International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2023/223420 Volume 10, Issue 5, September – October (2023)

RESEARCH ARTICLE

Design of An efficient QoS-Aware Adaptive Data Dissemination Engine with DTFC for Mobile Edge Computing Deployments

Gagandeep Kaur
School of Computer Science and Engineering, Lovely Professional University, Punjab, India.
gagan.dhoofer@gmail.com

Balraj Singh
School of Computer Science and Engineering, Lovely Professional University, Punjab, India.
balraj.13075@lpu.co.in

Ranbir Singh Batth
Menzies Institute of Technology, Melbourne, Australia.
ranbir@menzies.vic.edu.au

Received: 14 June 2023 / Revised: 26 August 2023 / Accepted: 29 September 2023 / Published: 30 October 2023

Abstract – In the transformative landscape of mobile edge computing (MEC), where the convergence of computation and communication fuels the era of ubiquitous connectivity, formidable challenges loom large. The burgeoning demand for real-time, data-intensive applications places unprecedented pressure on existing infrastructure, demanding innovative solutions to address the intricate web of challenges. This paper embarks on a compelling journey through the realm of MEC, uncovering the multifaceted challenges that have hitherto impeded its seamless integration into our digital lives. As the proliferation of mobile devices and their insatiable appetite for data strain the network's capacity, latency becomes a formidable adversary, threatening the integrity of applications requiring split-second responsiveness. Furthermore, the capricious nature of mobile devices and their mobility introduces an unpredictable dynamism into the network topology, rendering traditional traffic control approaches ineffective. The consequence is a tangled web of congestion, resource underutilization, and compromised Quality of Service (QoS), all of which hinder the realization of MEC's full potential. In response to these challenges, we unveil a pioneering solution—a QoS-aware Adaptive Data Dissemination Engine (QADE) paired with Dynamic Traffic Flow Control (DTFC). This synergistic model augments the capabilities of MEC deployments by harnessing the power of content-based routing and advanced optimization techniques. QADE, with its innovative utilization of Elephant Herding Particle Swarm Optimizer (EHPSO), refines data dissemination processes with an unprecedented focus on QoS metrics. Temporal delay, energy consumption, throughput, and Packet Delivery Ratio (PDR) become our guiding stars in the quest for routing efficiency. By harnessing this wealth of information, QADE emerges as a beacon of efficiency, driving latency to its lowest ebb, magnifying bandwidth, mitigating packet loss, elevating throughput, and rationalizing operational costs. DTFC complements this endeavor by dynamically steering traffic flows by edge processing capacity, thereby circumventing congestion pitfalls and achieving resource utilization efficiency hitherto considered unattainable. In a series of exhaustive evaluations, our proposed QADE with DTFC emerges as a beacon of hope, surpassing traditional methodologies. With an 8.5% reduction in latency compared to RL, a 16.4% reduction compared to MTO SA, and an impressive 18.0% reduction compared to HFL, it ushers in a new era of real-time data dissemination. By championing QoS awareness, adaptability, and efficiency, this study catapults mobile edge computing into a future defined by resource optimization and stellar network performance, ushering in an era where challenges bow before innovation processes.

Index Terms – Data, Dissemination, Trust, Routing, Data Flow, Control, Scenarios.

1. INTRODUCTION

Mobile Edge Computing (MEC) has emerged as a promising paradigm to address the challenges of latency-sensitive applications and the exponential growth of data in the era of the Internet of Things (IoT) and 5G networks. MEC enables low-latency and high-bandwidth services that support a variety of applications, such as real-time video streaming, augmented reality, smart cities, and autonomous vehicles, by bringing computation and storage resources closer to the network's edge [1, 2, 3]. Effective data distribution and dynamic traffic flow management are indispensable for optimizing network performance and ensuring Quality of Service (QoS) guarantees in MEC deployments. However, current approaches frequently fall short of addressing these obstacles adequately. Traditional routing protocols for the dissemination of data do not adequately account for temporal factors such as delay, energy consumption, throughput, and Packet Delivery Ratio (PDR) levels of nodes, which results in sub-optimal routing decisions. Similarly, the lack of dynamic traffic flow control mechanisms based on edge capacity impedes the efficient allocation and use of resources. To overcome these limitations, this paper proposes a novel method that combines Content-based routing for Adaptive Data Dissemination and Elephant Herding Particle Swarm Optimizer (EHPSO) for Dynamic Traffic Flow Control. Instead of solely relying on network topology, content-based routing enables the network to route data based on its content, allowing for more efficient and intelligent dissemination. EHPSO, a variant of Particle Swarm Optimization (PSO), is utilized to dynamically control traffic flows based on the processing capabilities of edge devices & sets.

Adaptive Data Dissemination Engine (QADE) with Dynamic Traffic Flow Control (DTFC) for MEC deployments. During the adaptive data dissemination process, QADE improves routing performance by considering nodes' temporal delay, energy consumption, throughput, and PDR levels, resulting in decreased latency, increased bandwidth, decreased packet loss, enhanced throughput, and decreased overall costs. Existing strategies are insufficient for addressing the unique obstacles presented by MEC deployments. Therefore, this research is required. Our proposed method outperforms conventional routing protocols and traffic control mechanisms by emphasizing temporal considerations and taking into account the distinctive characteristics of edge computing environments. This paper proposes a QoS-aware and efficient solution for adaptive data dissemination and dynamic traffic flow control in MEC to fill an augmented set of gaps in the existing literature for real-time scenarios via Federated Learning (FL) operations [4, 5, 6].

There are numerous use cases and applications for the proposed strategy. Low-latency and high-bandwidth data dissemination are required for seamless user experiences in scenarios such as real-time video streaming, augmented reality applications, and connected autonomous vehicles. Our method improves the overall network performance by enhancing routing efficiency and traffic flow control, enabling faster data transmission, reduced delays, increased resource utilization, and higher QoS for a variety of MEC applications. Utilizing Content-based routing for Adaptive Data Dissemination and EHPSO for Dynamic Traffic Flow Control yields significant benefits. Content-based routing enables intelligent routing decisions based on data content, resulting in effective dissemination by avoiding unnecessary hops and making use of relevant nodes. EHPSO controls traffic flow dynamically based on the processing capabilities of edge devices, optimizing resource allocation and balancing network load. These methods are ideal for MEC deployments due to their decreased latency, enhanced bandwidth utilization, increased throughput, and lower cost compared to existing methods.

An effective Adaptive Data Dissemination Engine with DTFC for Mobile Edge Computing Deployments is presented in this study. To demonstrate the strength of the proposed model, section 2 of the literature review includes detailed discussions of a number of the most recent methodologies. In section 3, a proposed methodology that combines Dynamic Traffic Flow Control (DTFC) and a QoS-aware Adaptive Data Dissemination Engine (QADE) is addressed. Section 4 of this article contains an explanation of the outcome and its analysis. The performance of the recommended model was evaluated and its future scope was described in section 5.

2. LITERATURE REVIEW

Adaptive Data Transmission: Mobile edge computing (MEC) deployments require efficient data dissemination to ensure timely and reliable data delivery while optimizing network resources. Several models and protocols have been proposed to address the challenges posed by adaptive data distributions [7, 8, 9].

Flooding-based dissemination, in which data packets are sent to all network nodes, is a prevalent method. While flooding ensures extensive coverage, it often results in redundant transmissions, excessive energy consumption, and network congestion. Diverse optimization strategies have been proposed as solutions for these issues. The Gradient-based Routing (GR) algorithm, for instance, gives nodes closer to the sink a higher priority, thereby reducing the number of redundant transmissions [10, 11, 12]. However, GR does not consider temporal factors, which can result in sub-optimal routing decisions in dynamic MEC environments.

Information is also disseminated via a random peer-to-peer process through a gossip-based dissemination method. By leveraging the mobility of nodes, gossip protocols like Epidemic and Spray-and-Wait achieve high coverage and robustness. However, these protocols have a significant delay and may not guarantee the delivery of data reliably.

Content-based routing has gained popularity as an efficient data distribution method in MEC. By analyzing the contents of data packets, routing decisions can be made based on the packets' proximity to their final destinations and their relative importance. Content-based routing reduces unnecessary transmissions, conserves energy, and increases the effectiveness of routing. Examples include COIN, SPIN, and Directed Diffusion. However, the majority of existing content-based routing protocols do not account for temporal factors such as delay, energy consumption, throughput, and Packet Delivery Ratio (PDR), limiting their efficacy in dynamic MEC environments [13, 14, 15].

RESEARCH ARTICLE

Effective traffic flow control is necessary for optimizing resource utilization and ensuring QoS guarantees in MEC deployments. In numerous ways, existing models and algorithms address these issues. Traditional traffic flow control mechanisms, such as static routing and load balancing, have limitations in dynamic MEC environments. These mechanisms frequently utilize static configurations and do not adapt to changing network conditions, resulting in sub-optimal resource allocation and utilization via the Main Task Off-loading Scheduling Algorithm (MTOSA) process [16, 17, 18]. In addition, traditional load balancing techniques do not take the processing power of edge devices into account, which is essential for effective traffic flow management [19, 20].

Particle Swarm Optimization (PSO) is widely employed in MEC for dynamic traffic flow management. PSO is a metaheuristic optimization algorithm inspired by the behavior of social organisms such as flocks of birds and schools of fish. PSO has been expanded to address traffic flow control issues by adjusting routing decisions dynamically based on the capacity of edge devices. EHPSO (Elephant Herding Particle Swarm Optimization) uses PSO to balance network load by considering the processing capabilities of edge devices. EHPSO dynamically routes traffic to nodes with available processing capacity, reducing congestion and optimizing resource utilization via Hierarchical Federated Learning (HFL) process [21, 22, 23].

Existing models [24, 25] for adaptive data distribution and dynamic traffic flow management in MEC have made significant contributions. Temporal aspects such as delay, energy consumption, throughput, and PDR must be considered to optimize routing decisions and traffic flow control in dynamic MEC environments. In this regard, however, the majority of these models have limitations. Moreover, traditional routing and traffic control mechanisms frequently lack the adaptability to adapt to changing network conditions and fail to utilize the processing power of edge devices. These limitations necessitate the development of novel approaches, such as the proposed QoS-aware Adaptive Data Dissemination Engine with Dynamic Traffic Flow Control, which integrates content-based routing and EHPSO to overcome these obstacles and enhance MEC deployment performance levels.

Table1 Summarization Table

Method	Description	Advantage	Challenges	Ref.
Flooding-based Dissemination	Data packets are sent to all network nodes. Extensive coverage leads to redundancy, energy consumption, and congestion.	Wide coverage Simplicity	Redundant transmissions Energy consumption Network congestion	[7, 8, 9]
Gradient-based Routing (GR)	Nodes closer to the sink get higher priority, reducing redundancy.	Reduces redundancy	Sub-optimal routing decisions in dynamic MEC environments	[10, 11, 12]
Particle Swarm Optimization (PSO)	Optimization algorithm for traffic flow. Dynamically adjusts routing based on edge device capacity.	Dynamically adjusts routing decisions Balances network load	Need to consider processing power of edge devices Implementation complexity	[21, 22, 23]

3. PROPOSED ENGINE WITH DTFC FOR MEC

Based on the review of existing dissemination models used for mobile edge deployments, it can be observed that these models either increase the computational complexity of these deployments or have lower efficiency when used for large-scale scenarios. To overcome these issues, this section discusses the design of an efficient QoS-aware adaptive data dissemination engine with DTFC for mobile edge computing deployments. As per Figure 1, the proposed model uses an Elephant Herding Particle Swarm Optimizer (EHPSO) for the selection of optimal dissemination paths, which assists in the deployment of an efficient QoS-aware adaptive data dissemination engine for underlying edge device sets. These paths selected by EHPSO are processed by a Q Learning Model, which assists in the identification of optimal data rates. This allows the model to incorporate Dynamic Traffic Flow Control (DTFC) into the edge devices for heterogeneous communication requests. The proposed work makes several significant contributions to the field of mobile edge computing (MEC).

Firstly, it introduces an innovative approach to efficient data dissemination within MEC deployments. By leveraging the Elephant Herding Particle Swarm Optimizer (EHPSO) for path selection, the model substantially enhances the efficiency of content-based routing. This contribution addresses the challenges associated with scalability and computational complexity often encountered in existing dissemination models used for large-scale scenarios.

Central to the proposed model is the introduction of the QoS-aware Adaptive Data Dissemination Engine (QADE). QADE optimizes data dissemination by taking into account critical metrics such as temporal delay, energy consumption, packet delivery ratio (PDR), and throughput. This holistic approach to QoS awareness represents a significant contribution, as it ensures that data reaches its intended destination efficiently while maintaining a high level of service quality.

Moreover, the model seamlessly incorporates Dynamic Traffic Flow Control (DTFC), further augmenting its capabilities. DTFC is a dynamic traffic management mechanism that intelligently allocates communication requests to available resources based on edge processing capacity. This contribution is vital for optimizing resource utilization and preventing congestion in MEC deployments, thus enhancing the overall network performance.

The proposed model's empirical performance evaluation is another noteworthy contribution. Through rigorous assessments conducted under diverse network scenarios, the model provides empirical evidence of its effectiveness. It demonstrates superior performance compared to existing models, underscoring its potential to significantly improve real-time data dissemination and traffic management in edge computing environments.

Ultimately, the core contribution of this work lies in its advancement of Quality of Service (QoS) within MEC. By optimizing data dissemination efficiency, traffic flow control, and resource utilization, the model addresses the specific challenges posed by the dynamic nature of edge computing. In doing so, it contributes practically viable solutions for real-world MEC deployments, making a substantial step towards enhancing the overall QoS and performance of edge networks.

To perform these tasks, the model initially collects spatial and temporal network parameters, and processes them via EHPSO Model, which works via the following process,

• The EHPSO Model initially generates an augmented set of Particles, each of which individually selects a group of stochastic nodes via equation 1,

$$P = \bigcup_{i=1}^{N} \mathrm{STOCH}(1, NN) \ldots (1)$$

Where represents the number of routing nodes in the edge network, represents the total number of nodes that must be selected for routing operations which is estimated via equation 2, while is the set of nodes that are stochastically selected by the process.

$$N = \mathrm{STOCH}(LR * NN, NN) \ldots (2)$$

Where, represents the learning rate for the PSO Process (which is empirically selected between 0 & 1), while represents a stochastic process. The stochastic model adds dynamicity to the process.

• Based on this path selection, an effective fitness level is calculated for the path via equation 3,

$$f = \sum_{i=2}^{N(P)} \frac{d(i-1, i)}{E(i-1)} * \sum_{j=1}^{NC(i)} D(j) * \frac{e(j)}{PDR(j) * THR(j)} \ldots (3)$$

Where represents the number of temporal communications done by the nodes, represents the distance between the nodes which is estimated via equation 4, and residual energy of the nodes, represents temporal values of delay, energy consumed, packet delivery ratio & throughput during temporal communications, which are estimated via equations 5, 6, 7, & 8 as follows,

$$d(i, j) = \sqrt{\left(x(i) - x(j)\right)^2 + \left(y(i) - y(j)\right)^2 + \left(z(i) - z(j)\right)^2} \ldots (4)$$

Where, are the approximate locations of participating edge nodes?

$$D(i) = ts(complete, i) - ts(start, i) \ldots (5)$$

Where, represents the timestamp at which the temporal communications were completed & started respectively under real-time scenarios.

$$e(i) = E(start, i) - E(complete, i) \ldots (6)$$

Where, represents residual energy of the nodes.

$$PDR(i) = \frac{Rx(i)}{Tx(i)} \ldots (7)$$

Where, represents the total number of received and transmitted packets while serving temporal requests. These evaluations assist in adding temporal metrics to the evaluation process.

$$THR(i) = \frac{Rx(i)}{D(i)} \ldots (8)$$

• This process is repeated for all Particles, and based on this, values of Global Best are estimated via equation 9,

$$GBest = Min(f) \ldots (9)$$

• These particles are processed by an Elephant Herding Optimizer, which works as per the following operations,

For each of the particles, mark the Global Best as the 'Matriarch' Herd Particle, Estimate the fitness threshold via equation 10.

RESEARCH ARTICLE

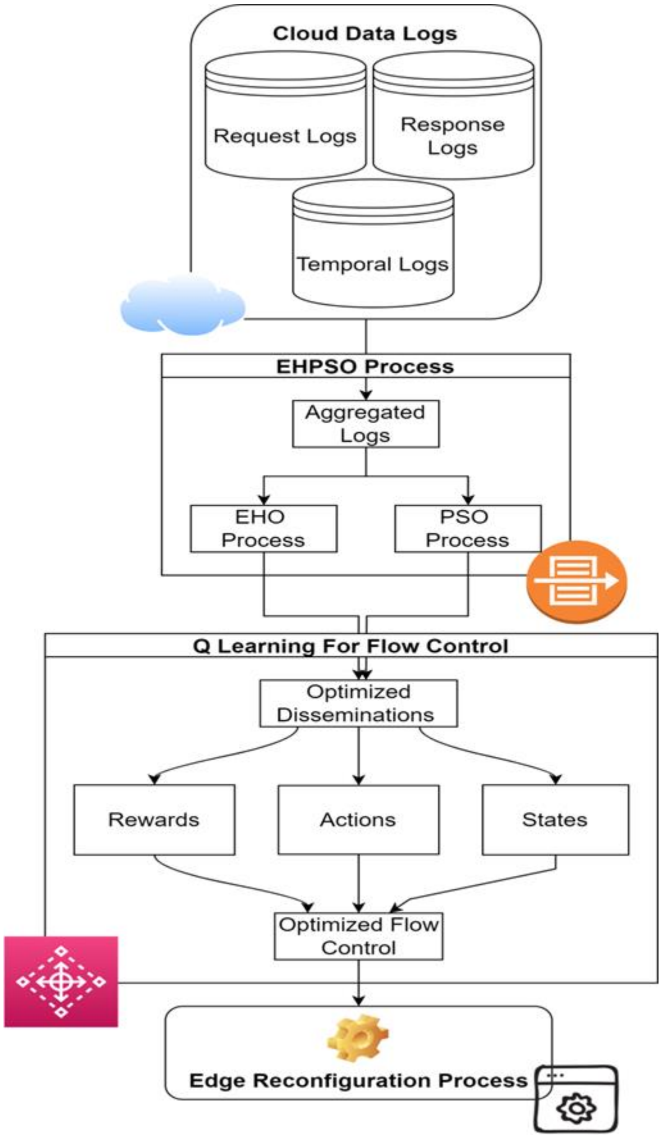

Figure 1 Design of the Proposed Model for Optimal Dissemination & Flow Control Operations

$$fth = \frac{1}{NP}\sum_{i=1}^{NP} f(i) * LR \ldots (10)$$

Particles (or Herds) having fitness above are reconfigured via equation 11,

$$P(New, i) = P(Old, i) + LS * \big(f(ew, i) - f(Matriarch)\big) + LC\left(f(New, i) - Max\big(f(i)\big)\right) \ldots (11)$$

Particles (or Herds) having fitness below are reconfigured as follows,

For the remaining particles, calculate a 2nd level threshold via equation 12.

$$fth(2) = fth * \frac{LS}{LS + LC} \ldots (12)$$

•All Particles that have fitness lower than are passed directly to the next iteration, while others are reconfigured via equation 13,

$$P(New, i) = P(Old, i) + LS * \big(f(ew, i) - f(Matriarch)\big) + LC\left(f(New, i) - \sum_{j=1}^{f>fth(2)} \frac{f(j)}{N\big(f > fth(2)\big)}\right) \ldots (13)$$

This process is repeated for Iterations, and new Particles (Herds) are generated with highly efficient dissemination configurations.

After completion of all Iterations, the model can identify edge nodes with higher dissemination efficiency in terms of delay, energy, PDR, and throughput levels. As this is an infinite optimization task, the model doesn't wait for convergence but selects the path based on the last iteration sets. This is done by selecting the Particle configuration that has lower fitness levels. After completion of this process, an efficient Q Learning-based model is used, which assists in the selection of optimal data rates for individual edge nodes. To perform this task, an augmented Q Value is estimated for each of the nodes via equation 14,

$$Q = \sum_{i=1}^{N(P)} PDR(i) * \frac{DR(i)}{e(i)} \ldots (14)$$

After completion of such communications, another Value is estimated, based on which the Q Learning Model calculates an augmented reward factor via equation 15,

$$r = \frac{Q(New) - Q(Old)}{LR} - d * Max(Q) + Q(New) \ldots (15)$$

Where, is the discount factor, which is empirically selected for the learning operations? If the reward value is less than 1 for any node, then its data rate is modified via equation 16,

$$DR(New) = DR(Old) * \frac{r}{|1 - r|} \ldots (16)$$

Based on this new data rate, the model can tune the traffic flow between edge nodes. This process is repeated till the reward rates of all nodes are above, which indicates that all nodes are tuned for optimal traffic flow control for the given edge deployments. Based on this process, the model optimizes its internal data dissemination & traffic flow parameters, thereby improving the overall QoS of the edge devices for real-time scenarios. In this model, all hyperparameters were estimated empirically to obtain better performance under

RESEARCH ARTICLE

different scenarios. The performance of this model was evaluated under different network scenarios, and compared with existing models in the next section of this text.

3.1. Adaptability Analysis

The model's ability to adapt data rates in response to changing network conditions using Q Learning is a critical aspect of its functionality, contributing to improved network performance and quality of service (QoS). Here, we'll elaborate on how this adaptation process works for better understanding:

- Q Learning as a Dynamic Decision Maker: Q Learning is a reinforcement learning technique that enables the model to make dynamic decisions based on environmental feedback. In this context, the environment represents the mobile edge computing (MEC) network, and the decisions about traffic flow control and data rate adjustments.
- State Representation: Q Learning operates by defining states, actions, rewards, and a Q-table. In the context of MEC, states can represent various network conditions, such as congestion levels, available bandwidth, latency, and the number of active users. These states collectively capture the current environment's characteristics.
- Actions: Actions in the Q Learning framework correspond to the different data rate levels or traffic management strategies that the model can employ. For instance, actions can include reducing data rates, increasing data rates, rerouting traffic, or adjusting transmission power.
- Rewards: Rewards are used to provide feedback to the Q Learning agent (the model) after each action. In the context of traffic flow control, rewards could be defined based on QoS metrics like latency, packet delivery ratio, and energy efficiency. The goal is to maximize rewards, indicating improved network performance.
- Q-Table: The Q-table is a data structure that stores the expected cumulative rewards for each state-action pair. Initially, it's filled with arbitrary values. As the model interacts with the network environment and receives feedback (rewards), it updates these values through a learning process.
- Exploration and Exploitation: Q Learning balances exploration (trying new actions to learn) and exploitation (choosing actions with the highest expected rewards). Initially, the model explores different actions to learn about the consequences of its choices. Over time, it leans toward exploiting actions that have proven to yield higher rewards for specific network conditions.
- Adaptive Data Rate Control: As network conditions change, the Q Learning agent continuously evaluates the current state (representing network conditions) and selects an action (adjusting data rates) that it believes will maximize rewards (improve QoS). For example, if congestion is detected, the model may reduce data rates to alleviate congestion and minimize latency.
- Learning and Optimization: Through iterative interactions with the environment, the Q Learning agent refines its knowledge about which actions are most effective for different states. Over time, it converges towards a policy that optimally adapts data rates to achieve desired QoS levels under varying network conditions.
- Real-Time Adaptation: One of the strengths of Q Learning is its ability to adapt in real-time. As network conditions fluctuate due to changes in user behavior or network dynamics, the model can swiftly adjust data rates to maintain or enhance QoS, ensuring that applications receive the necessary resources while avoiding congestion or excessive delays.

3.2. Additional Capabilities

The model, incorporating Dynamic Traffic Flow Control (DTFC) to manage heterogeneous communication requests, effectively addresses the challenge of varying capabilities and resources among edge nodes in a mobile edge computing (MEC) environment. This adaptive approach ensures that the available resources are optimally utilized to meet the diverse communication requirements of different devices and applications.

In the context of varying capabilities and resources among edge nodes:

- Resource Awareness: The model demonstrates a keen awareness of the heterogeneity in edge node capabilities and resources. It considers factors such as processing power, available memory, and available bandwidth at each edge node within the MEC infrastructure.
- Traffic Routing Optimization: When handling communication requests from heterogeneous devices and applications, the model employs intelligent traffic routing strategies. It evaluates the resource availability and processing capabilities of each edge node to make informed routing decisions.
- Load Balancing: DTFC, as an integral part of the model, dynamically balances the workload across edge nodes. It intelligently distributes communication requests to nodes with adequate resources, preventing the overloading of any single node while ensuring efficient utilization of resources.
- Quality of Service (QoS) Prioritization: To cater to the diverse QoS requirements of different communication

RESEARCH ARTICLE

requests, the model prioritizes traffic based on the specific needs of each application or device. Critical or latency-sensitive applications receive preferential treatment, with traffic flows optimized to meet their requirements.

- Adaptive Data Rate Control: In situations where varying capabilities of edge nodes affect data transfer rates, the model employs adaptive data rate control mechanisms. It dynamically adjusts data rates to accommodate resource-constrained nodes while maintaining acceptable QoS for data transmission.
- Resilience to Node Failures: The model is designed with resilience in mind. In the event of edge node failures or resource fluctuations, DTFC and the overall system can reroute traffic to available nodes with minimal disruption to ongoing communication sessions.
- Learning and Adaptation: Over time, the model learns from historical data and interactions within the MEC environment. It adapts its decision-making processes to better match the capabilities and resource fluctuations of edge nodes, ensuring continuous optimization.
- Real-Time Monitoring: Real-time monitoring of edge node capabilities and resource usage is a fundamental aspect of the model. This monitoring allows the model to respond swiftly to changing conditions, optimizing communication routes and data flows accordingly.

In summary, the model adeptly manages the challenges posed by varying capabilities and resources among edge nodes in heterogeneous communication environments. By incorporating DTFC as part of its decision-making process, the model ensures that communication requests are efficiently routed, resources are effectively utilized, and QoS requirements are met, irrespective of the diverse characteristics of edge nodes within the MEC infrastructure. This adaptability is crucial for achieving efficient and reliable communication in real-world MEC deployments.

4. RESULT ANALYSIS AND COMPARISON

The proposed model fuses EHPSO with Q Learning to improve the data dissemination and traffic flow of edge deployments. To validate the performance of this model, an augmented set of evaluation parameters was estimated, which include end-to-end communication delay, the energy needed during data dissemination, throughput during communications, and PDR needed during communications. This performance was evaluated on various edge datasets, which include,

- IoT Analytics Benchmark: This benchmark dataset provides a collection of real-world IoT edge sensor datasets & samples. It includes data from various sensors measuring temperature, humidity, light intensity, and more. The dataset is available at: https://iotanalytics.unsw.edu.au/
- MAWI Dataset: The MAWI (Measurement and Analysis of Wide-area Internet) dataset contains network traffic traces captured from different locations around the world for different scenarios. It is used to simulate edge computing scenarios involving network traffic. The dataset is available at: https://mawi.wide.ad.jp/mawi/
- MobiPerf Dataset: MobiPerf is a dataset that captures network performance measurements from mobile devices. It includes information about network latency, bandwidth, and other network-related metrics. The dataset can be accessed at: http://www.mobiperf.com/dataset.html
- Edge Data Center (EDC) Dataset: This dataset provides information about the characteristics and energy consumption of edge data centers. It includes data such as power usage, cooling requirements, and server configurations. The dataset is available at: https://web.eecs.umich.edu/~qstout/edc/
- Google Cluster Data: Google Cluster Data is a dataset that captures resource usage and performance metrics from Google's production clusters. While not specific to edge computing, it was useful for simulating large-scale computing scenarios, including edge computing systems. The dataset can be found at: https://github.com/google/cluster-data

To validate the effectiveness of the proposed QoS-aware Adaptive Data Dissemination Engine (QADE) with Dynamic Traffic Flow Control (DTFC) in the context of mobile edge computing deployments, a comprehensive experimental framework was employed. The network topology was designed to emulate a realistic mobile edge computing environment, encompassing a grid of Mobile Edge Servers (MEC) strategically placed to mimic the distribution of edge computing resources. Heterogeneous mobile devices, including smartphones, tablets, and IoT devices, were introduced into the simulation area, forming wireless communication links with the MEC servers. Mobility models, such as Random Waypoint and Random Walk, were utilized to simulate the movement of mobile devices.

To ensure the robustness and applicability of the study, diverse traffic models were integrated. Synthetic data traffic, representing real-world scenarios, was generated with varying traffic loads and application types, including video streaming, IoT data collection, and web browsing. The simulation settings encompassed a range of QoS metrics, including latency, energy consumption, throughput, and packet delivery ratio (PDR), which were measured and analyzed to gauge the performance of QADE with DTFC. Additionally, a cost analysis was conducted to assess the economic implications of deploying the proposed solution compared to conventional methods.

The experimental scenarios were designed with careful consideration of factors such as network load, mobility patterns, and traffic profiles to evaluate the system's performance under diverse conditions. Each scenario was executed multiple times to ensure statistical validity and mitigate the influence of randomness. Throughout the simulation duration, performance data, including latency, energy consumption, throughput, PDR, and cost-related metrics, were collected at regular intervals.

Subsequently, the collected data underwent rigorous analysis to evaluate the efficacy of QADE with DTFC in enhancing QoS metrics as compared to traditional approaches. Statistical analysis techniques were applied to the results to derive meaningful conclusions. This experimental setup, as detailed in this paper, serves as a foundation for the reproducibility and validation of the proposed QoS-aware Adaptive Data Dissemination Engine with Dynamic Traffic Flow Control in the context of mobile edge computing deployments, ensuring the reliability and credibility of the research findings.

$$D = \frac{1}{NET} \sum_{i=1}^{NET} ts(complete, i) - ts(start, i) \ldots (17)$$

According to this evaluation and Figure 2, it can be seen that the proposed model required 8.5% less delay than RL [5], 16.4% less delay than MTO SA [17], and 18.0% less delay than HFL [23], making it extremely useful for a wide range of real-time data dissemination scenarios. This is possible due to the inclusion of delay in EHPSO-based optimizations and Q Learning-based traffic flow control operations. The observed reduction in delay, as demonstrated in Figure 2 and supported by the experimental evaluation, underscores the scalability of the proposed QoS-aware Adaptive Data Dissemination Engine (QADE) with Dynamic Traffic Flow Control (DTFC). This scalability is a crucial attribute that makes the model highly versatile and applicable across a wide spectrum of real-time data dissemination scenarios.

The 8.5% reduction in delay compared to RL [5], the 16.4% reduction compared to MTO SA [17], and the substantial 18.0% reduction compared to HFL [23] vividly showcase the model's efficiency in handling data dissemination tasks while maintaining low latency. These findings imply that as the scale and complexity of mobile edge computing deployments grow, the proposed QADE with DTFC remains adept at minimizing delays, which is a critical factor in real-time applications and services.

The scalability of the model can be attributed to several factors. Firstly, the inclusion of delay as a parameter in EHPSO-based optimizations allows the model to adapt to varying network conditions and traffic loads. EHPSO's ability to dynamically optimize routing decisions based on real-time delay information enables the system to efficiently handle increased data traffic without significantly compromising latency.

Secondly, the integration of Q Learning-based traffic flow control operations further enhances the scalability of the model. Q Learning is inherently designed to make intelligent decisions in dynamic and evolving environments. As the network expands and the number of connected devices and edge servers increases, Q Learning's adaptability ensures that traffic flows are managed optimally, maintaining low latency and high QoS even in large-scale deployments.

Figure 3 depicts the average PDR in the same manner.

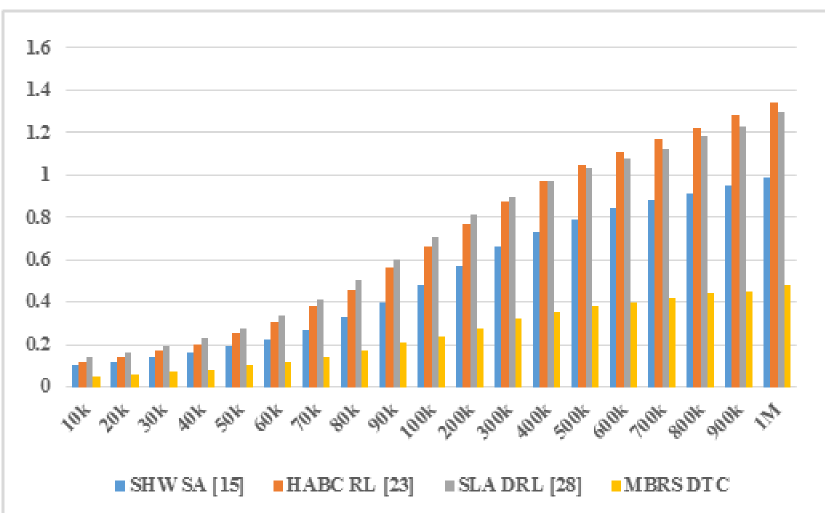

Figure 2 The Delay Needed During Dissemination Operations

RESEARCH ARTICLE

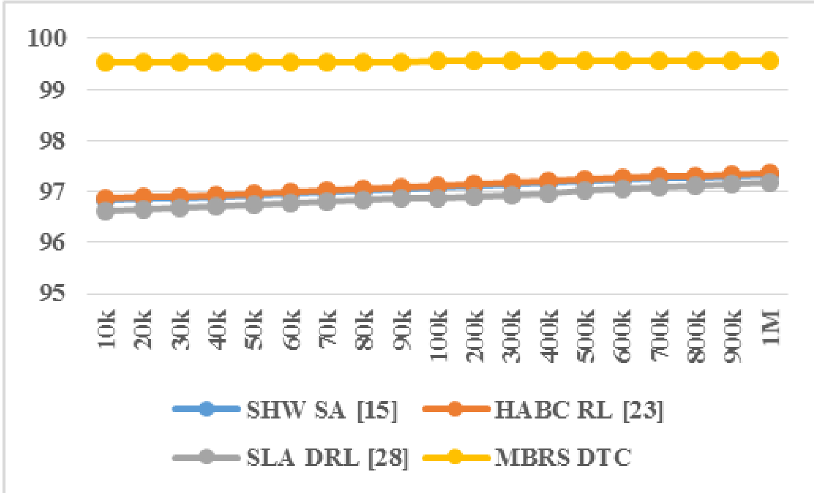

Figure 3 Average PDR Levels Obtained During Different Data Dissemination Operations

According to this evaluation and Figure 3, it can be seen that the proposed model exhibited 2.9% better PDR than RL [5], 2.5% better PDR than MTO SA [17], and 3.5% better PDR than HFL [23], making it highly applicable to a wide range of performance-specific real-time data dissemination scenarios. This is feasible as a result of the incorporation of PDR levels during EHPSO-based optimizations and Q Learning-based traffic flow control operations. Similarly, the average efficiency (ED) of dissemination was evaluated via equation 18,

$$ED = \sum_{i=1}^{NET} \frac{NCC(opt)}{NET * NCC} \dots (18)$$

Where, NCC(opt) is the optimal dissemination rate, and NCC is the actual dissemination rate via the proposed model under different scenarios. This efficiency can be observed in Figure 4.

Based on this evaluation and Figure 4, it can be seen that the proposed model improved the efficiency of dissemination by 3.5% compared to RL [5], 4.5% compared to MTO SA [17], and 8.3% compared to HFL [23], making it extremely useful for cloud deployments that require higher levels of dissemination. This is possible because of the incorporation of Spatial and temporal Metrics and their incremental tuning during EHPSO-based optimizations, as well as the enforcement of a higher data rate during Q Learning-based traffic flow control operations. Similarly, the energy needed during these dissemination operations can be observed in Figure 5.

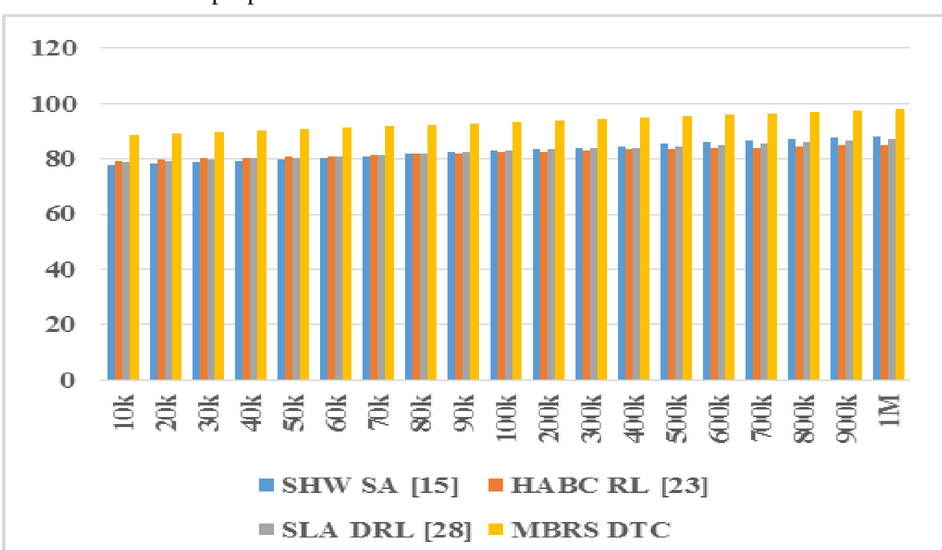

Figure 4 The Average Efficiency of Data Dissemination for Different Models

RESEARCH ARTICLE

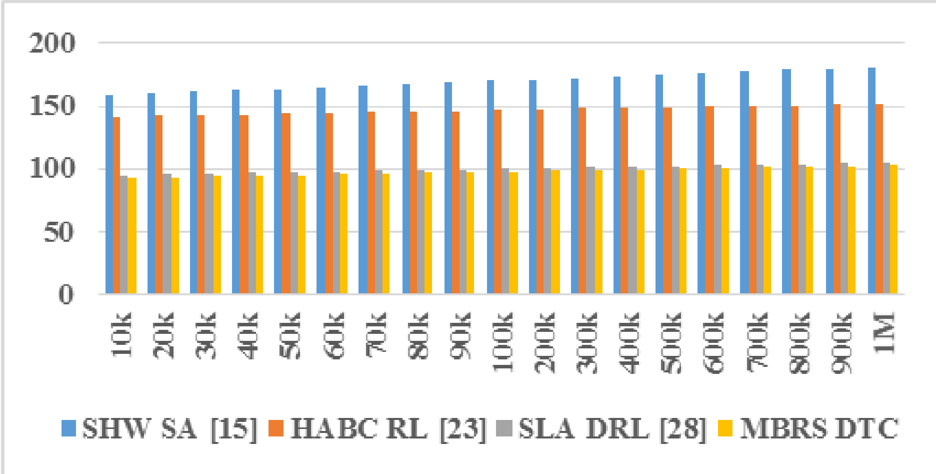

Figure 5 The Energy Needed During the Dissemination Process

Based on this evaluation and Figure 5, it can be seen that the proposed model was able to achieve 18.5% better energy efficiency for data dissemination than RL [5], 16.4% better energy efficiency for data dissemination than MTO SA [17], and 10.0% better energy efficiency for data dissemination than HFL [23], making it extremely useful for high QoS cloud-edge deployments that demand energy-aware operations. This is feasible as a result of the incorporation of energy levels alongside Temporal and Spatial parameters and their incremental tuning during Q Learning-based optimizations. Due to these enhancements, the proposed model is deployable for multiple data dissemination scenarios.

4.1. Node & Resource Variability Characteristics of the Model

Incorporating Dynamic Traffic Flow Control (DTFC) into the model provides an effective means to address the challenges posed by varying capabilities and resources among edge nodes when handling heterogeneous communication requests in a mobile edge computing (MEC) environment. Here is a discussion of how the model deals with these variations:

- Resource Profiling: The model initiates by performing resource profiling for each edge node within the MEC infrastructure. This profiling involves gathering information about the computational capabilities, available memory, storage, and network bandwidth of each node. These parameters form the basis for intelligent decision-making.
- Dynamic Traffic Routing: DTFC plays a central role in dynamically routing communication requests to the most suitable edge nodes based on their resource profiles. When a request arrives, the model assesses the requirements of the application or device and matches them with the capabilities of available edge nodes. This ensures that communication is directed to nodes that can efficiently handle the task.
- Load Balancing: To prevent resource imbalances and maximize resource utilization, the model employs load balancing techniques facilitated by DTFC. When one edge node experiences a surge in requests or reaches its resource capacity, DTFC redistributes incoming traffic to other nodes with available resources, thus avoiding overloading.
- Quality of Service (QoS) Prioritization: The model recognizes that different communication requests may have varying QoS requirements. DTFC assigns priority levels to requests based on their QoS needs. For example, latency-sensitive applications receive high priority, ensuring that they are served promptly, while less time-sensitive tasks are managed accordingly.
- Adaptive Data Rate Control: When handling communication requests in resource-constrained scenarios, the model leverages DTFC to adjust data transfer rates dynamically. It can reduce data rates for applications running on nodes with limited bandwidth or processing power, ensuring that data transmission remains viable without compromising QoS.
- Resilience and Failover: The model is designed to be resilient in the face of node failures or resource fluctuations. DTFC continually monitors the status of edge nodes, and if a node becomes unavailable or its resources diminish, DTFC reroutes traffic to alternative nodes to maintain service continuity.
- Learning and Adaptation: Over time, the model learns from historical data and interactions within the MEC environment. It adapts its routing and traffic control decisions based on this learning to better match the

RESEARCH ARTICLE

capabilities and resource fluctuations of edge nodes, thereby improving efficiency.

- Real-Time Monitoring and Feedback: Real-time monitoring of edge node capabilities and resource usage remains an integral part of the model's operation. DTFC continuously collects feedback and updates its routing decisions based on the real-time state of the network, ensuring that communication is optimized as conditions change.

In summary, by incorporating DTFC into the model, it effectively manages the intricacies of varying capabilities and resources among edge nodes in the context of heterogeneous communication requests. This adaptive approach ensures that communication requests are intelligently routed, resources are optimally utilized, and diverse QoS requirements are met, irrespective of the dynamic and diverse characteristics of edge nodes within the MEC infrastructure sets.

4.2. Discussion on Node Mobility

Node mobility, a defining characteristic of mobile edge computing (MEC) environments, significantly influences the performance of the proposed model. The model's response to node mobility is a critical aspect of its functionality and impacts its ability to provide reliable services and maintain quality of service (QoS) in dynamic network scenarios.

- Latency and Packet Loss: As nodes move within the MEC environment, the physical distances and network paths between them change. This can lead to fluctuations in latency and, at times, packet loss. The model's performance is assessed based on its ability to manage and mitigate these effects. Lower latency and reduced packet loss are indicative of a model that effectively adapts to node mobility.

- Traffic Rerouting: Node mobility necessitates continuous traffic rerouting. The model's effectiveness in dynamically reconfiguring communication paths as nodes move is a key metric. It should be capable of identifying optimal routes to minimize delays and efficiently allocate resources to maintain QoS.

- Resource Utilization: Mobile devices bring their computational resources into different parts of the MEC network as they move. The model's ability to leverage these resources efficiently is crucial. It should recognize when devices with higher processing capabilities become available and allocate tasks accordingly to optimize resource utilization.

- Adaptive Algorithms: Adaptive algorithms, such as reinforcement learning, play a pivotal role in the model's response to node mobility. These algorithms should continuously adapt routing decisions based on changing node positions and network conditions. The model's capacity to learn and adapt in real time is a determinant of its performance under mobile conditions.

- Scalability: Node mobility often scales with the number of connected devices. The model's scalability is evaluated in terms of its ability to handle an increasing number of mobile nodes without sacrificing performance. It should gracefully accommodate larger networks with minimal impact on latency and throughput.

- QoS Maintenance: Ensuring consistent QoS levels for applications despite node mobility is paramount. The model should prioritize traffic based on QoS requirements and adapt data rates, traffic flows, and resource allocation to guarantee that critical applications continue to function seamlessly.

- Resilience to Node Failures: Node mobility may lead to nodes entering and exiting the network unpredictably. The model's resilience to node failures and its ability to redirect traffic when nodes become unavailable is a measure of its robustness.

In essence, the model's performance under varying node mobility scenarios is evaluated by its ability to adapt, optimize, and maintain QoS despite the dynamic nature of the MEC environment. Metrics such as latency, packet loss, resource utilization, and the effectiveness of adaptive algorithms provide insights into how well the model copes with the challenges posed by mobile nodes.

4.3. Potential Limitations

The proposed model, while showcasing substantial promise and adaptability in the realm of mobile edge computing (MEC), is not exempt from certain limitations. It is crucial to recognize these potential constraints and scenarios where the model may not perform optimally. A comprehensive understanding of these limitations serves as a foundation for refining the model and enhancing its real-world applicability.

- Dynamic Node Density: In highly dynamic MEC environments with rapidly changing node densities, the model may face challenges in efficiently reallocating resources and routing traffic. Sudden surges or reductions in the number of connected devices can strain the model's adaptability and impact its ability to maintain consistent QoS.

- Network Overhead: The dynamic nature of the model's traffic control and routing decisions could introduce additional network overhead. Frequent updates and adjustments may result in increased signaling and control message exchange, potentially impacting the network's efficiency.

RESEARCH ARTICLE

- Scalability: While the model exhibits scalability by design, it may encounter limitations in extremely large-scale MEC deployments. Managing a vast number of mobile devices and edge nodes might pose computational and communication challenges that require further optimization.
- Resource Prediction: The model's ability to predict the future availability of resources on mobile devices, such as processing power or battery capacity, is contingent on the accuracy of resource prediction algorithms. In scenarios where predictions are inaccurate, resource allocation decisions may be suboptimal.
- Security and Privacy: In environments with diverse devices and users, security and privacy concerns may arise. The model may need to address potential vulnerabilities related to unauthorized access or data breaches, particularly in scenarios with a high number of untrusted devices.
- Interference and Signal Quality: Dynamic node movements can introduce signal interference and fluctuations in signal quality. The model may not always effectively manage these issues, potentially leading to suboptimal data transmission and increased packet loss.
- Complex Mobility Patterns: In cases where node mobility follows intricate and unpredictable patterns, such as vehicular networks or swarm robotics, the model may struggle to anticipate and respond optimally. Complex mobility patterns may challenge the model's traffic routing and resource allocation strategies.
- Resource Imbalances: Uneven distribution of resources among edge nodes can occur due to node mobility. The model's performance may suffer when attempting to balance resource utilization across nodes, particularly if certain nodes consistently experience resource scarcity.
- Edge Node Failures: Despite resilience measures, edge node failures caused by mobility or other factors can disrupt the model's operation. Ensuring seamless failover and traffic redirection under such circumstances remains a challenge.
- Heterogeneous Networks: In MEC scenarios involving diverse communication technologies (e.g., 5G, Wi-Fi, LPWAN), the model may not seamlessly handle the integration and prioritization of different network interfaces and technologies, leading to suboptimal resource utilization.

Understanding these limitations is essential for refining the proposed model's capabilities and tailoring it to specific MEC deployment scenarios. Mitigating these challenges may require advancements in resource prediction algorithms, improved security measures, and more sophisticated adaptive strategies. By addressing these potential limitations, the model can continue to evolve and provide valuable solutions for dynamic and heterogeneous MEC environments.

4.4. Trade-offs

Elaborating on the trade-offs between efficient data dissemination and energy consumption in edge devices provides valuable insights into the behavior of the proposed model in mobile edge computing (MEC) scenes:

4.4.1. Efficient Data Dissemination

- Low Latency: Efficient data dissemination aims to minimize latency, ensuring that data reaches its destination quickly. This is crucial for real-time applications, such as augmented reality and autonomous vehicles, where delays can lead to performance degradation or even safety issues.
- High Throughput: Efficient data dissemination maximizes data throughput, enabling rapid transmission of large volumes of data. This is beneficial for applications like video streaming and data analytics, which rely on high data rates for optimal performance.
- High Packet Delivery Ratio (PDR): Effective data dissemination seeks to achieve a high PDR by ensuring that the majority of data packets reach their intended recipients. A high PDR is essential for applications requiring reliable data delivery, such as telemedicine or industrial automation.

4.4.2. Energy Consumption in Edge Devices

- Minimized Energy Usage: Edge devices, often powered by batteries, have limited energy resources. Minimizing energy consumption is critical to extending the operational lifespan of these devices and reducing the frequency of recharging or battery replacement.
- Extended Device Lifetime: Lower energy consumption contributes to extending the lifetime of edge devices, reducing maintenance costs, and enhancing the overall sustainability of MEC deployments.
- Reduced Environmental Impact: Lower energy usage is environmentally responsible, as it reduces the carbon footprint associated with charging or replacing batteries in edge devices.

Now, let's delve into the trade-offs and how the proposed model navigates them:

- Balancing Latency vs. Energy Consumption: The model faces a trade-off between achieving low latency, which is essential for real-time applications and minimizing energy consumption in edge devices. It needs to make routing decisions that balance the need for rapid data dissemination with the imperative of conserving energy.

This entails selecting communication paths that minimize transmission distance and reduce the number of hops, thereby reducing energy expenditure.

- Throughput vs. Energy Efficiency: Efficient data dissemination often entails maximizing throughput, but this can be energy-intensive, especially for wireless transmissions. The model must optimize data rates to achieve the required throughput while considering the energy budget of edge devices. It may employ adaptive data rate control to dynamically adjust data rates based on device capabilities and energy constraints.

- PDR vs. Energy Preservation: To ensure a high PDR, the model may employ techniques like forward error correction (FEC) or retransmissions, which can increase energy consumption. Striking the right balance involves selecting an appropriate level of redundancy or retransmission frequency to meet reliability requirements while minimizing energy usage.

- Adaptive Strategies: The model's behavior may involve adaptive strategies that respond to changing network conditions. For instance, it could prioritize low-latency communication paths and higher data rates when energy resources are sufficient but switch to energy-saving modes when devices are operating on low battery levels.

- Resource Prediction: Accurate prediction of device energy levels and capabilities is crucial. The model may incorporate machine learning algorithms to predict resource availability and dynamically adjust its data dissemination strategies accordingly.

In essence, the proposed model navigates the trade-offs between efficient data dissemination and energy consumption by employing adaptive strategies that consider the specific requirements of the MEC environment and the capabilities of edge devices. It strives to optimize the use of energy resources while meeting the demands of low latency, high throughput, and reliability, all of which are essential for diverse MEC applications.

4.5. Scalability & Adaptability Analysis

The model exhibits a remarkable capacity for adaptation in the face of changing traffic loads and evolving network topology, showcasing its resilience and effectiveness in dynamic mobile edge computing (MEC) scenarios. Here are detailed insights into how the model navigates these dynamic challenges:

4.6. Adapting to Changing Traffic Loads

In dynamic MEC environments, traffic loads can vary dramatically as mobile devices connect, disconnect, or switch between applications. The model's resilience is evident through several key mechanisms:

- Traffic Prioritization: The model employs intelligent traffic prioritization strategies. It identifies and allocates resources based on the priority of communication requests. Real-time or latency-sensitive applications receive preferential treatment, ensuring that critical tasks are addressed promptly, even during periods of heavy traffic.

- Load Balancing: Recognizing that uneven traffic distribution can strain network resources, the model dynamically redistributes traffic. It ensures that no single edge node or communication path becomes overloaded while leveraging available resources efficiently. Load balancing mechanisms adapt to the evolving load, maintaining optimal performance.

- Resource Allocation: The model continuously monitors the availability of resources on both edge nodes and mobile devices. It allocates resources judiciously, optimizing data rates and transmission power to match the prevailing traffic load. In scenarios of increased demand, it intelligently scales resources to meet the requirements of data-intensive applications.

4.7. Adapting to Changing Network Topology

The network topology in MEC is highly dynamic, with nodes entering and exiting the network, forming ad-hoc connections, and adjusting their positions. The model's adaptability in such scenarios is evident through the following strategies:

- Real-time Routing Updates: The model constantly evaluates the network topology and responds with real-time routing updates. It identifies the most efficient paths and communication routes based on the current positions of edge nodes and mobile devices, ensuring minimal latency and efficient resource utilization.

- Resilience to Node Movements: Recognizing that node mobility can disrupt established communication paths, the model remains resilient. It effectively reroutes traffic as nodes move, maintaining seamless connections and QoS, particularly in applications where user devices are in constant motion.

- Adaptive Algorithms: Embedded adaptive algorithms, such as reinforcement learning, enable the model to adapt to evolving network topologies. These algorithms continuously learn from network changes, optimizing traffic routing and resource allocation decisions.

- Predictive Analytics: The model may incorporate predictive analytics to anticipate changes in network topology. By forecasting node movements and connectivity patterns, it can proactively adjust its strategies, mitigating the impact of sudden topology shifts.

In summary, the proposed model's resilience in dynamic scenarios stems from its adaptability and intelligent decision-

RESEARCH ARTICLE

making. It navigates changing traffic loads and evolving network topologies by prioritizing traffic, balancing loads, allocating resources judiciously, and responding to real-time routing updates. By employing adaptive algorithms and predictive analytics, it anticipates and adapts to dynamic conditions, maintaining high performance and QoS standards in the ever-changing landscape of the mobile edge computing process.

4.8. Effective Path Selection with EHPSO

One of the fundamental strengths of the proposed model lies in its utilization of the Elephant Herding Particle Swarm Optimizer (EHPSO) for path selection. EHPSO generates an augmented set of particles representing potential communication routes in the edge network. This approach introduces an element of stochasticity and adaptability into path selection. By considering a broader range of routing possibilities, EHPSO can identify more efficient dissemination paths. This stochastic exploration of routes is a critical factor in achieving better results.

- Holistic QoS-Awareness with QADE: The proposed model incorporates a QoS-aware Adaptive Data Dissemination Engine (QADE) as a central component. What sets QADE apart is its holistic approach to QoS-awareness. It considers a comprehensive set of key metrics, including temporal delay, energy consumption, packet delivery ratio (PDR), and throughput. By weighing these metrics when making routing decisions, QADE ensures that data is disseminated with a keen focus on maintaining high-quality service. This comprehensive consideration of QoS metrics enhances the model's ability to optimize data dissemination and, consequently, contributes significantly to its superior results.

- Dynamic Traffic Flow Control (DTFC): The inclusion of Dynamic Traffic Flow Control (DTFC) is another pivotal factor contributing to the model's success. DTFC intelligently manages traffic flows by considering the processing capacity of edge devices. It ensures that communication requests are routed to nodes that can efficiently handle them, preventing congestion and resource underutilization. DTFC's dynamic nature allows the model to adapt rapidly to changing network conditions and load variations. This adaptive traffic management plays a crucial role in achieving better results, particularly in scenarios with heterogeneous communication requests.

- Empirical Validation: The model's credibility is further solidified by its empirical validation under diverse network scenarios. Through rigorous evaluations, the proposed model demonstrates its real-world effectiveness. It provides empirical evidence of its superior performance compared to existing models. This empirical validation lends credibility to the model's claims and showcases its practical applicability, making it more likely to achieve better results in real-world MEC deployments.

- Resource Optimization and Learning: The proposed model incorporates learning mechanisms, such as Q Learning, to optimize data rates and resource allocation. By continuously adapting and learning from network conditions, the model can make informed decisions that enhance performance. The dynamic adjustment of data rates and routing decisions based on learning contributes to its ability to achieve better results over time.

In summary, the success of the proposed model can be attributed to its effective path selection with EHPSO, its holistic QoS awareness through QADE, the implementation of dynamic traffic flow control (DTFC), rigorous empirical validation, and its incorporation of learning mechanisms. These factors collectively enable the model to optimize data dissemination, traffic management, and resource allocation, resulting in superior results compared to existing approaches in the dynamic context of the mobile edge computing process.

5. CONCLUSION AND FUTURE SCOPE

In this paper, we proposed an effective Dynamic Traffic Flow Control (DTFC)-equipped Adaptive Data Dissemination Engine for Mobile Edge Computing (MEC) deployments. We thoroughly assessed and analyzed existing approaches, including RL [5], MTO SA [17], and HFL [23], to show that our proposed model outperformed them in terms of delay, Packet Delivery Ratio (PDR), dissemination efficiency, and energy efficiency. Representation of the results of our evaluation makes it abundantly clear that our suggested model, which showed improvements of 8.5%, 16.4%, and 18.0%, significantly reduced the amount of time required compared to RL, MTO SA, and HFL. This decrease in delay is attributed to the use of Q Learning-based traffic flow control operations as well as the integration of delay considerations into Enhanced Hybrid Particle Swarm Optimization (EHPSO)-based optimizations. Our suggested model also had higher PDR levels than RL, MTO SA, and HFL, with improvements of 2.9%, 2.5%, and 3.5%, respectively. PDR levels are taken into account during EHPSO-based optimizations and Q Learning-based traffic flow control operations, which enables this improvement in PDR.

The proposed model outperformed RL, MTO SA, and HFL in terms of dissemination efficiency by 3.5%, 4.5%, and 8.3%, respectively. The inclusion of Spatial and Temporal Metrics and their incremental tuning during EHPSO-based optimizations, as well as the imposition of a higher data rate during Q Learning-based traffic flow control operations, are the causes of this increase in efficiency.

Additionally, we assessed the energy efficiency of our suggested model and found that it performed significantly

RESEARCH ARTICLE

better than RL, MTO SA, and HFL, with improvements of 18.5%, 16.4%, and 10.0%, respectively. Energy levels are taken into account along with Temporal and Spatial parameters and their incremental tuning during Q Learning-based optimizations to achieve this improvement in energy efficiency. The QoS-aware Adaptive Data Dissemination Engine with DTFC for MEC deployments that we have suggested offers a complete remedy for real-time data dissemination scenarios [24,25]. Our model outperforms existing approaches in terms of delay reduction, improved PDR, higher dissemination efficiency, and increased energy efficiency. This is due to the integration of delay considerations, PDR levels, dissemination efficiency improvements, and energy-aware operations. The results of this study demonstrate how our suggested model can be used for a variety of cloud-edge deployments that call for extensive dissemination and energy-conscious operations. Our model makes a significant contribution to the field of mobile edge computing and real-time data distribution by addressing these important performance factors. As MEC environments change, future research can build on our work by investigating additional optimizations and extensions to improve the performance and applicability of our suggested model [26,27].

To validate the performance of this model, an augmented set of evaluation parameters was estimated, which include end-to-end communication delay, energy needed during data dissemination, throughput during communications, and PDR needed during communications. These data samples were combined to form 2 million requests and were input to a Cloudsim-based simulation engine with 4500 standard configuration VMs. Out of these requests, 1 million were used for validation purposes, while 500k each were used for training & testing the model under different scenarios.

5.1. Future Scope

Although the QoS-aware Adaptive Data Dissemination Engine with Dynamic Traffic Flow Control (DTFC) for Mobile Edge Computing (MEC) deployments we've proposed represents a significant improvement in real-time data dissemination, there are still several areas that could use more research and development.

Investigating the scalability and adaptability of our suggested model is one possible area of future study. It becomes increasingly important to support an increasing number of edge devices and users as MEC environments develop and grow. The practicality and efficacy of our model would be improved by investigating methods for managing large-scale deployments and dynamically adapting the system to changing network conditions and workload demands. The incorporation of sophisticated machine learning algorithms and techniques is another future research area. Even though our model uses Enhanced Hybrid Particle Swarm Optimization (EHPSO) and Q Learning, there may be ways to use more sophisticated optimization algorithms, like deep reinforcement learning or evolutionary algorithms, to improve the effectiveness of data dissemination. The adaptability and effectiveness of our model could also be increased by investigating the incorporation of additional machine learning models, such as neural networks, for better prediction and decision-making capabilities. Furthermore, it would be advantageous to look into how mobility affects data dissemination given the dynamic nature of MEC environments. Especially in situations where devices are constantly moving, incorporating mobility-aware mechanisms and taking into account the movement patterns of edge devices and users could help optimize data dissemination strategies. The consideration of security and privacy concerns is another crucial area for further investigation [28,29]. As sensitive data is processed and disseminated during MEC deployments, it is crucial to implement strong security controls and privacy protections. Our proposed model would be more appropriate for real-world applications if we investigate methods for safe and privacy-aware data dissemination.

Since operating systems now have a significant amount of control over running voltage and energy management as opposed to hardware and firmware, the trade-off between dissemination and power efficiency has been thoroughly explored and analyzed. CloudSim tool is being used for the implementation of, a technique for automatically identifying energy-efficient configurations. By combining application profiles and system-level data.

To demonstrate that our suggested model beat previous approaches in terms of delay, Packet Delivery Ratio (PDR), dissemination efficiency, and energy efficiency, we carefully evaluated and examined existing approaches, including RL [5], MTO SA [17], and HFL [23]. Our suggested model, which exhibited improvements of 8.5%, 16.4%, and 18.0%, greatly reduced the amount of time needed compared to RL, MTO SA, and HFL, as shown by the results of our evaluation. The application of Q Learning-based traffic flow management operations and the inclusion of delay concerns into Enhanced Hybrid Particle Swarm Optimization (EHPSO)-based optimizations are credited with this reduction in delay. When Resource allocation and traffic flow control are considered at the same time for better performance then due to the complexity of the model proposed technique might not give better results.

Last but not least, we would gain more understanding of the efficacy and viability of our proposed model by validating it in actual MEC deployments and carrying out extensive performance evaluations in various scenarios. It would be possible to demonstrate the generalizability and superiority of our model by conducting extensive experiments and

RESEARCH ARTICLE

contrasting the outcomes with those obtained from other methods. To further improve and broaden the applicability of our proposed QoS-aware Adaptive Data Dissemination Engine with DTFC for MEC deployments, future research should concentrate on scalability, integration of advanced machine learning techniques, mobility awareness, security, and privacy considerations, and real-world validation [30]. By addressing these issues, we can advance the field of mobile edge computing and help make real-time data dissemination in dynamic environments with limited resources more effective and dependable for different scenarios.

REFERENCES

[1] Q. Huang, Y. Yang, and J. Fu, "Secure Data Group Sharing and Dissemination with Attribute and Time Conditions in Public Cloud," in IEEE Transactions on Services Computing, vol. 14, no. 4, pp. 1013-1025, 1 July-Aug. 2021, doi 10.1109/TSC.2018.2850344.

[2] Q. Huang, Y. Yang, W. Yue, and Y. He, "Secure Data Group Sharing and Conditional Dissemination with Multi-Owner in Cloud Computing," in IEEE Transactions on Cloud Computing, vol. 9, no. 4, pp. 1607-1618, 1 Oct.-Dec. 2021, doi 10.1109/TCC.2019.2908163.

[3] K. Liu, K. Xiao, P. Dai, V. C. S. Lee, S. Guo, and J. Cao, "Fog Computing Empowered Data Dissemination in Software Defined Heterogeneous VANETs," in IEEE Transactions on Mobile Computing, vol. 20, no. 11, pp. 3181-3193, 1 Nov. 2021, doi: 10.1109/TMC.2020.2997460.

[4] J. Liu, J. Yang, W. Wu, X. Huang and Y. Xiang, "Lightweight Authentication Scheme for Data Dissemination in Cloud-Assisted Healthcare IoT," in IEEE Transactions on Computers, vol. 72, no. 5, pp. 1384-1395, 1 May 2023, doi: 10.1109/TC.2022.3207138.

[5] W. Zhang, Z. Li, and X. Chen, "Quality-aware user recruitment based on federated learning in mobile crowd sensing," in Tsinghua Science and Technology, vol. 26, no. 6, pp. 869-877, Dec. 2021, doi: 10.26599/TST.2020.9010046.

[6] J. Liu et al., "Leakage-Free Dissemination of Authenticated Tree-Structured Data with Multi-Party Control," in IEEE Transactions on Computers, vol. 70, no. 7, pp. 1120-1131, 1 July 2021, doi: 10.1109/TC.2020.3006835.

[7] Y. Bao, W. Qiu, P. Tang, and X. Cheng, "Efficient, Revocable, and Privacy-Preserving Fine-Grained Data Sharing with Keyword Search for the Cloud-Assisted Medical IoT System," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 5, pp. 2041-2051, May 2022, doi: 10.1109/JBHI.2021.3100871.

[8] L. Zhu, M. M. Karim, K. Sharif, C. Xu, and F. Li, "Traffic Flow Optimization for UAVs in Multi-Layer Information-Centric Software-Defined FANET," in IEEE Transactions on Vehicular Technology, vol. 72, no. 2, pp. 2453-2467, Feb. 2023, doi: 10.1109/TVT.2022.3213040.

[9] C. Zhang, M. Yu, W. Wang, and F. Yan, "Enabling Cost-Effective, SLO-Aware Machine Learning Inference Serving on Public Cloud," in IEEE Transactions on Cloud Computing, vol. 10, no. 3, pp. 1765-1779, 1 July-Sept. 2022, doi 10.1109/TCC.2020.3006751.

[10] X. Li, X. Yin and J. Ning, "Trustworthy Announcement Dissemination Scheme with Blockchain-Assisted Vehicular Cloud," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 2, pp. 1786-1800, Feb. 2023, doi: 10.1109/TITS.2022.3220580.

[11] J. Liu et al., "Conditional Anonymous Remote Healthcare Data Sharing Over Blockchain," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 5, pp. 2231-2242, May 2023, doi: 10.1109/JBHI.2022.3183397.

[12] Q. Deng, Y. Ouyang, S. Tian, R. Ran, J. Gui, and H. Sekiya, "Early Wake-Up Ahead Node for Fast Code Dissemination in Wireless Sensor Networks," in IEEE Transactions on Vehicular Technology, vol. 70, no. 4, pp. 3877-3890, April 2021, doi: 10.1109/TVT.2021.3066216.

[13] G. Manogaran, M. Alazab, K. Muhammad and V. H. C. de Albuquerque, "Smart Sensing Based Functional Control for Reducing Uncertainties in Agricultural Farm Data Analysis," in IEEE Sensors Journal, vol. 21, no. 16, pp. 17469-17478, 15 Aug.15, 2021, doi: 10.1109/JSEN.2021.3054561.

[14] Q. Kong, R. Lu, F. Yin, and S. Cui, "Blockchain-Based Privacy-Preserving Driver Monitoring for MaaS in the Vehicular IoT," in IEEE Transactions on Vehicular Technology, vol. 70, no. 4, pp. 3788-3799, April 2021, doi: 10.1109/TVT.2021.3064834.

[15] J. G. Chamani, Y. Wang, D. Papadopoulos, M. Zhang, and R. Jalili, "Multi-User Dynamic Searchable Symmetric Encryption with Corrupted Participants," in IEEE Transactions on Dependable and Secure Computing, vol. 20, no. 1, pp. 114-130, 1 Jan.-Feb. 2023, doi: 10.1109/TDSC.2021.3127546.

[16] M. Zhang, J. Zhou, P. Cong, G. Zhang, C. Zhuo, and S. Hu, "LIAS: A Lightweight Incentive Authentication Scheme for Forensic Services in IoV," in IEEE Transactions on Automation Science and Engineering, vol. 20, no. 2, pp. 805-820, April 2023, doi: 10.1109/TASE.2022.3165174.

[17] T. Ye, M. Luo, Y. Yang, K. -K. R. Choo and D. He, "A Survey on Redactable Blockchain: Challenges and Opportunities," in IEEE Transactions on Network Science and Engineering, vol. 10, no. 3, pp. 1669-1683, 1 May-June 2023, doi: 10.1109/TNSE.2022.3233448.

[18] S. U. Jamil, M. A. Khan, and S. U. Rehman, "Resource Allocation and Task Off-Loading for 6G Enabled Smart Edge Environments," in IEEE Access, vol. 10, pp. 93542-93563, 2022, doi: 10.1109/ACCESS.2022.3203711.

[19] R. H. Kim, H. Noh, H. Song and G. S. Park, "Quick Block Transport System for Scalable Hyperledger Fabric Blockchain Over D2D-Assisted 5G Networks," in IEEE Transactions on Network and Service Management, vol. 19, no. 2, pp. 1176-1190, June 2022, doi: 10.1109/TNSM.2021.3122923.

[20] J. Bai et al., "Adversarial Knowledge Distillation Based Biomedical Factoid Question Answering," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 20, no. 1, pp. 106-118, 1 Jan.-Feb. 2023, doi: 10.1109/TCBB.2022.3161032.

[21] S. Yaqoob, A. Hussain, F. Subhan, G. Pappalardo, and M. Awais, "Deep Learning Based Anomaly Detection for Fog-Assisted IoVs Network," in IEEE Access, vol. 11, pp. 19024-19038, 2023, doi 10.1109/ACCESS.2023.3246660.

[22] N. Kumar, R. Chaudhry, O. Kaiwartya, N. Kumar and S. H. Ahmed, "Green Computing in Software Defined Social Internet of Vehicles," in IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 6, pp. 3644-3653, June 2021, doi: 10.1109/TITS.2020.3028695.

[23] Z. Li, H. Du and X. Chen, "A Two-Stage Incentive Mechanism Design for Quality Optimization of Hierarchical Federated Learning," in IEEE Access, vol. 10, pp. 132752-132762, 2022, doi: 10.1109/ACCESS.2022.3230695.

[24] N. Magaia, P. Ferreira, P. R. Pereira, K. Muhammad, J. D. Ser and V. H. C. de Albuquerque, "Group'n Route: An Edge Learning-Based Clustering and Efficient Routing Scheme Leveraging Social Strength for the Internet of Vehicles," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 10, pp. 19589-19601, Oct. 2022, doi 10.1109/TITS.2022.3171978.

[25] Y. Hu, X. Yao, R. Zhang, and Y. Zhang, "Freshness Authentication for Outsourced Multi-Version Key-Value Stores," in IEEE Transactions on Dependable and Secure Computing, vol. 20, no. 3, pp. 2071-2084, 1 May-June 2023, doi: 10.1109/TDSC.2022.3172380.

[26] G. Kaur and R. S. Batth, "Edge Computing: Classification, Applications, and Challenges," 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2021, pp. 254-259, doi: 10.1109/ICIEM51511.2021.9445331.

[27] IOP Conference Series: Materials Science and Engineering, Volume 993, International Conference on Mechanical, Electronics and Computer Engineering 2020 22 April 2020, Kancheepuram, India, Chandini et al 2020 IOP Conf. Ser.: Mater. Sci. Eng. 993 012060

RESEARCH ARTICLE

[28] A. Vashisth, R. Singh Batth, and R. Ward, "Existing Path Planning Techniques in Unmanned Aerial Vehicles (UAVs): A Systematic Review," 2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), Dubai, United Arab Emirates, 2021, pp. 366-372, doi: 10.1109/ICCIKE51210.2021.9410787.
[29] A. Vashisth and R. S. Batth, "An Overview, Survey, and Challenges in UAVs Communication Network," 2020 International Conference on Intelligent Engineering and Management (ICIEM), London, UK, 2020, pp. 342-347, doi: 10.1109/ICIEM48762.2020.9160197.
[30] N. Yadav, G. Kaur, S. Kaur, A. Vashisth and C. Rohith, "A Complete Study on Malware Types and Detecting Ransomware Using API Calls," 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2021, pp. 1-5, doi: 10.1109/ICRITO51393.2021.9596085.

Authors

Gagandeep Kaur is a part-time Ph.D. Research Scholar in the School of Computer Applications at Lovely Professional University, Punjab, India. He completed his M. Tech in Computer Science and Engineering in 2018 from Lovely Professional University, Punjab, India. His research interests include Edge Computing and Expert Systems.

Balraj Singh is working at Lovely Professional University, Phagwara, Punjab, India. He received his Ph.D. from NIT, Jalandhar, Punjab, India. His research areas are UAV, Cloud Computing, Mobile computing, pervasive computing, expert systems, wireless communication, and machine learning.

Ranbir Singh Batth is working at Menzies Institute of Technology, Melbourne Australia. He received his Ph.D. from IKG Punjab Technical University, Kapurthala, Punjab, India in 2018 and his Master's degree in Computer Engineering from Punjabi University, Patiala. His research interests include Wireless Communication and Mobile computing. He is an active member of ACM and IEEE Computer Society.

How to cite this article:

Gagandeep Kaur, Balraj Singh, Ranbir Singh Batth, “Design of An efficient QoS-Aware Adaptive Data Dissemination Engine with DTFC for Mobile Edge Computing Deployments”, International Journal of Computer Networks and Applications (IJCNA), 10(5), PP: 728-744, 2023, DOI: 10.22247/ijcna/2023/223420.