Improved Delay and PDR For Iov-Fog Nets Using Fractional Mayfly Optimization Algorithm

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Abstract. The integration of the automobile industry with communication technology has led to the concept of the Internet of Vehicles (IoV). It is a self-organized network that consists of vehicles and RSUs and employs Infrastructure-to-Vehicle (I2V) and Vehicle-to-Vehicle (V2V) data transmission mechanisms. The IoV system uses an efficient service message transmission protocol, the Fractional Mayfly algorithm (FMA), for reliable broadcasting of service information. Experimental results indicate that the FMA-based scheduling method is superior in terms of delay and PDR, particularly for 100 and 150 vehicles. The Fog Computing approach is also used for communication and data processing in the IoV system.
keywords: IoV, Fractional Mayfly algorithm (FMA), I2V, V2V, Fog Computing Technology.

1.Introduction

The increasing growth in the automobile industry has resulted in serious traffic congestion, creating a demand for driving ease and safety. As a solution, the Internet of Vehicles (IoV) has become a research hotspot, facilitating communication between vehicles and roadside units (RSUs) to reduce road accidents and increase safety. The IoV network leverages fog computing technology for efficient communication and data processing. Different categories of communication occur in fog-enabled vehicle communication, including V2V, I2V, vehicle-to-fog, RSU-to-fog, and cloud-to-fog-server. The technology employed by the Internet of Vehicles enables the effective processing of data from various environments, as well as service messages that impact the location where the vehicle is situated.

2. Literature Survey

Various methods for data transmission are continuously being researched. One such method is the network-assisted service message transmission (NA-SMT) protocol, designed by Khan et al.[1] This protocol selects relay vehicles based on higher channel quality indicators (CQI) to efficiently disseminate service messages from roadside units (RSUs) to vehicles. Another method, the Fog-Assisted Cooperative Protocol (FACP), was developed by Javed et al.[2] for uplink and downlink traffic message transmission using fog RSUs. These methods demonstrate ongoing efforts to improve communication and data processing in the IoV-fog system.

3. The architecture

System Model consists of wireless communication technology that allows vehicles to communicate with each other, with infrastructure, and with other devices like pedestrians, bicycles, and smart phones. This is known as cellular vehicle-to-everything (C-V2X) communication. It consists of multiple layers: cloud layer, fog layer, and IoV layer. Figure 1 depicts the model.

3.1. Cloud layer

At the highest level of the network structure, there are two primary tasks involved: intelligent data analytics and data prediction processes within a cloud-based application.

3.2. Fog Layer

The layer between the cloud and the IoV layer is called the fog layer. It acts as an intermediary between end-user devices and data centers, providing storage, computation, and network services. So, it can be said that the fog server acts as a middle layer.

3.3. IoV LAYER

It is at the bottom of the IoV model, which comprises of multiple vehicles and RSUs. The communication between the vehicles and RSUs is facilitated through C-V2X transceivers, which establish connections between them. Vehicle-to-vehicle communication occurs over V2V connections, while vehicle-to-RSU transmission takes place over I2V connections. The focus of this study is on the transmission of information from the base station to the user equipment (downlink service information comm.) that happens during the transmission from the RSU to the vehicle.

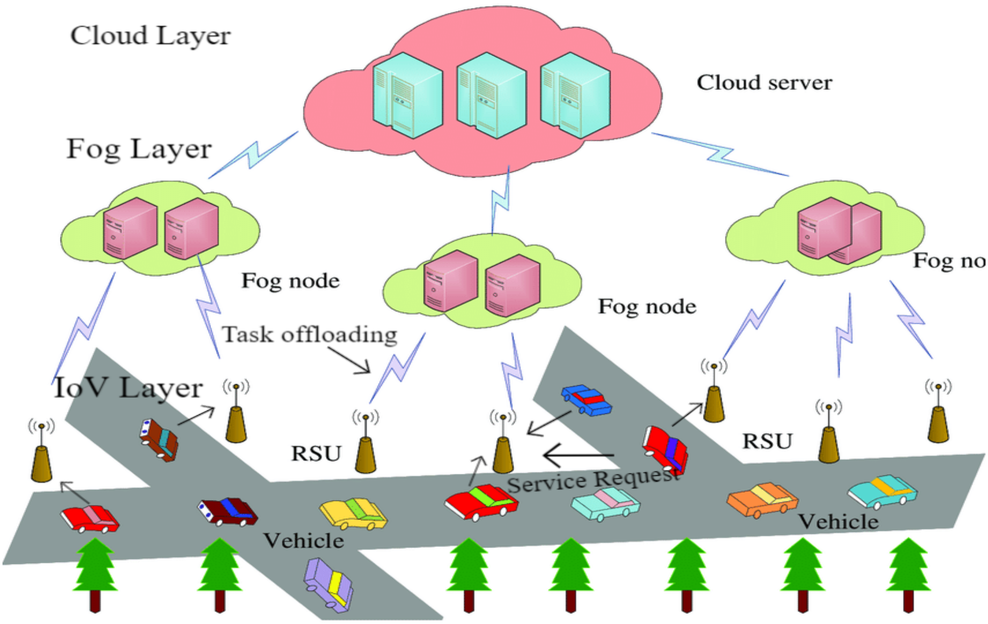

Figure 1 Architecture of IoV-fog

4. Proposed FMA-based model

FMA-based scheduling involves the following steps:
• To begin the process, the simulation of the vehicle on the IoV-Fog network must be initiated, followed by scheduling the data transmission process.
• To simulate vehicles and analyze their data, a vehicle sends a service request to a Roadside Unit (RSU). The RSU receives the request, processes it, and transfers it to a data analytics center for further processing.
• The center then responds with a service message, which the RSU relays to a relay vehicle. This happens with I2V scheduling. The selection of the relay vehicle is based on several factors, such as Drel (distance to the vehicle), Dmax (maximum distance for reliable communication), and CQI (Channel Quality Indicator).
• When a vehicle is far from the RSU and needs to request a service message, a cooperative vehicle is selected through V2V scheduling.
The RSU executes I2V scheduling to schedule the transmission of downlink reply messages across all sub-channels within the interface. V2V scheduling, on the other hand, is used by the RSU to relay scheduling information to all vehicles. For V2V scheduling, the relay vehicle must be positioned in close proximity to the reply vehicle, ideally within the Drel.

4.1. Simulation of vehicles

To ensure efficient transmission of messages between RSU and vehicles in the network, the proposed method involves simulating the vehicles and implementing I2V and V2V scheduling. This step aims to optimize the communication process and enhance the overall performance of the network.

4.2. Service Request

According to the proposed method, vehicles send CQI, Drel, and Dmax values to specific RSUs at regular intervals to request service messages. Once the RSUs receive the requests, they forward them to the data analytics center, which then sends responses to the RSUs. The RSUs then use this information to schedule service message transmission to the vehicles. The goal is to optimize the performance of the fog network by improving the scheduling of I2V and V2V messages.

4.3. Relay vehicle selection

In I2V scheduling, the relay automobile is picked withinside the vehicular network, and it's far finished the usage of FMA.
The vehicle with the highest fitness value is selected and given priority to transmit the first message in K, which is a queue that stores requests from the data analytics center to send the message to the vehicle from RSU.

4.3.1. Solution encoding

In this, a vehicle is selected to which the message is sent from the RSU, represented as a vector of size [1 x n], where n is equal to the total number of messages in K.

Figure 2 Solution Encoding for I2V scheduling.

4.3.2. Fitness function

The fitness factor (F) is used to determine the most suitable vehicle for message transmission from the RSU, and is calculated as follows:

$$F=(CQI+(1-D^{rel})+(1-D^{max}))/3 \quad (1)$$

where:
CQI is a metric used in wireless communication systems to indicate the quality of the channel between the transmitter and the receiver., and is given by the equation:

- $$CQI = -10c\log10D+R \quad (2)$$
- Drel is the relative distance between the vehicle and the RSU (relative to the maximum communication range of the RSU), and is a value between 0 and 1.
- Dmax is the maximum distance between the vehicle and the RSU (in meters) and is used to normalize the Drel value.

4.3.3. Algorithmic of the proposed FMA

This algorithm is inspired by the behavior of mayflies, where males fly around in a specific pattern to attract females, who then evaluate the quality of the patterns before choosing a mate. By simulating this behavior, we can optimize the selection process and produce fitter offspring. Here is the algorithm based on the behavior of mayflies:

1. Initialize a population of male and female mayflies.
2. Each male mayfly will fly around in a specific manner, creating a unique path.

$$G^{x+1}_{sm}=G^{x}_{sm}+M^{x+1}_{sm} \tag{3}$$

$$M^{x+1}_{sm}=M^{x}_{sm}+b_1e^{-axp2}(pbest_{sm}-G^{x}_{sm})+b_2e^{-axg2}(gbest_m-G^{x}_{m}) \tag{4}$$

$$G^{x+1}_{sm} = G^{x}_{sm} + M^{x}_{sm+} b_1e^{-axp2}(pbest_{sm}-G^{x}_{sm}) + b_2e^{-axg2}(gbest_m-G^{x}_{m}) \tag{5}$$

$$G^{x+1}_{sm} - G^{x}_{sm}= M^{x}_{sm}+ b_1e^{-axp2}(pbest_{sm}-G^{x}_{sm}) + b_2e^{-axg2}(gbest_m-G^{x}_{m}) \tag{6}$$

From this, we can say,

$$pbest=G^{x+1}_{sm:} if\ F(G^{x+1}_{sm})<F(pbest) \tag{7}$$

$$gbest \in \{pbest_1,pbest_2,...,pbest_j \mid F(pbest)=min\{F(pbest_1),F(pbest_2,........,F(pbest_j))\} \tag{8}$$

3. Each female mayfly will evaluate the paths of nearby male mayflies and choose the one with the highest fitness score.

$$A^{x+1}_{s}=A^{x}_{s}+M_{x+1s} \tag{9}$$

This equation represents the change in position (A^{x+1}_{s} - A^{x}_{s}) of the female mayfly (s th) between two consecutive steps (x and x+1) in the mth dimension, which is equal to the influence of the environment (M^{x+1}_{s}) on the mayfly's position at step x+1.

4. The chosen male mayfly will mate with the female mayfly, passing on its genes to the offspring.
5. Repeat steps 2-4 for a certain number of generations or until a desired fitness score is achieved.
6. Terminate the algorithm and output the fittest offspring.

Algorithm1: Pseudo code of Proposed FMA

1. Input: Parameters (*Msm, b1, b2, pbest, gbest*)
2. Initialize male and female populations of mayflies
3. Determine the fitness measure for each mayfly and select the one with the highest fitness
4. Repeat the following steps until the termination condition is met:
   a. Perform mating between male and female mayflies to produce offspring
   b. Evaluate the fitness of the offspring
   c. Evaluate the feasibility of the offspring
   d. Update the population with the offspring based on certain selection criteria
5. End (Termination condition is met)

Algorithm: Pseudocode for proposed FMA

4.4. V2V scheduling

Scheduling statistics are broadcasted to all vehicles and maintains a queue of relay vehicles for reply messages. This aids in V2V scheduling by facilitating communication between vehicles.

4.4.1. Solution encoding

The cooperative vehicle helps determine the solution for selecting the relay and destination vehicles, as shown in Figure 3.

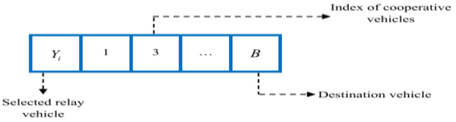

Figure 3 Solution Encoding for V2V scheduling

5. RESULTS AND DISCUSSION

5.1. Experimental setup

MATLAB tool is required for simulating the method.

5.2. Evaluation metrics

Two evaluation metrics used in I2V and V2V scheduling are delay and PDR. Delay measures the time taken for service messages to be generated at various rates. PDR is calculated by dividing the total number of successfully delivered data packets by the total number of packets sent from the source to the destination node. These metrics help to determine the efficiency of the scheduling algorithm and the effectiveness of the communication network.

5.3. Simulation results

At time 1.00, Figure four depicts the simulation effects of the network, which models a network of vehicles.

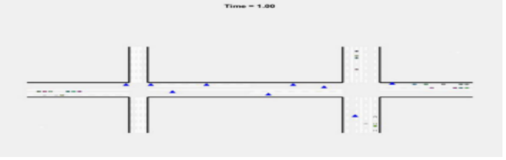

Figure 4 Simulation results.

5.4. Comparative methods

To assess the efficiency of the approach, evaluation techniques: NA-SMT, deep learning, and reinforcement learning are employed.

5.5. Comparative analysis

A comparative analysis is done on the proposed FAM-based scheduling with 100 vehicles and 150 Vehicles. NA-SMT, deep learning, reinforcement learning, and the proposed FMA-based scheduling algorithms were evaluated.

5.5.1. With 100 vehicles

In Figure 5(A), the delay analysis is presented, showing that at time 100 s, the proposed FMA-based scheduling has the lowest delay of 1s compared to rest evaluation techniques, which had delays of 2s, 8s, and 10s.Similarly, Figure 5(B) presents the PDR analysis, indicating that at 250s, the proposed FMA-based scheduling has the highest PDR of 84% compared to others which had PDRs of 82%, 81%, and 81%.

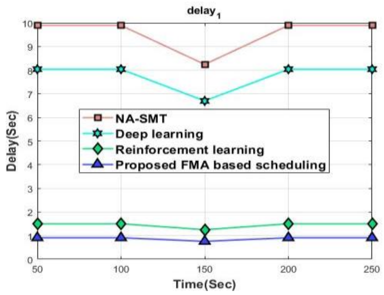

Figure 5(A)

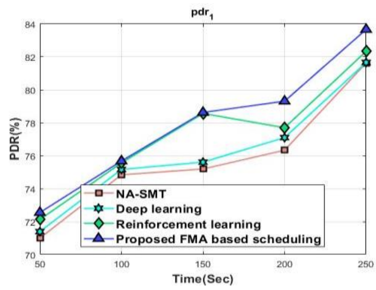

Figure 5(B)

5.5.2. With 150 vehicles

The analysis of delay and PDR in the IoV-fog network is presented in Figures 6(A) and 6(B). At time 100 s, Figure 6(A) shows that the delay faced by these algorithms was 1s, 2s, 8s, and 10s, respectively. On the other hand, Figure 6(B) presents the PDR analysis, indicating that the PDR measured by these algorithms at 250s was 83%, 82%, 82%, and 81%, respectively

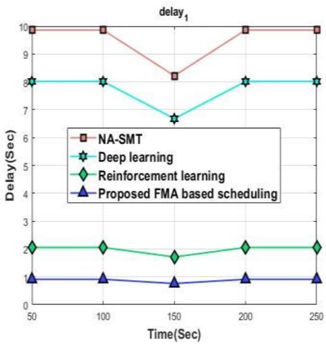

Figure 6(A)

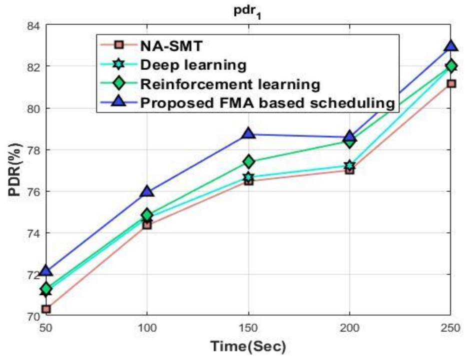

Figure 6(B)

6. Comparative discussion

The developed approach was used to measure delay and PDR in an IoV-fog network with 100 vehicles, resulting in values of 1s and 84%, respectively. When the number of vehicles was increased to 150, the FMA-based scheduling algorithm was used, resulting in a delay of 1s and a PDR of 83.00%.

7. Conclusion

The IoV-fog system's scheduling algorithm efficiency was evaluated using delay and PDR analysis, as shown in Figures 5(A), 5(B), 6(A), and 6(B). The proposed approach selects the best CQI relay vehicle with higher data rates to disseminate service messages from RSUs to vehicles. However, processing becomes difficult with a high number of vehicles, so hybrid optimization algorithms should be considered. These findings provide valuable insights into the effectiveness of scheduling algorithms and communication networks in the IoV-fog system.

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