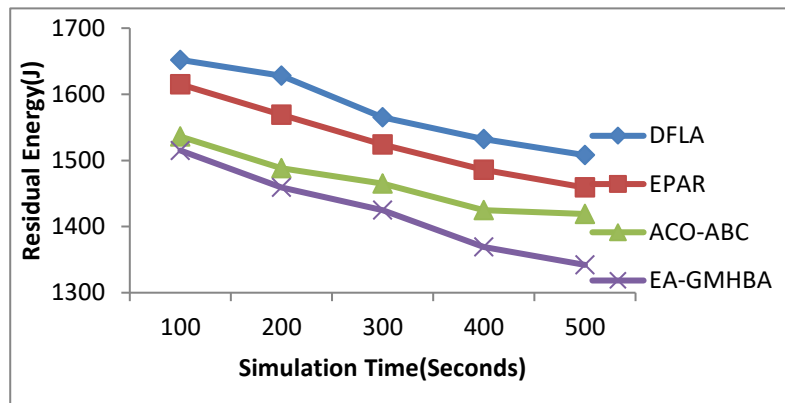
Parked vehicles: In certain cases, the initial RE of both LB and unbalanced systems is the same when it comes to parked vehicles. This is because the FN is originally used in close proximity to IoT devices. After a while, the FN nearer the FGW become heavily loaded. Thus, EC was raised.

Vehicles in urban scenario: Vehicles travel between 50 and 60 km/h on average in urban areas. Additionally, these vehicles become caught in traffic and stop at traffic signals. The goal of the suggested method is to use these cars as fog devices while taking mobility into account. Because closer FN is used, the EC of the two methods is initially equal. However, as time passes in Fig. 8a, the EC in the suggested method decreases because of the capacity-based LB's effective LD. As a result, the network resources are used effectively, optimizing the vehicular fog network's EC.

When contrasting the imbalanced load strategy with the LB technique, the RE of the FN is higher. The NL is raised as a result. Notably, one of the most important aspects of EVs is battery life.

Table 2. Performance Comparison of existing algorithms Across Different Metrics in Residual Energy (Parked Vehicle)

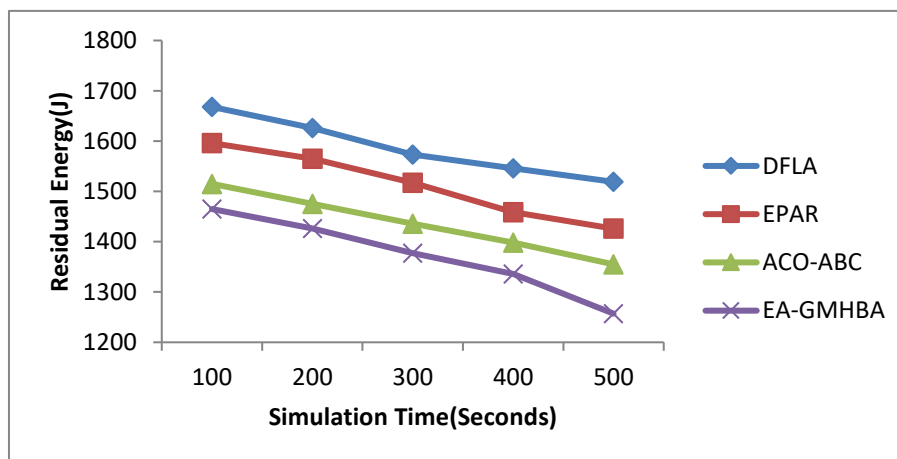
Metrics/ Methods	DFLA	EPAR	ACO-ABC	EA-GMHBA
100	1652	1615	1536	1515
200	1628	1569	1488	1459
300	1565	1524	1465	1425
400	1532	1486	1425	1369
500	1508	1459	1419	1342



Residual energy vs. routing protocols (Parked vehicles)

Table 3. Performance Comparison of existing algorithms Across Different Metrics in Residual Energy (Urban Area)

Metrics/ Methods	DFLA	EPAR	ACO-ABC	EA-GMHBA
100	1668	1596	1515	1465
200	1626	1565	1475	1426
300	1573	1517	1436	1377
400	1546	1459	1398	1336
500	1519	1426	1355	1257



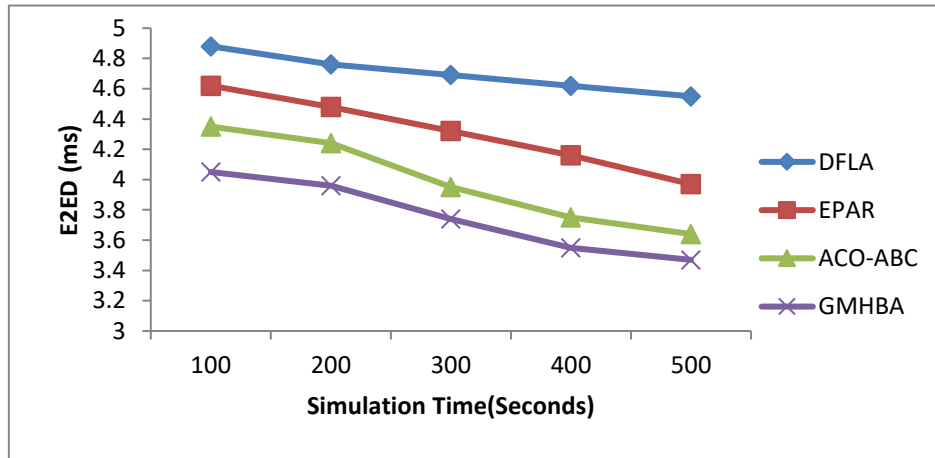
Residual energy vs. routing protocols (vehicles in an urban area)

Figure 3. Residual Energy Vs. Routing Protocols

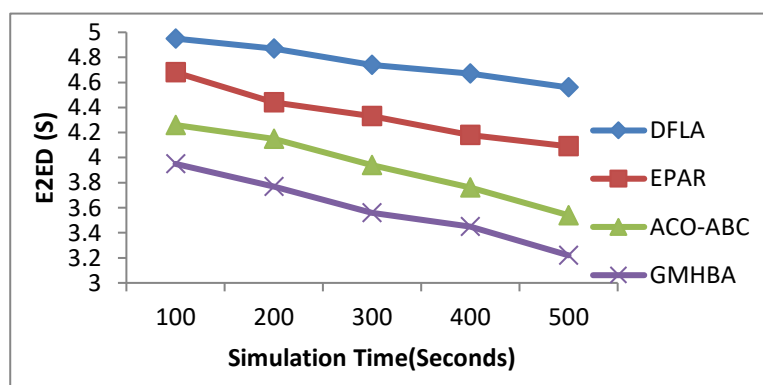
Network load is effectively distributed among FN in Figure 3(a). Thus, EC of the network is reduced. However, as time passes in Figure 3b, the suggested approach's EC decreases because of the capacity-based LB's effective LD. As a result, the network resources are used effectively, optimizing the vehicular fog network's EC. Proposed system has lesser residual EC of 1342 J, and 1257 J for 500 seconds in parked vehicles and urban area. The existing methods such as DFLA, EPAR, and ACO-ABC has higher EC of 1519 J, 1426 J, and 1355 J for 500 seconds in vehicles urban area.

Table 4. Performance Comparison of existing algorithms Across Different Metrics in End to End Delay (Parked Vehicle)

Metrics/ Methods	DFLA	EPAR	ACO-ABC	GMHBA
100	4.88	4.62	4.35	4.05
200	4.76	4.48	4.24	3.96
300	4.69	4.32	3.95	3.74
400	4.62	4.16	3.75	3.55
500	4.55	3.97	3.64	3.47

**End To End Delay Vs. Routing Protocols (Parked Vehicles)****Table 4. Performance Comparison of existing algorithms Across Different Metrics in End to End Delay (Urban Area)**

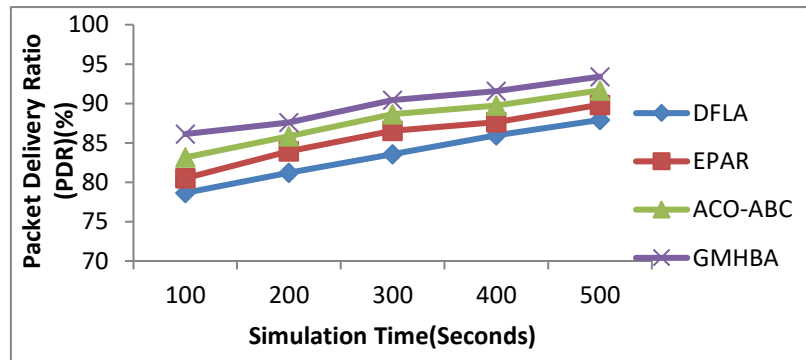
Metrics/Methods	DFLA	EPAR	ACO-ABC	GMHBA
100	4.95	4.68	4.26	3.95
200	4.87	4.44	4.15	3.77
300	4.74	4.33	3.94	3.56
400	4.67	4.18	3.76	3.45
500	4.56	4.09	3.54	3.22

**E2ED Vs. RP (Vehicles In An Urban Area)****Figure 4. E2ED Vs. RP**

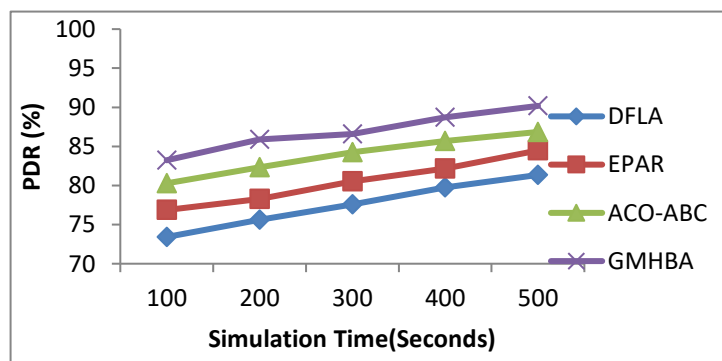
The E2ED of the suggested strategy is lower than that of the other approaches because of capacity-based LB, as seen in Figure 4(a). On the other hand, the recommended balanced technique balances the weighing queue's dimension, which lowers the E2ED, because of capacity-based LD among FN. In Figure 4(b), the E2ED is shown. To lessen network congestion, the suggested LB technique effectively divides the load among FN that are idle. The suggested method effectively divides the load among FN according to FN's processing capability. Proposed system has lesser E2ED of 3.47 ms, and 3.22 ms for 500 seconds in parked vehicles and urban area. The existing methods such as DFLA, EPAR, and ACO-ABC has higher end to end delay of 4.55 ms, 3.97 ms, and 3.64 ms for 500 seconds in parked vehicles.

Table 5. Performance Comparison of existing algorithms Across Different Metrics in Packet Delivery Ratio (Parked Vehicles)

Metrics/ Methods	DFLA	EPAR	ACO-ABC	GMHBA
100	78.65	80.51	83.15	86.12
200	81.19	83.95	85.83	87.57
300	83.56	86.52	88.65	90.44
400	85.98	87.61	89.73	91.57
500	87.91	89.84	91.67	93.41

**PDR Vs. RP (Parked Vehicles)****Table 6. Performance Comparison of existing algorithms Across Different Metrics in Packet Delivery Ratio (Urban Area)**

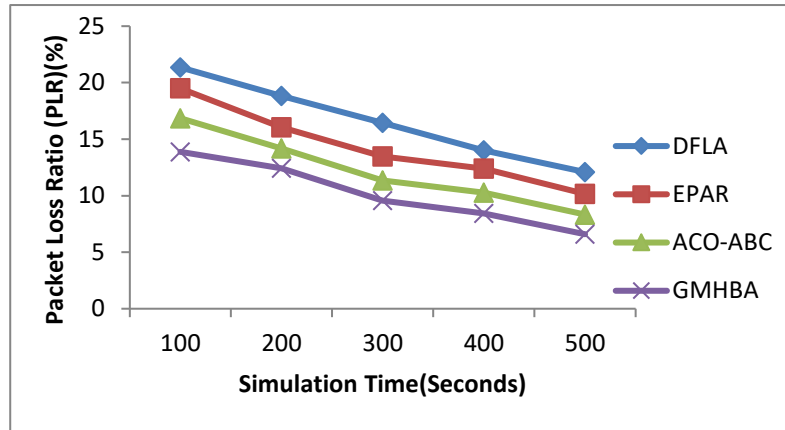
Metrics/Methods	DFLA	EPAR	ACO-ABC	GMHBA
100	73.42	76.87	80.28	83.23
200	75.63	78.26	82.35	85.88
300	77.58	80.54	84.24	86.57
400	79.76	82.17	85.67	88.72
500	81.35	84.48	86.85	90.18

**PDR Vs. RP (Vehicles In An Urban Area)****Figure 5. PDR Vs. RP**

PDR of the RP in parked vehicles is displayed in Figure 5a. The PDR of the suggested method is higher than that of the other approaches. The network's effective LD is the reason for its consistent PDR. The PDR of RP for vehicles in an urban area is shown in Figure 5b. The suggested LB technique shows an enhanced PDR and effectively balances the load among clusters, whether or not they are within the FGW range. Suggested system has higher PDR of 93.41%, and 90.18% for 500 seconds in parked vehicles and urban area. DFLA, EPAR, and ACO-ABC methods has lesser PDR of 87.91%, 89.84%, and 91.67% for 500 seconds in parked vehicles.

Table 7. Performance Comparison of existing algorithms Across Different Metrics in Packet Loss Ratio (Parked Vehicles)

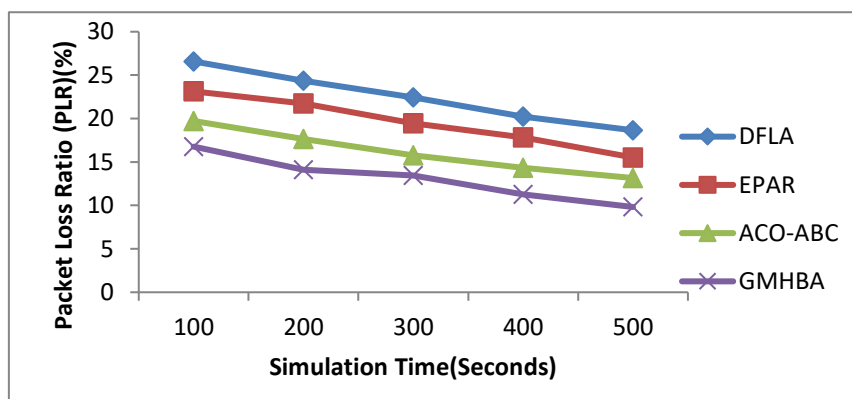
Metrics/Methods	DFLA	EPAR	ACO-ABC	GMHBA
100	21.35	19.49	16.85	13.88
200	18.81	16.05	14.17	12.43
300	16.44	13.48	11.35	9.56
400	14.02	12.39	10.27	8.43
500	12.09	10.16	8.33	6.59



PLR Vs. RP (Parked Vehicles)

Table 8. Performance Comparison of existing algorithms Across Different Metrics in Packet Loss Ratio (Urban Area)

Metrics/ Methods	DFLA	EPAR	ACO-ABC	GMHBA
100	26.58	23.13	19.72	16.77
200	24.37	21.74	17.65	14.12
300	22.42	19.46	15.76	13.43
400	20.24	17.83	14.33	11.28
500	18.65	15.52	13.15	9.82



PLR Vs. RP (Vehicles In An Urban Area)

Figure 6. PLR Vs. RP

Figure 6a shows PLR of the routing methods in parked vehicles. The proposed approach has lesser PLR when compared to the other methods. Figure 6b shows the PLR of routing methods for vehicles in urban area. Proposed system has lesser PLR of 6.59%, and 9.82% for 500 seconds in parked vehicles and urban area. DFLA, EPAR, and ACO-ABC methods has higher PLR of 18.65%, 15.52%, and 13.15% for 500 seconds in vehicles in urban area.

CONCLUSION AND FUTURE WORK

The DC technique for vehicular fog networks is suggested in this research. The network has been effectively divided into vehicle clusters. The foraging behaviour of HB for CHS based on vehicle proximity and velocity had an impact on GMHBA. RM in vehicular fog computing is made easier by the division of the vehicular

network into clusters. In order to find its food, GMHBA HB uses both its sense of smell and digging as an alternate method. For both intra-cluster and inter-cluster LD of IoT tasks, the capacity-based LB method is employed.

Metrics like RE, E2ED, PDR, and PLR are used to assess the outcomes of the suggested system and current techniques. Additionally, the results indicated that while the vehicle resources travelling on roads can potentially be used for IoT duties, there is a great deal of potential to utilize the automobile resources in parking areas and urban areas as FN. The network's energy deception is reduced, latency is also decreased, and PDR is higher when compared to other approaches because of the best CH and resource selection. To further enhance the EC and network performance, the current system has been used in the future to schedule IoT queries in the vehicular fog network using a learning-based approach

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