J Grid Computing (2024) 22:25
https://doi.org/10.1007/s10723-024-09747-5

RESEARCH

Smart City Transportation: A VANET Edge Computing Model to Minimize Latency and Delay Utilizing 5G Network

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Received: 31 May 2023 / Accepted: 15 January 2024 / Published online: 8 February 2024

Abstract Smart cities cannot function without autonomous devices that connect wirelessly and enable cellular connectivity and processing. Edge computing bridges mobile devices and the cloud, giving mobile devices access to computing, memory, and communication capabilities via vehicular ad hoc networks (VANET). VANET is a time-constrained technology that can handle requests from vehicles in a shorter amount of time. The most well-known problems with edge computing and VANET are latency and delay. Any congestion or ineffectiveness in this network can result in latency, which affects its overall efficiency. The data processing in smart city affected by latency can produce irregular decision making. Some data, like traffics, congestions needs to be addressed in time. Delay decision making can make application failure and results in wrong information processing. In this study, we created a probability-based hybrid Whale -Dragonfly Optimization (p–H-WDFOA) edge computing model for smart urban vehicle transportation that lowers the delay and latency of edge computing to address such issues. The 5G localized Multi-Access Edge Computing (MEC) servers were additionally employed, significantly reducing the wait and the latency to enhance the edge technology resources and meet the latency and Quality of Service (QoS) criteria. Compared to an experiment employing a pure cloud computing architecture, we reduced data latency by 20%. We also reduced processing time by 35% compared to cloud computing architecture. The proposed method, WDFO-VANET, improves energy consumption and minimizes the communication costs of VANET.

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Keywords Internet of vehicles · Smart city development · Vehicular ad hoc network · Edge computing · Internet of things

1 Introduction

The primary goal of the method of urbanization, which includes societal growth, financial growth, and preservation of the environment, is to ensure good quality of life (QoL) for every individual [1]. Therefore, metropolitan regions are currently seeing substantial population expansion. Based on the United Nations (UN) [2], urban areas will house 68% of the global population by the decade 2050, including a projected 416 million Indians [2]. In 2018, urban areas housed 55% of the globe's people. Finding strategies for the future that minimize forthcoming obstacles while ensuring a high level of existence in every element of one's life is now necessary.

Smart cities have been the most popular answer to all urbanization-related issues in the past few decades. It uses technology for communication and information (ICT) to achieve the best possible outcomes across various municipal functions. Although there are numerous additional urban types that smart cities need, such as data towns, electronic cities, and teli cities, to be understood as fully functioning smart cities, there are many more reasons for a city to be smart in addition to the use of ICT in a smart city [3–5]. Studies have suggested specific examples of a possible smart city, where long-term viability technology, security, convenience, and connection play key roles in making the city smart and providing a good standard of life to the people to develop a highly urbanized population.

The primary objective of the smart city is an intelligent transport system powered by vehicular ad hoc networks (VANETs). The smart city's traffic flow and general driving experience are both enhanced by VANETs. By offering emergency message transmission and traffic forecasting, VANETs reduce the danger of accidents and congestion on the roads in real life. By providing precise information on the state of the streets, VANETs are essential to autonomous vehicles. Additionally, VANETs offer various services, including fault identification, traffic safety, planning of resources, usage decrease, etc. [6].

A virtualized and software network architecture, including software-defined networking (SDN), network function virtualization (NFV), and multi-access edge computing (MEC), is a key component of a 5G mobile system. 5G-VANET based on SDN should be implemented to accommodate the increasing data traffic, connected gadgets, various network administration, and vehicle movement. The framework provides a rational, centralized, and programmed method of designing networks to address the drawbacks of conventional networks, such as the requirement for reconfiguration and resolving links for every vehicle in a VANET, as well as having to make the most of network assets while decreasing path-recovery delay due to the use of distributed processes [7, 8].

In this study, we concentrate on reducing the latency and minimizing the energy consumption, communication costs, and delay of edge computing to prevent the situations. Although fog responds to VANET requests more quickly than the cloud, it still has numerous difficulties, including response delays, inconsistent interaction, safety issues, variation, and high levels of movement [9]. As far as we know, prior research has yet to examine cloud and edge computing in the context of VANETs employing a 5G network. In this piece of study, we have attempted to address this problem. We have concentrated on one of the most critical problems with VANETs: a reaction time delay. Our effort intends to address the shortcomings of edge computing, such as lag and wait, and offer a high-speed data transfer rate by utilizing a 5G cellular network. Cloud computing is an invention that could make intelligent cities secure and environmentally friendly.

The main contribution of the proposed method is given below:

- A unique technique is created to decrease the usage of energy, latency as well, and edge computing delays in intelligent city vehicles.
- A suggested edge computing system uses various mathematical equations to implement calculations of the delay and latency of data transport.
- Probability-based hybrid Whale -Dragonfly Optimization provides secure communication between vehicles and RSUs and minimizes energy consumption during data transmission.

The remainder of this study is structured as follows: in Section 2, we summarise the related work and discuss our additions, while Section 3 describes the specifics of the system model and problem formulation. Sections provide descriptions of the Smart City Transportation based on Edge Computing, VANET, and Optimization Methods. Section 4 provides information on performance evaluation. Section 5 concludes and suggests areas for future research.

2 Literature Survey

The author [10] examined strategies, cutting-edge technologies, and new issues and challenges related to smart vehicle mobility in smart cities. The audit's indication of the domain's description was highly accurate. However, many factors advantageous to implementing smart cities were disregarded, including providing the public with requirements and advantages, improving vehicle data confidence, and proper management design. The approach to auditing needed to be more precise, and the process for selecting papers must be explained. According to more recent definitions of "smart cities," these are urban clusters where various Internet of Things (IoT) gadgets and sensors are used to collect information before using it to oversee enormous resources effectively.

The author provided a "fast hybrid multi-site offloading of computation method" [11]. This method quickly transfers the job, and to find the optimal one, they created two ways. A further investigation [12] proposed a creative concept that leverages vehicle adaptation and vehicular fog computing to turn connected automobiles into mobile fog nodes that provide useful and on-demand vehicular fog computing services. By coincidence, all the cars in these pieces have impetus problems, which the fog nodes should consider.

To reduce delay and ensure the integrity of the vehicular network system, the author [13–15] proposed an agreement-based method for assessing the stability and dependability of the automotive data system inside a fog computing network. The researcher describes an architecture with fog assistance [16, 17] for a smooth changeover. The design suggested allowing scattered applications like Vehicle-to-Everything (V2X) to fulfill crucial demands like time-sensitive and safety-sensitive network management. Using vehicle-to-infrastructure, or V2I, interaction, the author [18] presents a traffic control technique. Vehicles send messages to each RSU, and when they come across a traffic jam, they contact the nearest RSU to get details about adjacent roadways. This information can be used to find detours for each vehicle [19].

The author [20] provides a capacity-based distributing loading technique for automotive fog-distributed computation powered by a cluster to process IoT workloads effectively. The authors propose a dynamic clustering strategy that considers vehicles' position, velocity, and trajectory when building clusters that act as a pool of computing power. The article presents a method of recognition that could be utilized for forecasting a vehicle's following location within the network's dynamic structure to identify a vehicle that has left the cluster of vehicles. The authors also provide a capacity-based demand-distribution approach for distributing the load equally within and between groups in the vehicular fog system [21, 22].

The author [23] developed a multivariant-stream analysis (MVSA) approach to recognize DDoS attacks on VANET. Maintaining several operational tiers shielded the network from distributed denial of service assaults. The effectiveness of this strategy depends on each car's capacity to communicate via the roadside unit. The researcher [24] offered a way to identify DDoS attacks utilizing big data technology. Two elements of the described method are the real-time network traffic-collecting unit and the traffic-detection modules. Additionally, major suspicious assaults were stored, and data processing was accelerated using Sparks and HFSA-VANET.

Many research papers in the available literature concentrate on traffic-shaping techniques based on channel estimation and network adaptability. By utilizing a machine learning system to modify the video coding parameters in the best possible way, this research, on the contrary, resolves the traffic shaping problem. The author [25] presented adaptive traffic shaping for multimedia streaming for real-time transportation across the following wireless multimedia sensor networks. The researcher created A routing protocol [26, 27] that uses the reinforcement learning algorithm QLAODV to handle network status data and improve accuracy. In addition, the author [28, 29] suggested a network choice technique based on reinforcement learning that understands the channel's situation to lower IoT device latency for large, interconnected IoT networks [30, 31].

To improve security and privacy, this idea incorporates several cutting-edge technologies, including blockchain, encryption, and search algorithms [32, 33]. This technique works well for dividing areas at various depths. To detect cars, the system would isolate the areas of the picture where disparity values indicate that objects are present at a distance usually associated with automobiles [34–36]. In order to identify and categorise objects (such as other cars, pedestrians, and traffic signs) and comprehend traffic conditions and road layout, this entails evaluating data from cameras, LiDAR, radar, and other sensors [37–39]. When time is of the essence, as in coordinated missions involving numerous AUVs, finite-time control is advantageous [40, 41]. This is a crucial component since, in many underwater operations, time is of the essence because of mission objectives, environmental factors, and battery life constraints [42–44]. One vehicle's state can influence the state estimations of other vehicles in a cooperative localisation system [45, 46]. This recognises that the surroundings in which transportation systems function are dynamic and unpredictable. Scheduling is difficult because of bad weather, road closures, traffic congestion, and fluctuating demand for transportation services [47–49]. By using this word, it is indicated that the Internet of Vehicles' network infrastructure consists of elements from three different domains: space (satellites), air (drones or aerial vehicles), and ground (vehicles and infrastructure) [50–52]. To guarantee precise monitoring while averting instability or collisions, the UAV must adjust and make judgments in real time [53, 54].

Individual studies have focused on dynamic clustering strategies for effective IoT workload processing in vehicular fog systems, as well as separate approaches for detecting DDoS attacks, but there appears to be a gap in integrating these two aspects. Innovative would be a combined approach that manages dynamic clustering based on vehicular data (position, velocity, trajectory) while also incorporating robust security measures against DDoS attacks within the same framework. Traffic shaping techniques and DDoS attack detection are mentioned separately in the studies. Unexplored territory could be the development of a system that combines traffic shaping for real-time multimedia streaming with advanced security protocols, ensuring both efficient data transmission and network security.

3 Proposed Methodology

The urban community or area connected with advanced technologies for improving the life style of residents and enhancing basic amenity services are called smart city. This feature ensures the sustainable life and future for living community. some components that specifically used in smart city applications are IoT devices for collecting the traffic data, pollution data and public safety applications. The communication technologies like 5G and multi- access edge computing (MEC) are used for high speed data communication. Vehicle with wireless communication models are used for intelligent transportation model. Further in software development side, cloud, edge and optimization algorithms are used.

For smart cities to achieve responsive and adaptable network architectures, 5G-VANET, SDN, NFV, and MEC must be integrated. 5G-VANET allows for high-speed, low-latency vehicular communications, which is critical for real-time applications. SDN improves network flexibility by providing centralized control and dynamic resource management. NFV allows network functions to be virtualized, reducing hardware dependence and increasing scalability. MEC processes data at the network edge, which reduces response times and core network load. These technologies, when combined, form a synergistic framework that supports the diverse and demanding needs of smart city ecosystems, thereby driving efficiency and innovation.

We present the model we've suggested in this section. A smart city has multiple edge nodes linked together, and the vehicles are VANET-equipped. We are choosing a node that carries the fewest demands or tasks and will deliver the inquiry to that node. We will periodically update the selected node to assess its current load. If the node's load stays constant, it will go through the request and carry it out correctly. We shall determine the importance of the request for attempting to get into the node if we obtain the node's overloaded condition. If the priority level is elevated, we will route the inquiry via a new node that is close by and has the least load. If the service request has a low priority, it will be processed at the data centre first before being executed after being sent immediately to the cloud. Figure 1 shows the architecture of the proposed method.

The challenges in urbanization are congestion in one of the most pressing issues in urban areas. The p–H-WDFOA model aims to address this by optimizing traffic flow and signal management, resulting in smoother vehicle movement and shorter travel times. Because of congested roads, urban areas frequently face difficulties in managing emergency vehicle responses. The model seeks to address this by allowing for more efficient routing of emergency

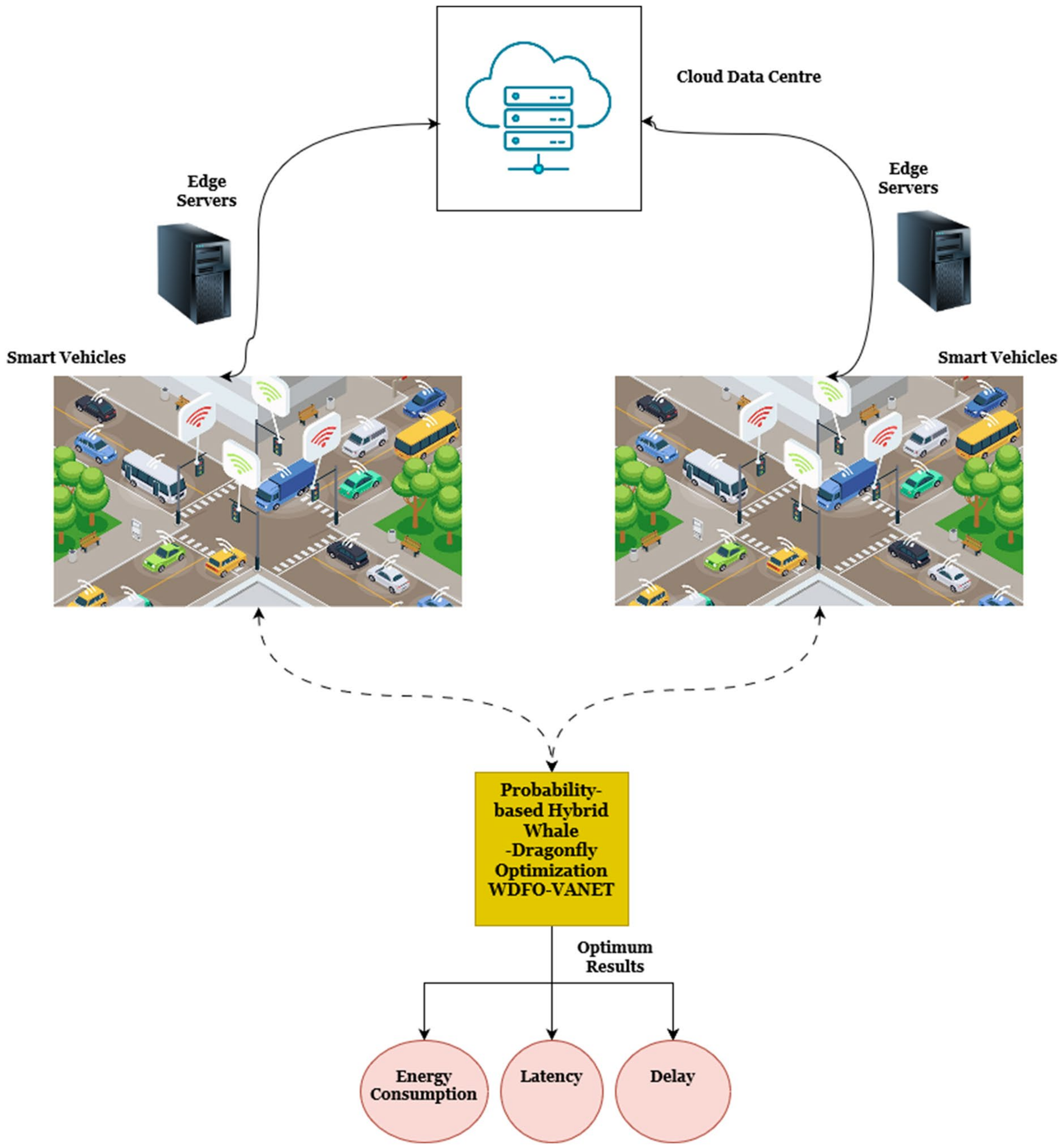

Fig. 1 Architecture of Proposed Method

vehicles, resulting in faster response times during critical situations.

This model cleverly combines the Whale Optimization Algorithm (WOA) and the Dragonfly Algorithm (DA), using a probability mechanism to switch between these techniques based on real-time scenarios. The primary goal of this hybrid model is to significantly reduce the delays and latency issues that are commonly associated with edge computing systems. The p–H-WDFOA model addresses the critical needs of real-time data communication and efficient traffic management within urban vehicle networks, making it a potentially transformative solution for modern, intelligent transportation systems in urban settings. In Fig. 2 shows the architecture of Edge computing.

VANET model in the smart city application helps in managing the traffics in real time. This helps to communicate traffic data among the centralized traffic management systems for effective traffic management and minimize the congestions. Some applications including dynamic traffic light operations, route optimization and monitoring traffics has essential importance in developing the smart city. The road safety is widely used and critical aspect makes drivers to make preventive steps. this early warning models reduce the accidents and improves life in smart city. Autonomous vehicles are an important component of smart cities, and VANETs are essential to their operation. These networks enable self-driving vehicles to communicate with one another and with traffic infrastructure, sharing information about traffic conditions, roadworks, and other pertinent data.

3.1 Edge Computing Architecture

The edge computing framework comprises several layers, such as virtualization and physical, observation, transportation, safety, transient ability, and processing frames, which together make up a massive network of innumerable interconnected devices.

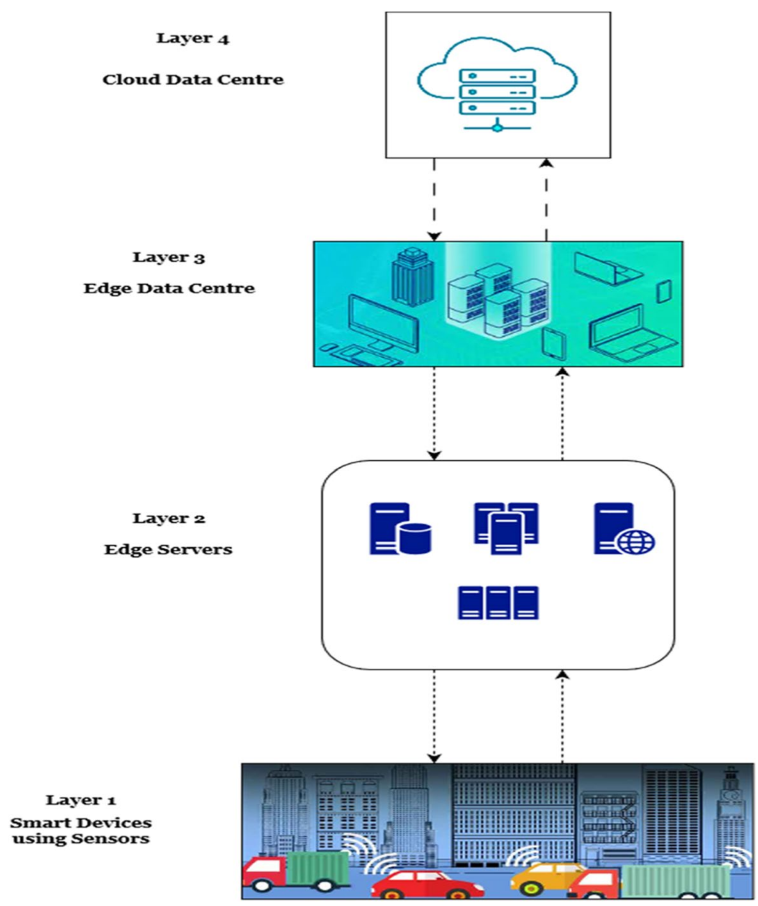

Fig. 2 Edge Computing Architecture

Several high-level creative layers, such as those for virtualization and vehicle communication security, are required for smart city advancement. Here, we demonstrate the most well-liked four-layered, four-tiered edge computing design, as seen in Fig. 2. The four key elements of the overall edge computing systems make up this bottom-to-top design.

3.1.1 Smart Devices Using Devices Layer 1

Layer 1, which includes smart objects and gadgets, including intelligent homes, cars, cell phones, detectors, and smartwatches, is the only layer accessible to users. Layer one gadgets are linked to the edge layer through WiFi, Bluetooth, Zigbee, 3G, 4G, and 5G. Due to this, the transmission of the data has low latency and minimal delay. This stratum covers only a tiny geographic area.

3.1.2 Edge Server Layer 2

The core layer of the design is where edge computing is located. It comprises numerous edge nodes with connectivity capabilities like switches, routers, pathways, etc., and computational assets like central processing units and storage spaces. RAM, etc. This layer is also known as an intermediate layer because of its connections to the topmost layer and the first layer. The top layer remains physically at the network's edge. For instance, edge nodes are typically deployed in the infrastructure along roadways and buildings.

3.1.3 Edge Data Centre Layer 3

This layer collects the data from the edge server, which is then processed for transmission. Next, the data is transformed into the final layer.

3.1.4 Cloud Layer 4

The cloud layer, the highest component of edge computing design, comprises large data centres and potent processors that can process any volume of complex data. The cloud is not advised for applications that require immediate responses because data centres are frequently dispersed over large distances and have remote locations. Especially in edge design, this layer is coupled to the central layer.

3.2 Probability-based Hybrid Whale -Dragonfly Optimization with VANET

The Probability-based Hybrid Whale -Dragonfly Optimization with VANET minimizes energy consumption, latency, and delay.

A probabilistic model was added to get the vehicle's most recent location. To do this, the cross-over probability was changed, which improved the proposed strategy's effectiveness and accessibility to the population. Equation (1) provides additional details on the crossover technique.

$$pr_n^m(t+1) = \begin{cases} pr_n^m(t) \text{ } if \text{ } b < cpr \\ pr_n^m(t+1) \text{ } if \text{ } b \geq cpr \end{cases} \tag{1}$$

Here pr_n^m is the m$^{\text{th}}$ input obtained from the present nth agent, b denotes the population's randomized nodes or search cars, and cpr indicates the crossing possibility used to calculate the method's operating time and speed of convergence.

The Eq. 1 significance lies in its decision-making process for updating each agent's position. At each iteration of the optimization algorithm, a random number b is generated for each agent and compared to the crossover probability cpr. If b is less than cpr, the agent stays in the same position $pr_n^m(t)$. If b is greater than or equal to cpr, the agent's position is updated to $pr_n^m(t+1)$, a new position that may be a better solution.

If cpr is reduced, the technique will run more slowly, converge more rapidly, and have a narrower population variation. The calculation for cpr's number is as follows:

$$cpr - c + (0.5 - c)\_\sin(t.\frac{\pi}{2}.tmax) \tag{2}$$

The permissible range of possibilities for the steady state c, which controls the oscillations of the parameter cp, is [0, 0.5], and tmax is the most significant number of repetitions permitted. We might improve the range and precision of vehicle position predictions by modifying cpr as indicated in Eq. (2).

The hybrid whale-dragonfly optimization-based VANET (H WDFOA-VANET) is a dependable resource administration system that reduces latency, delay, and energy consumption. The origins of the WOA and DF optimization strategies are then examined separately after a description of the suggested H-WDFOA strategy. A changing VANET situation is described by H-WDFOA, which combines the whale and dragonfly optimization methods. The H-WDFOA was used to distribute bandwidth and get routing for the vehicle. The standard navigation process also caused latency and bandwidth consumption to obtain the designated path. It was challenging at a crucial moment for safety. Therefore, to address this problem, the effective H-WDFOA method was applied to minimize energy consumption.

This suggested methodology couple's probability-based WOA and DF methodologies in a VANET system observe the impact of QoS value. The whale optimization algorithm (WOA) creation considered humpback whales' hunting habits. Right now, the ideal tactic for the humpback whale is to locate its prey and encircle it, but WOA believes that its prey is a goal. The most effective search agent is considered after evaluating the current approach. In the beginning stages, the various vehicle parameters—including productivity, the number of nearby cars, velocity, acceleration, distance, and velocity—were employed as the initial population. The following is how this action is expressed mathematically:

$$M = |V.P^{*}(t) - X(t)| \tag{3}$$

$$P(t+1) = P^{*}(t) - B.M \tag{4}$$

Here t denotes repetition, B and V denote parameter vectors, P* denotes the optimal solution's location vectors, and P is the location vector. The P* of the process is frequently modified to determine the optimum option.

$$B = 2x * r - x \tag{5}$$

$$V = 2.x \tag{6}$$

Here, the value of r is an arbitrary number between 0 and 1. The variable's value is lowered from 2 to 0 throughout the extraction and investigation phases. Significant modifications in the stage were visible during the period [1,1]. The vehicle could shift from its initial location to a different one. The conceivable achievable positions in the 2D space of the interval [1,1] ranged from X and Y through X* and Y*. Additionally, the position was achieved by revising the process and was quantitatively expressed as

$$M = |V.P_{rand} - P| \tag{7}$$

$$P(t+1) = V.P_{rand} - B.M \tag{8}$$

This updated spiral method can be built to analyze the separation between cars. The following equation determines this procedure:

$$P(t+1) = M\}.e^{sr}.\cos\cos(2\pi r) + P^{*}(t) \tag{9}$$

The artificial positioning of the dragonfly, i.e., location (X) and step (Δ V), has been modified in an investigation area for growth and replication. The progression vectors show how the characters and dragonflies grow over time.

$$\Delta X_{t+1} = \left(\omega W_i + mA_i + nC_i + pF_i + qE_i\right) + \overline{\omega}\Delta X_t \tag{10}$$

4 Result Analysis

This part concludes with a presentation of the experiment's findings. We developed three potential scenarios for the edge and cloud servers at the time of the experiment. To determine the transmission postponement, we placed a heavy load on the edge nodes in the first edge case. In this case, we handled 50 high-priority requests that were submitted to the edge nodes [1]. To test how well the edge performs under heavy demand, we have set the node burden here to 80%. First-edge case details are provided in Table 1.

To assess the transmission delay, we delivered an average demand to the edge nodes in the second edge situation. In this case, we handled 15 low-priority requests and 35 high-priority queries delivered to the

Table 1 Simulation Environment for Edge Scenario 1

Parameters Used	Values
No of Requests	50
High Priority	50
Low Priority	0
Mode of Communication	5G
Nodes Used	10
Nodes for Load	80%
Overloaded Nodes	4
Time taken for Simulation	30 s

fog nodes. Five low-priority queries were also forwarded to the cloud by us. To test the effectiveness of the edge under a medium load, we have set the node load to 60%. The second edge situation is presented in Table 2.

In the final edge situation, we tested the communication delay by applying a minimal load to the edge nodes. In this case, the edge nodes handled 25 requests with a high priority and 25 requests with a low priority. Five low-priority requests were also forwarded to the cloud by us. To demonstrate the effectiveness of the edge at a low load, we have set the node load to 30% in this case. The third edge situation is detailed in Table 3.

This scenario simulates peak traffic hours in urban areas, when congestion is at its peak. The goal is to put the model to the test in terms of efficiently managing and rerouting traffic in order to reduce delays and congestion. It is based on real-world scenarios such as rush hour in major cities. This scenario tests the model's ability to prioritize emergency vehicles (such as ambulances and fire trucks) in the midst of regular traffic. It is critical for determining how the model facilitates faster emergency response, which is a major challenge in densely populated cities. Simulating areas with varying traffic densities (such as transitioning from urban to suburban areas) puts the model to the test. It addresses the issue of ensuring efficient vehicle communication and routing across varying urban densities.

In Fig. 3 shows the end-to-end delay for three different scenarios with vehicle requests. It shows that the scenario 3 attains minimum delay during communication. In Scenario 3, a strategy is used in which the edge nodes handle a mix of high and low priority requests, with some low-priority requests being offloaded to the cloud. The node load is set to 30%, indicating that the edge nodes are operating at a low load. This is likely to result in more efficient request processing due to the availability of computational resources and less network congestion. This helps to achieve minimum delay.

Table 2 Simulation Environment for Edge Scenario 3

Parameters Used	Values
No of Requests	50
High Priority	25
Low Priority	25
Mode of Communication	5G
Nodes Used	5
Nodes for Load	30%
Overloaded Nodes	2
Time taken for Simulation	30 s

Table 3 Simulation Environment for Edge Scenario 2

Parameters Used	Values
No of Requests	50
High Priority	35
Low Priority	15
Mode of Communication	5G
Nodes Used	10
Nodes for Load	60%
Overloaded Nodes	2
Time taken for Simulation	30 s

The proposed method WDFO-VANET also evaluates the high-priority requests, low-priority requests, energy consumption, throughput, and communication costs. The proposed method is compared with existing methods such as p-WOA, H-WDFOA-VANET and RMDRL.

For high priority and low priority requests it uses cloud scenarios. We replicated equivalent situations for the cloud, as shown in Table 4, 5, and 6, to contrast the outcome with the cloud.

In the first cloud scenario, we placed minimal demand on the cloud server. In this case, we transmitted and carried out 25 requests with a high

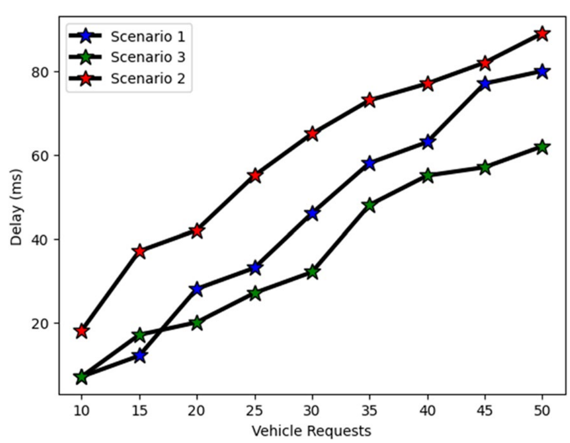

Fig. 3 End to End Delay

Table 4 Simulation Environment for Cloud Scenario 1

Parameters Used	Values
No of Requests	50
High Priority	25
Low Priority	25
Mode of Communication	5G
Time taken for Simulation	30 s

Table 5 Simulation Environment for Cloud Scenario 2

Parameters Used	Values
No of Requests	50
High Priority	35
Low Priority	15
Mode of Communication	5G
Time taken for Simulation	30 s

Table 6 Simulation Environment for Cloud Scenario 3

Parameters Used	Values
No of Requests	50
High Priority	50
Low Priority	0
Mode of Communication	5G
Time taken for Simulation	30 s

priority and 25 requests with a low priority to the cloud. For the second cloud situation, we put a medium demand on a cloud server. There are 35 requests with a high priority and 15 requests with a low priority were sent to the cloud and carried out in this case. We put an enormous load on the cloud server in our third situation with the cloud. We submitted 50 high-priority queries to the cloud under this instance, and they were all fulfilled. In Fig. 4 shows the end-to-end delay for clous scenario. It shows that the 3 scenario takes minimum latency. In Fig. 5 shows the energy consumption taken for vehicle requests.

In Figs. 6 and 7 shows the evaluation of communication costs and throughput. The proposed method achieves minimum communication costs and throughput taken for each vehicle requests.

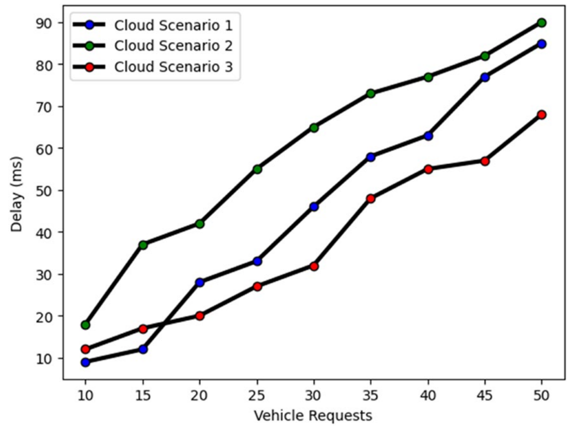

Fig. 4 End to End Delay for Cloud Scenario

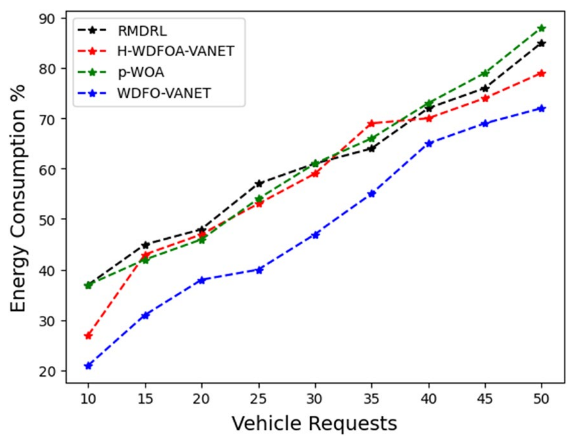

Fig. 5 Energy Consumption using different methods

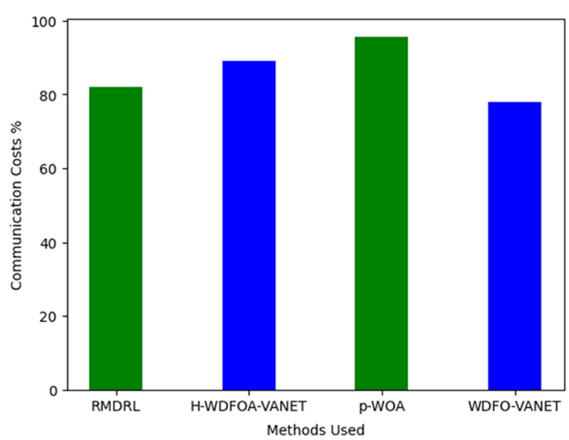

Fig. 6 Evaluation of Communication costs

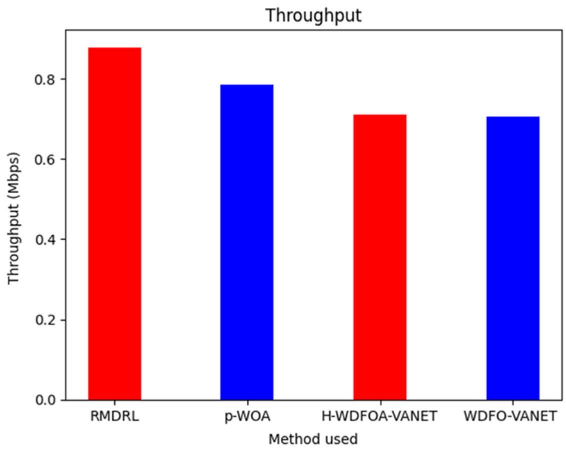

Fig. 7 Evaluation of Throughput

5 Conclusion

Our main goal is to create a smart city, and edge computing is a vital part of that. Our research into various edge computing problems revealed that latency and delays present challenging problems. Due to the time-sensitive nature of VANET applications, we chose VANETs for installation-edge computing. The results demonstrate that our suggested methodology improved communication effectiveness between cars while significantly reducing lag and latency. The current research investigation examined several efficient techniques for reducing vehicular data transmission delays and latency when using the fog computing model. By calculating the information at the closest edge nodes, communication between cars with identical network-based connectivity allowed for faster data calculation and transfer rates. By moving information and queries to the accessible computers, the adoption of 5G-based MEC servers enabled us to replace the user's network connection with nearby servers, which decreased the queuing time. To solve these challenges, we developed a probability-based hybrid whale-dragonfly optimisation (p–H-WDFOA) edge computing approach to smart urban vehicle transportation. To improve the edge technological assets and meet the latency and quality of service (QoS) requirements, the 5G localised Multi-Access Edge Computing (MEC) servers were also used, significantly reducing the delay and latency. We lowered the latency of data by 15% compared to an experiment using only a cloud computing infrastructure. We also cut processing time by 30% compared to cloud computing. The WDFO-VANET approach is suggested to optimise the use of energy while lowering VANET transmission expenses.

Authors' Contributions Mengqi Wang: Conceptualization, Methodology, Formal analysis, Supervision, Writing—original draft, Writing—review & editing.

Jiayuan Mao: Investigation, Data Curation, Validation, Resources, Writing—review & editing.

Wei Zhao: Investigation, Data Curation, Validation, Resources, Writing—review & editing.

Xinya Han: Investigation, Validation, Resources, Writing—review & editing.

Mengya Li: Formal analysis, Supervision, Writing.

Chuanjun Liao: Formal analysis, Supervision, Writing.

Haomiao Sun: Investigation, Resources, Writing—review & editing.

Kexin Wang: Investigation, Resources, Writing—review & editing.

The contribution of the first and second authors are equivalent in this research work.

Funding This article has been supported under Project Supported by Scientific and Technological Research Program of Chongqing Municipal Education Commission (Grant No. KJQN202202402) "Research on the digital rural grassroots data quality management system".

Data Availability The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics Approval and Consent to Participate Not applicable.

Consent for Publication Not applicable.

Competing Interests The authors declare that they have no competing interests.

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