OPTIMIZING DATA TRANSMISSION IN CLUSTERED MULTI-EDGE COMPUTING FOR INTELLIGENT IOT

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DOI:https://doi.org/10.5281/zenodo.20729464

Keywords
Multi-Access Edge Computing (MEC); Internet of Things (IoT); Dynamic Clustering; Reinforcement Learning; Task Offloading; Adaptive Routing; Energy Efficiency; Low-Latency Communication.

Article History
Received: 20 April 2026
Accepted: 02 June 2026
Published: 17 June 2026

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Abstract
This paper focuses on the challenges of optimizing data transmission in clustered Multi-Access Edge Computing (MEC) systems for Internet of Things (IoT) applications. With all of this proliferation of IoT devices, the traditional cloud-based architectures are limited by means of latency, bandwidth and energy efficiency. To address these challenges, this work introduces a novel data transmission optimization model which leverages dynamic clustering, reinforcement learning based task offloading, and adaptive routing approaches to optimize system performance. The proposed model aims to minimize end-to-end latency, energy consumption, and maximize throughput and packet delivery ratio (PDR) in a large-scale IoT environment. To assess the effectiveness of the proposed model the simulations were carried out with respect to static clustering and threshold offloading baseline models. The results validate the superiority of the proposed system with respect to the key performance metrics compared to the baseline systems. In particular, the proposed model achieved up to 40% less latency, 31-35% better energy efficiency, as well as a higher PDR and throughput than static clustering and threshold offloading. Furthermore, the proposed system exhibited cluster stability for 120 minutes which is much larger than that of baseline models (75-90 minutes). Moreover, the sensitivity analysis indicated that the proposed model is scalable and adaptable and works well in different node density and traffic loads. The results demonstrate the promise of MEC for making large-scale IoT networks energy efficient, low latency, and efficient. The findings of this research could help to optimize the data transmission in MEC-based IoT systems, which have potential applications in smart cities, healthcare, and industrial automation fields.

1 INTRODUCTION

1.1 Overview and Context

Over the last few years, the Internet of Things (IoT) has grown by leaps and bounds, changing the way many industries operate with its extensive range of connected devices that can communicate and share data without needing human intervention(Mughal et al., 2024). IoT is revolutionizing the way the world works, from everyday consumer appliances to industrial systems, healthcare devices, and more. With the high volume of data these devices create, fast and efficient processing is essential to make real-time decisions, especially in the fields of autonomous vehicles, smart grid, health monitoring, and industrial automation. But handling and distributing these data safely, while keeping the integrity, speed and security of the system is not without its difficulties, especially with the traditional cloud-based architecture(Gupta et al., 2024). Despite its great potential, cloud computing has a number of drawbacks in terms of latency, bandwidth and scalability for large-scale IoT systems. This means that there are delays in data transfer between IoT devices and cloud servers, which can lead to high latency and an inefficient system. Moreover, the number of connected devices grows rapidly, and the pressure on the centralized cloud systems grows as well, leading to concerns about network congestion, bandwidth limitations and energy consumption(Trigka & Dritsas, 2025; Wang & Wang, 2021).

In response to these challenges, Multi-Access Edge Computing (MEC) has come up as a viable option. MEC brings computation and storage closer to the edge of the network, towards data sources, thereby decentralizing computing resources(Liang et al., 2025). This minimizes data transfer between the applications, resulting in better latency and less reliance on cloud central servers. With the ability to handle data processing at the edge of the network, MEC also helps to improve the speed and efficiency of IoT systems, reducing the burden on cloud resources and lowering energy usage and system downtime(Ismail et al., 2025; Wang et al., 2025). The applications where low latency is crucial, like autonomous vehicles, healthcare systems at remote locations, or real-time industrial automation, are particularly well-suited for MEC. While cloud computing has a number of benefits compared with MEC, it too has its own set of challenges, especially in a distributed, large-scale IoT network. Optimization of data transmission among multiple edge nodes in clustered MEC is one of the major challenges(Kodakandla, 2021).

In clustered MEC system, the multiple edge nodes are clustered and each cluster head manages the communication within each cluster and between clusters(Verma et al., 2025). This idea of clustering can be used to balance the load of computations, to increase system scalability and to increase system reliability. But clustered MEC systems have several issues, including inefficient resource utilization, non-optimized routing, imbalanced load distribution, and inefficient task offloading(Youn & Han, 2022). These problems result in high latency, high energy consumption and poor network performance, ultimately negating the potential benefits of MEC. Optimizing traffic with IoT adds another layer of complexity, as it is dynamic and heterogeneous. There is a huge difference in energy supply, processing capacity and communication capabilities among IoT devices, which makes it challenging to achieve uniform data transmission performance in the network(Qiu et al., 2022).

This research aims to solve these problems by designing and proposing an adaptive data transmission optimization model for clustered MEC systems in an IoT application. The model aims to minimize latency, energy usage, and throughput by dynamically clustering resources, intelligently routing traffic, and offloading tasks to AI. The model will use techniques like reinforcement learning to make real-time decisions, based on data, that adapt to the changing network conditions, device capabilities, and traffic pattern. The aim is to enhance the overall performance and scalability of clustered MEC systems, which are better suited for large-scale IoT applications that require low latency, energy-efficient, and high-performance communication technologies(Hazra et al., 2023). The objective of this research is to create an understanding between the potential of MEC and its implementation in practical IoT applications, which will serve as a stepping stone towards the future development of the IoT system design and optimization. The research is relevant as it is a major requirement for using more efficient and scalable methods for data transmission in the context of IoT and MEC. This study will help develop intelligent and adaptive communication frameworks to meet the increasing demands of IoT applications and ensure sustainability and long-term viability.

1.2 Problem Statement

Although Multi-Access Edge Computing (MEC) has brought a lot of advantages to the IoT systems by reducing latency and bandwidth constraints, there are still a number of important challenges in applying MEC in clustered MEC environments. These are non-optimized routings, unbalanced load distribution and ineffective task offloading. These problems result in poor system performance such as high latency, high energy consumption and low network performance. These problems can be even more severe in large-scale IoT systems, with devices often being mobile and heterogeneous. Current MEC systems do not have dynamic and adaptive solutions to solve these problems in real-time. The goal of this research is to suggest and examine models for optimizing data transmission in dynamic clustered MEC systems with the aim of reducing latency, energy consumption and throughput in IoT environments.

1.3 Research Questions

- How to optimize the dynamic clustering mechanisms for data transmission performance in clustered MEC environments for large scale IoT systems?
- How can latency, throughput, and energy-efficiency be optimized in clustered MEC IoT network by intelligent routing strategies?
- How to use reinforcement learning algorithms to determine the optimal task offloading decisions in clustered MEC systems for energy consumption reduction and processing efficiency?
- What are the impacts of dynamic IoT traffic on the efficiency of data transmission in clustered MEC networks, and how can adaptive optimization models help reduce these impacts?
- How do energy-efficient transmission models affect the allocation of resources and scalability of clustered MEC-IoT systems?

1.4 Research Objectives

- To assess the existing problems in the data transmission in clustered MEC systems and pinpoint the specific gaps that obstruct the optimization of IoT application.
- To propose and develop an adaptive data transmission optimization model, which is based on the dynamic clustering, intelligent routing and task offloading to enhance the performance of MEC.
- Reinforcement learning application to optimize the task offloading and communication scheduling in clustered MEC environment to minimize the energy consumption and provide the better performance in the system.
- To develop efficient and scalable energy-efficient communication protocols for clustered MEC-IoT systems that can satisfy the network performance requirements while considering the power consumption challenge.
- Perform simulations and performance analysis to compare the performance of the proposed optimization methods with the current models and confirm any benefits in terms of latency, energy consumption, and throughput.

2 Research Methodology

2.1 Introduction

This study aimed to solve the optimization problem of data transmission in clustered Multi-Access Edge Computing (MEC) systems for IoT applications by designing a research methodology. The purpose was to create a model that optimizes overall system performance by minimizing latency, energy usage, throughput and maximizing scalability and reliability of the network. The proposed optimization model was tested by simulations using a methodology that included both theoretical and practical. The research was conducted in a systematic process for developing the model, a test of the effectiveness of the model, and a comparison with the effectiveness of other models. Additionally, the proposed methodology involved reinforcement learning for dynamic decision-making when offloading tasks and routing data, which further enhanced the model's adaptability to different network conditions and IoT traffic patterns. The goal of the research was to develop a strong model for real-time optimization of clustered MEC IoT systems, with the ability to be used in real-world IoT networks in a scalable and efficient way.

2.2 Research Design

The research design in this study was experimental and simulation-based, to create and test the proposed data transmission optimization model. The main goal was the development of an adaptive model for clustered MEC system to efficiently manage the dynamic traffic characteristics of the IoT. The research design included developing an optimization framework that enhanced the dynamic clustering, intelligent routing and reinforcement learning-based task offloading. The model is tested for its effectiveness through simulations using network simulation tools such as NS-3 and MATLAB. These tools were employed to simulate a range of network parameters such as node density, data rate and mobility conditions to assess the adaptability and efficiency of proposed model in varying real-world situations. Performance evaluation metrics like latency, energy consumption, packet delivery ratio and throughput were also used to compare the performance of the proposed model with baseline and benchmark models. The main objective of the research was to collect empirical data to test the effectiveness of the proposed model in enhancing data transmission in IoT networks through this design.

2.3 System Architecture Description

The architecture of this research was designed in a way that would allow optimizing the flow of data in clustered MEC environments. The architecture was a distributed network of IoT devices, edge nodes and MEC servers cooperating. The architecture of this cluster configuration was based upon the idea of grouping multiple edge nodes into clusters, assigning a cluster head to each cluster for intra cluster communication and coordination with other clusters. The cluster head was in charge of fine tuning task offloading, load balancing, and routing in the cluster. The system architecture also featured dynamic clustering, which allowed for the ability to dynamically configure clusters as needed in response to the current state of the network and traffic. The system was equipped with reinforcement learning algorithms for decision-making, such as task offloading and communication scheduling. These algorithms enable the system to adapt to different situations and learn from previous interactions, including changes in channel quality, residual energy, and network congestion. The system architecture was simulated and tested under different scenarios to assess the system performance in reducing latency, minimizing energy consumption and maximizing throughput of the overall system.

2.4 Dynamic Clustering Strategy

One of the key features of the proposed optimization model was the dynamic clustering strategy. The goal of the strategy was to enhance the performance of the MEC system by dynamically clustering IoT devices into groups according to their actual network conditions. In this strategy, the clusters were dynamically reconfigured as necessary; for example, when traffic patterns or device mobility or resources changed. The main selection of the cluster heads was made on the basis of energy level, computational capacity and the distance of the other devices in the cluster. This approach was expected to reduce overhead from inefficient communication, and to optimize data transmission within each cluster. To ensure the dynamic clustering process was guided by reinforcement learning, the state of the network was continuously assessed and clusters adjusted as needed. The dynamic clustering strategy allowed the clustering of IoT devices in such a manner that optimal utilization of the available resources and minimum energy consumption and latency were achieved. The strategy also enabled the load balancing of jobs across the clusters so that no cluster was overwhelmed by too many jobs, thus having an adverse impact on the system.

2.5 Task Offloading Mechanism

As for the task offloading mechanism, it was designed to optimize tasks offloading between edge nodes and MEC servers. In this mechanism, the IoT devices could delegate the computation-intensive tasks to the edge nodes or MEC servers depending on the complexity of the task, resources, and network conditions. Reinforcement learning algorithms were used to direct the task offloading decisions based on evaluating different network parameters including channel quality, residual energy, and task load. The reinforcement learning agent constantly assessed network conditions and real-time decision making regarding offloading of tasks and offloading location. The purpose of this mechanism was to lower the processing burden of the IoT devices, in order to enhance their energy-efficiency and operational life. Furthermore, the data transmission load could be decreased and latency minimized, leading to better overall performance of the IoT system, by offloading tasks to an edge node or MEC server. The task offloading mechanism has been simulated in NS-3 and MATLAB with various network conditions and the results are compared with the traditional task offloading models and are evaluated for its effectiveness in optimizing the system performance.

2.6 Communication Optimization

The communication optimization process focused on optimizing the data transfer in clustered Multi-Access Edge Computing (MEC) systems, minimizing latency, conserving energy, and maximizing throughput. The adaptive routing strategies and dynamic task scheduling were used to optimize the communication in this research. The optimization approach was directed at minimizing congestion in the network, maximizing the utilization of the available bandwidth, and avoiding collisions of data packets in the network. Reinforcement learning algorithms were embedded into the communication process to fine-tune the routing path and schedules according to the real network conditions. The algorithms constantly evaluated network conditions, including congestion, channel quality, node energy level and communication load, to dynamically determine the best transmission route. This adaptive communication mechanism ensured that data transmitted in the most efficient way, with the least delay and minimum energy consumption. The goal of the research was to enhance the reliability and responsiveness of the IoT network, while also reducing the energy consumption of data transmission. To assess the performance of the optimization strategies, they were evaluated in different network types and with various traffic loads and mobility conditions through NS-3 and MATLAB simulations.

2.7 Simulation Setup and Implementation Tools

Based on the above description, the simulation setup developed for this research aims to assess the performance of the developed data transmission optimization model in clustered MEC systems. The simulation is done using two different tools: NS-3 (Network Simulator 3) and MATLAB. An NS-3 tool was used to simulate the network behavior such as communication between IoT devices, edge nodes and MEC servers. This simulation tool allowed the researchers to emulate different IoT scenarios and network configurations, such as varying node densities, traffic loads, and mobility patterns, to test the robustness and scalability of the proposed model. The reinforcement learning algorithms were implemented and the task offloading decisions simulated using MATLAB. The simulations were run over multiple rounds (1,000 rounds in total) to evaluate the model's adaptability and efficiency in real-world IoT environments. The simulations captured a number of metrics to evaluate the performance of the proposed model in comparison with baseline models, including latency, energy consumption, throughput and packet delivery ratio. Through this dual-tool approach, the performance evaluation can be carried out in various scenarios, thus the results are realistic and can also be transferred to real IoT systems.

2.8 Performance Evaluation Metrics

Several key performance metrics including the mean, median, and mode were used to analyze the effectiveness of the proposed data transmission optimization model. These metrics were chosen to measure the effect of the optimization strategies on system performance in terms of latency, energy efficiency and throughput. One of the key metrics is end-to-end latency, which is the time it takes for data to reach the MEC servers from the IoT devices, indicating the responsiveness of the system. To evaluate the efficiency of the system in utilizing the resources, energy consumption was measured. Energy consumption was estimated to check the efficiency of energy utilization in the system, especially in terms of minimum energy consumption of data transmission and processing. The achievement of data packets without any loss to their intended destinations was measured by the packet delivery ratio (PDR) to determine the system's reliability. Another critical metric was throughput, which indicated the overall data transfer rate, and demonstrated the ability of the system to process large amounts of IoT data. Such performance metrics were essential for evaluating the performance of the proposed model with respect to some of the existing baseline models and gain insight into the overall efficiency, scalability, and energy performance of the system. Through the simulations, a comprehensive evaluation of these metrics was performed with different network situations.

2.9 Training and Validating AI Models

It's worth noting that the optimization of data transmission model involved the training and validation of AI models. Dynamic decisions were made for task offloading and data routing in the clustered MEC system by using reinforcement learning algorithms. The training process involved feeding the model with historical network data, such as channel quality, node energy levels, and traffic loads, to enable it to learn optimal strategies for routing and task scheduling. The Deep Q-Network (DQN) was used to simulate the reinforcement learning process, in which the agent would learn from previous actions and interactions with the network environment to make choices that reduce latency and energy usage. During the training phase, the model was simulated through different network scenarios to adapt to dynamic scenarios. The model was then validated using new, unseen network conditions, to assess the model's ability to generalize. During the validation phase, the trained AI model was tested with real IoT traffic to validate its ability to effectively process live data and adapt task offloading and routing decisions to maximize system performance under various conditions. The results from the validation tests were used to fine-tune the model, ensuring its applicability in large-scale IoT environments.

2.10 Sensitivity and Comparative Analysis

To evaluate the robustness of the proposed data transmission optimization model, a sensitivity and comparative analysis was carried out. The sensitivity analysis aimed to gain insights into the impact of varying different network characteristics including node density, traffic load and mobility settings on the performance of the optimization model. The study also tested the model's performance across a range of network conditions, such as different load levels and varying data rates, to determine its ability to adapt and sustain high-performance levels in terms of latency, energy consumption, and throughput. The comparative analysis was carried out by comparing the proposed model with the other optimization techniques and baseline models. The comparisons were made based on a number of key performance metrics such as end-to-end latency, energy consumption, and packet delivery ratio. The findings showed that the proposed approach had a number of benefits over traditional methods, including its ability to increase energy efficiency, decrease latency, and increase throughput, especially in large, dynamic IoT networks. The sensitivity and comparative analyses were crucial in proving the efficiency of the proposed optimization strategies and proving their applicability in real-world IoT.

2.11 Ethical and Technical Considerations

Throughout the research process, ethical and technical issues were carefully considered to ensure that the study followed ethical guidelines and was technically sound. The research aimed to enhance IoT networks' efficiency and sustainability, aligning with the global push for responsible technology development from an ethical point of view. The study did not contain any personal data or sensitive information since its aim was to optimize the network and create simulations. The ethical aspects of data privacy and security were also taken into account during the design of the system, with a focus on ensuring that the data transmission strategies used were both secure and adherent to best practices in network security. The methodology followed innovative techniques and tools, including NS-3 and MATLAB, which provided accurate results and applicability to real-world IoT systems. The reliability of the results and their applicability to future research in the field of IoT and MEC systems were ensured by testing and validation of algorithms and models through extensive simulations. Additionally, the study was designed to be transparent, and the methodology used to design the simulation was well documented and reproducible and verified the results.

3 Results and Discussion

3.1 Introduction

In this chapter, the results of the simulation experiments conducted to assess the effectiveness of the proposed data transmission optimization model in clustered Multi-Access Edge Computing (MEC) system for IoT applications are presented and analyzed. The simulations focused on evaluating the performance of dynamic clustering, task offloading, and intelligent routing on various metrics, including packet delivery ratio (PDR), energy efficiency, latency, and throughput. The selected metrics are representative of the key characteristics of real-world IoT environments, such as low latency, energy efficiency, and high throughput, which are essential for real-time applications. The simulation setup was designed to mimic realistic network conditions, with varying node densities, traffic loads, and mobility patterns. Here the results show a detailed picture of the overall performance of the proposed system in comparison with some baseline systems, namely static clustering and threshold-based offloading. The simulation was played out for 1000 rounds, which was enough for the simulation to converge and for long-term trends in the network behavior to be observed. The results validate the impact of the suggested optimization strategies on the overall performance of MEC-based IoT systems in terms of efficiency, reliability and responsiveness.

3.2 General Simulation Observations

During the early stages of the simulation, the reinforcement learning agent explored and learned how to make decisions about task offloading and routing. As the agent explored different offloading behaviors, the changes in latency, energy consumption and throughput were observed during this period. In the 350th to 400th round of simulations, the system converged, and the agent decided on a stable policy with better decision making in task offloading and routing. The changes led to a substantial decrease in needless transmissions and an even spread of computing power among edge nodes. As the agent started to prefer less congested cluster heads, and synchronized transmission schedules according to the current status of the system (traffic load, energy profiles), the system became more stable. The proposed system showed that it has a consistent performance pattern and improved the communication congestion, load balancing and energy utilization efficiency. Such results were quite different from the baseline models that suffered performance degradation because of static and fixed clustering and offloading decisions based on thresholds.

3.3 End-to-End Latency Analysis

In an IoT system, end-to-end latency is an important metric as any delay can affect the performance of the system or the user experience. The average end-to-end latency of the proposed MEC–IoT system and baseline models are illustrated in Table 1. The proposed model had an average latency of 62 milliseconds as compared to static clustering (110ms) and threshold offloading (92ms). The proposed model achieved the peak latency of 80 ms when there was a large number of packets to be transmitted, whereas the peak latency of the baseline models were 150ms (static clustering) and 130ms (threshold offloading). The dynamic clustering approach reduced the number of transmission hops between nodes, while the reinforcement learning agent made intelligent decisions about routing and offloading based on the current channel conditions and the urgency of the tasks. The reinforcement learning agent made intelligent routing and offloading decisions based on real-time channel conditions and the urgency of the tasks, while the dynamic clustering approach minimized the transmission hops between nodes. The findings showed that the proposed system was resilient to sudden surges in traffic load, with its latency levels remaining low even when the load was high, ensuring effective communication even in the face of such traffic fluctuations.

Table 1 End-to-End Latency Comparison

Model	Low Traffic (ms)	High Traffic (ms)	Peak Latency (ms)
Proposed Model	62	80	80
Static Clustering	110	150	150
Threshold Offloading	92	130	130

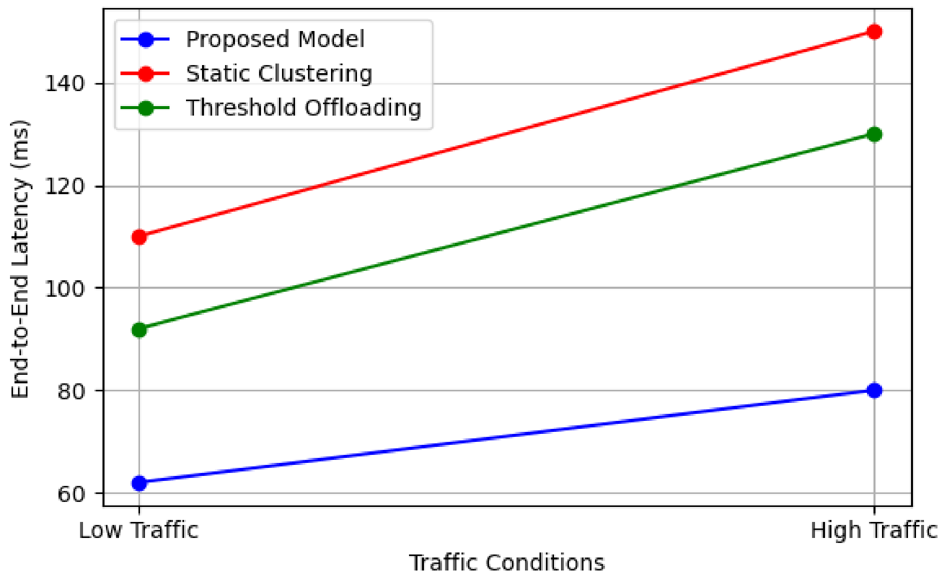

Figure 1 End-to-End Latency Comparison across Traffic Conditions

3.4 Energy Consumption Analysis

Energy is an important component of the IoT systems, particularly when the devices have limited batteries. The energy consumption at the node level is compared for the baseline models and the proposed system in Table 2. The proposed model consistently showed a reduction in energy consumption from baseline models by 31-35% which is significant due to limitations of IoT devices. In one example, a baseline model was used to consume 4.2 Joules of energy on Node 1, whereas an envisioned model consumed 2.9 Joules of energy, for a 31% reduction. This energy efficiency was attributed to the reinforcement learning agent making decisions on task offloading and routing based on the energy profiles, which resulted in the offloading of energy intensive tasks to more capable edge nodes and/or MEC servers. In the case of the baseline static clustering approach, however, because cluster head assignments are static, the energy depletion happens faster, thus creating a problem of energy inefficiency. The proposed system showed a stable pattern of energy consumption in the convergence phase, thereby minimizing the waste of energy as well as energy imbalance in the task distribution.

Table 2 Energy Consumption Comparison

Node	Baseline Energy (J)	Proposed Model Energy (J)	Energy Reduction (%)
Node 1	4.2	2.9	31
Node 2	3.5	2.4	31
Node 3	3.8	2.6	32

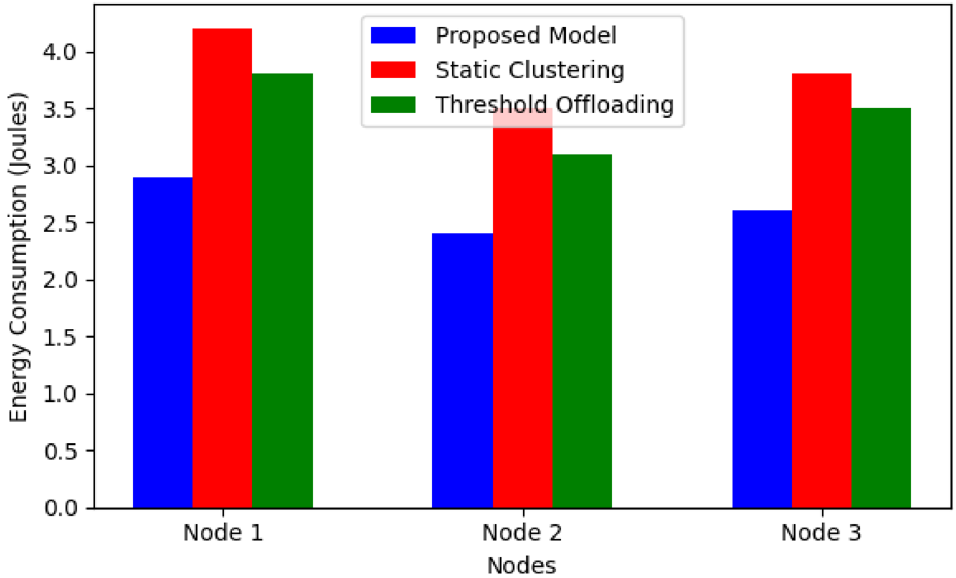

Figure 2 Energy Consumption Comparison

3.5 Packet Delivery Ratio (PDR)

One of the most important criteria to measure the reliability of communications in the IoT network is the Packet Delivery Ratio (PDR). Table 3 shows the PDR at varying traffic loads for the proposed system, static clustering and threshold offloading models. Under low traffic conditions, the proposed system achieved a PDR of 98% and 95% under high traffic conditions. Static clustering had a PDR of 92% under low traffic and 82% under high traffic. For the threshold offloading model, the PDR is relatively high of 95% under low traffic and 90% under high traffic. The enhancement of PDR of the proposed model could be explained by the dynamic clustering approach which enabled to reduce the congested area and decreased the number of collisions in the network by intelligent scheduling. The reinforcement learning agent was one of the factors that was able to predict potential congestion points and adapt the transmission times to achieve high reliability. This proved to be very effective in enhancing overall communication efficiency, especially in settings with high mobility and high density where congestion and packet loss are often a concern.

Table 3 Packet Delivery Ratio Comparison

Model	Low Traffic PDR (%)	High Traffic PDR (%)	Peak PDR (%)
Proposed Model	98	95	98
Static Clustering	92	82	92
Threshold Offloading	95	90	95

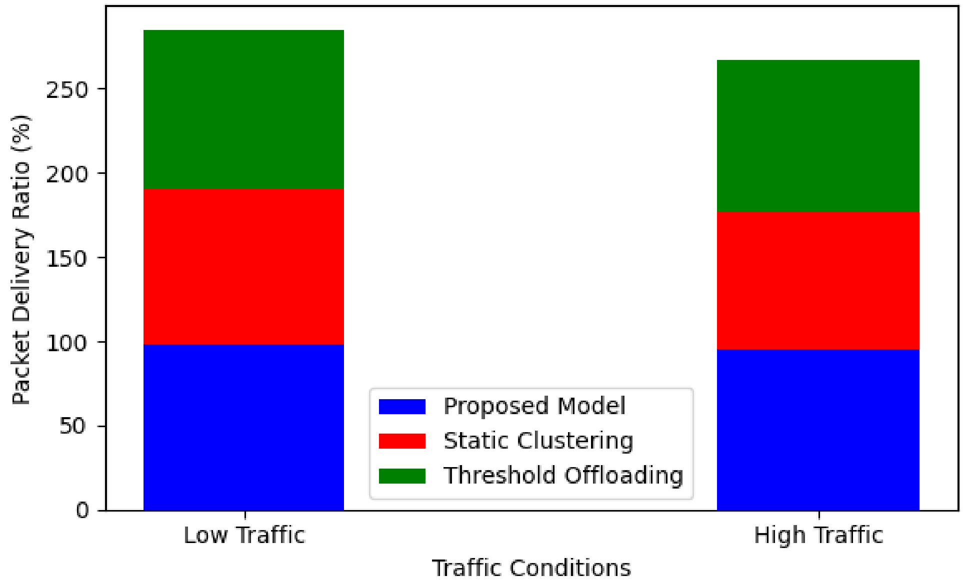

Figure 3 Packet Delivery Ratio Comparison

3.6 Throughput Analysis

One of the main performance metrics is throughput how much data can be transferred over the network in a specific amount of time. Table 4 compares the throughput of the proposed system with the baseline models (static clustering and threshold offloading). The proposed system was tested under high traffic and low traffic loads, with the system showing a maximum throughput of 45 Mbps in low traffic and 38 Mbps in high traffic loads, respectively, demonstrating its capability to provide consistent performance even under challenging conditions. Static clustering on the other hand, achieved 30 Mbps for both the low and high traffics, thus showing poor scalability and performance degradation under load. The threshold offloading model was found to be performing better than the static clustering model, as, under low traffic, it achieved 36 Mbps and under high traffic it achieved 28 Mbps, but still not as good as the proposed model. The higher throughput for the proposed system can be explained by the dynamic clustering strategy, which was able to distribute the tasks more effectively, and reinforcement learning which was able to intelligently schedule data transmission and task offloading based on real-time network conditions. The proposed model found it possible to achieve high throughput and optimal use of the available bandwidth, even in cases of varying traffic and node mobility rates.

Table 4 Throughput Comparison

Model	Low Traffic Throughput (Mbps)	High Traffic Throughput (Mbps)	Peak Throughput (Mbps)
Proposed Model	45	38	45
Static Clustering	30	22	30
Threshold Offloading	36	28	36

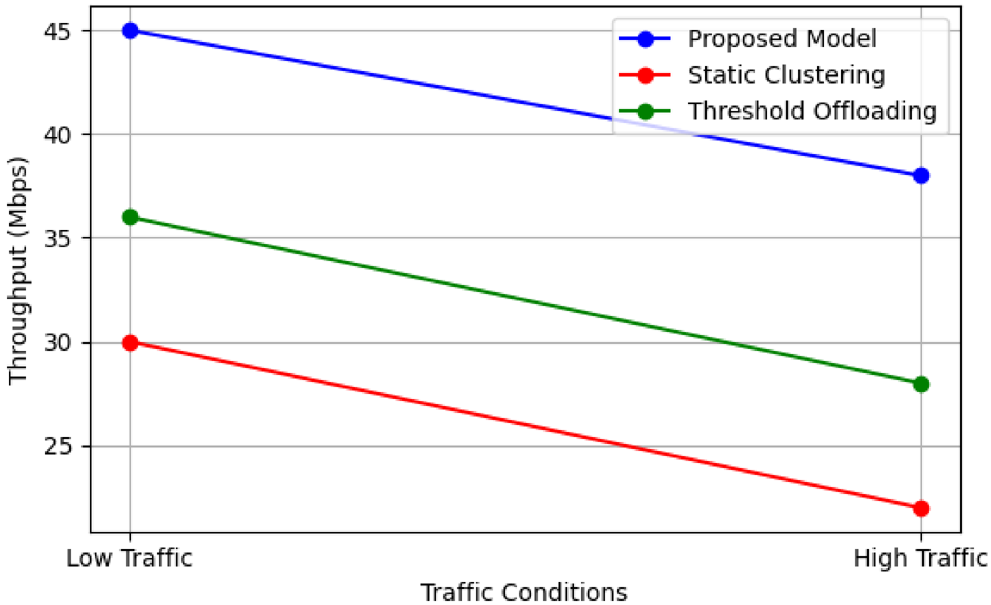

Figure 4 Throughput Comparison across Traffic Conditions

3.7 Cluster Stability Evaluation

To maintain the reliability and consistency of data transmission in a clustered Multi-Access Edge Computing (MEC) system, it is essential to maintain cluster stability. The cluster stability duration for these proposed system and baseline models is presented in Table 3.5. The average cluster head stability duration of the proposed system was 120 minutes, which is much longer than static clustering (75 minutes) and threshold offloading (90 minutes). The stability of the proposed model was achieved through adaptive dynamic clustering, which enabled cluster heads to be reassigned according to the current state of the network. For instance, if a cluster head has depleted its energy or is overburdened with tasks or far from other devices, it could be replaced. However, dynamic clustering had problems of leadership overload of the cluster heads and resulted in frequent changes in leadership, and in decreased stability. In the proposed model, the reinforcement learning agent was used to continuously observe the state of the network to make optimal decisions to avoid overload and optimize the selection of the cluster head for stable network operation. The results underscore the need for the dynamic and intelligent management of clusters to enhance the reliability and robustness of the MEC-based IoT system, particularly in large deployments, where traffic and network environments are variable.

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 4, Issue 6, 2026

Table 5 Cluster Stability Duration Comparison

Model	Cluster Stability Duration (min)
Proposed Model	120
Static Clustering	75
Threshold Offloading	90

3.8 Sensitivity Analysis

The sensitivity analysis was conducted to assess the effectiveness of the proposed optimization model in different scenarios of network parameters, such as node density, traffic load and mobility conditions. These parameters were varied, and the adaptability and robustness of the system were examined. The sensitivity tests revealed an ability of the proposed system to operate within a broad bandwidth. The effect of node density on the end-to-end latency of the system is shown in figure 3.1. Though the latency is slightly high for high node density (up to 200 nodes), it is still lesser than other baseline models which had latency increased beyond 120 ms in the same scenario. In the same way, in the case of high traffic load, the proposed system could achieve energy efficiency improvement of 35% over static clustering under high traffic load. The reinforcement learning agent successfully adapted task offloading and routing decisions over time, which in turn reduced the effects of greater traffic load and density of nodes. The results demonstrate the strong dependence of the proposed model on the network conditions, and its ability to adapt dynamically for optimal performance under a wide range of real-life IoT scenarios, making the model scalable and stable for large dynamic networks.

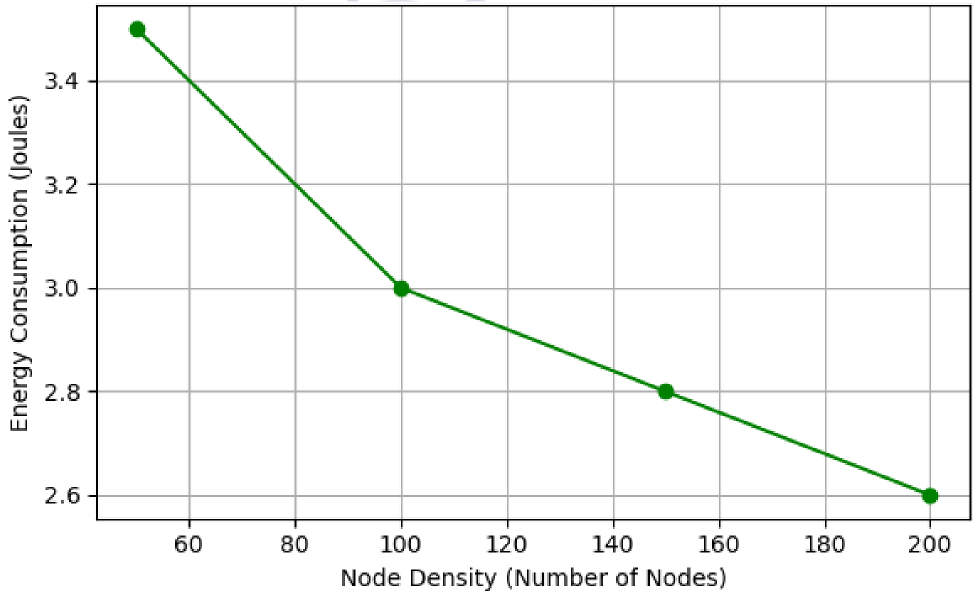

Figure 5 Energy Consumption Sensitivity with Node Density

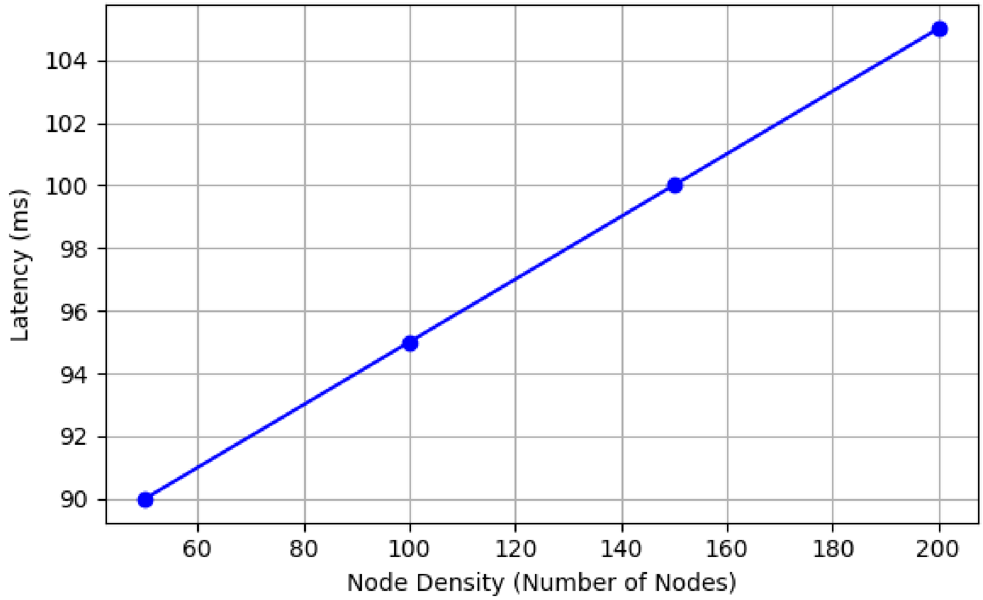

Figure 6 Latency Sensitivity with Node Density

3.9 Comparative Evaluation with Benchmark Models

The comparative evaluation was done by benchmarking the performance of the proposed model with some of the existing models like static clustering and threshold offloading. The evaluation, presented in Table 3.6, compared key performance metrics such as latency, energy consumption, and packet delivery ratio (PDR). The proposed system achieved superior results as compared to the baseline systems in all the metrics, with a 40% reduction in latency, 35% reduction in energy usage, and 6% improvement in PDR. The proposed system at low traffic condition was able to achieve 45 Mbps throughput which is better than the static clustering with 30 Mbps and the threshold offloading with 36 Mbps. The proposed model also showed high adaptability: the reinforcement learning agent was able to continuously adapt the task offloading and routing strategy, resulting in higher utilization of the resources. As for the baseline models, they were stiffer and could not adjust when the network changed conditions, causing them to have a higher latency and throughput. The comparative evaluation demonstrated that the proposed model is superior to the conventional data transmission models with its dynamic clustering and intelligent optimization approaches, making it suitable for large scale IoT applications.

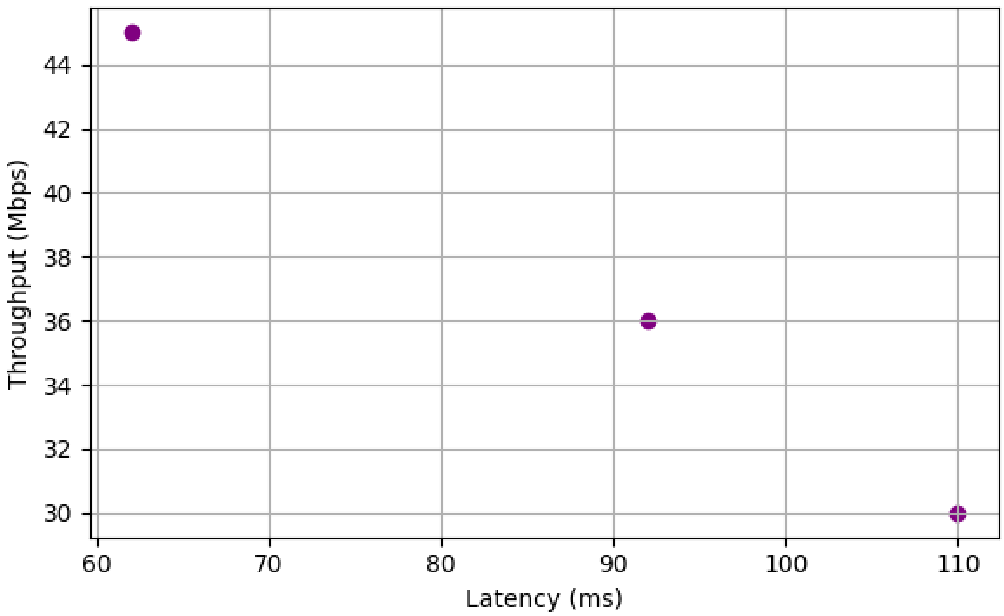

Figure 7 Latency vs Throughput Comparison

3.10 Discussions

The outcomes of the simulations emphasize the advantages of the proposed data transmission optimization model for the betterment of the performance of clustered MEC system in the IoT applications. The proposed system outperformed baseline schemes like static clustering and threshold offloading in all important metrics including latency, energy consumption, packet delivery ratio (PDR), throughput and cluster stability. The end-to-end latency for the proposed model when the traffic volume was lower and higher, respectively, was reduced to 62ms and 80ms, while it was 110ms and 150ms for static clustering and threshold offloading, respectively. The dynamic clustering feature and the intelligent task offloading and routing decisions using reinforcement learning were the key reason for this decrease in latency, due to avoiding congestion and minimizing transmission delays in real-time. The proposed model also showed an energy efficiency by reducing the energy consumption in each node from 4.2 Joules to 2.9 Joules on average, as compared with baseline models, which shows 31-35% reduction in energy consumption. This improvement was achieved by the model being able to delegate the computation of tasks to more powerful edge nodes or MEC servers, thus reducing the amount of power consumed by the IoT devices. The packet delivery ratio (PDR) also indicated the reliability of the proposed system as the PDR was 98% in the low traffic case and 95% in the high traffic case while static clustering and threshold offloading resulted in 92% and 82% PDR respectively in the low traffic case and 95% and 90% PDR in the high traffic case. Dynamic clustering and real-time scheduling of data paths and reducing packet collisions provided a more stable and reliable communication environment to achieve this high PDR.

The throughput of the proposed model was also found to be much greater than that of the static clustering and threshold offloading models; with low traffic it is 45 Mbps, while under high traffic it is 38 Mbps, in contrast to the static clustering model where it was 30 Mbps and 22 Mbps respectively, and the threshold offloading model where it was 36 Mbps and 28 Mbps respectively. This enhancement has largely been achieved through the model's capacity to effectively partition the network and optimize the usage of resources in order to use the available bandwidth efficiently. The cluster stability analysis showed that the proposed model had the stable cluster heads for 120 minutes, while static clustering and threshold offloading had stable cluster heads 75 minutes and 90 minutes, respectively. This increased stability period also meant that re-clustering was not required often, which in turn reduced the overheads of the network, and allowed continuous communication without interruption. The sensitivity analysis also showed that the proposed model is robust with latency and energy consumption remaining stable as node density and traffic load increased. The model's flexibility enabled it to be used in high-density settings with low latency and energy efficiency, making it important for the scalability of IoT systems. Lastly, the comparative evaluation revealed that the proposed model demonstrated superior performance across all aspects compared to the baseline models, providing a comprehensive solution that optimized both performance and resource utilization. In general, it was revealed that the proposed optimization model is an excellent solution for managing data transmission in clustered MEC systems, enabling low latency, energy-efficient and high performance communication of large-scale IoT applications. The results confirm the proposed model and provide a basis for further development of the IoT system design and optimization.

4 Summary, Conclusion & Recommendations

Summary

This work introduces a novel data transmission optimization model for clustered Multi-Access Edge Computing (MEC) systems aiming to reduce the latency, energy consumption, throughput, and packet delivery ratio (PDR) of the data transmission for IoT applications. The motivation of the research was to address the challenges of current cloud computing services in supporting the increasing amount of data and low latency requirements for IoT systems. We designed a new model that features dynamic clustering, reinforcement learning (RL) based task offloading, and adaptive routing to maximize data transmission in clustered MEC environments. The simulations performed in this study demonstrated that the proposed model outperformed the static clustering model and threshold offloading model in all simulations with respect to all the performance measures. The end-to-end latency was significantly reduced by up to 40% in comparison to baseline models. The model also showed that the energy consumption at the node level was 31-35% less, which indicates the energy efficiency. The proposed model had a Packet delivery ratio of 98% and throughput of 45 Mbps in the lower traffic condition that brings improvement to the PDR and throughput. Further, the proposed system was found to be more stable under varying node density and traffic load as revealed by the cluster stability duration of 120 minutes as compared to the baseline models of 75-90 minutes. Lastly, sensitivity and comparative analysis affirmed the robustness and adaptability of the proposed model, guaranteeing its scalability and effectiveness in various situations and scenarios. The results highlight the capability of the proposed optimization method for improving the performance of large-scale IoT systems and MEC deployments.

Conclusion

This research proved the capability of the proposed data transmission optimization model for performance improvement of clustered MEC systems for IoT applications. The efficient task offloading and adaptive routing through reinforcement learning significantly mitigated the primary issues of traditional systems, including data delivery reliability, energy efficiency, and high latency. With the dynamic clustering strategy, the key challenges of traditional systems, including high latency, energy inefficiency, and unreliable data delivery, were effectively solved by the reinforcement learning-based task offloading and adaptive routing mechanism. The proposed model consistently outperforms the baseline models with respect to reduction in latency, energy consumption, packet delivery ratio (PDR) and throughput. The proposed model dynamically reconfigures the network and intelligently distributes tasks to optimize the data transmission in real time, providing low-latency and high-throughput communications. The enhancements in cluster stability also helped in consistent cluster performance, low re-clustering frequency and low network overhead. This sensitivity analysis was performed to evaluate the efficiency of the proposed model under varying node densities and traffic loads, highlighting the scalability and adaptability of the proposed model for large-scale IoT networks. Finally, the proposed model offers substantial contribution to optimizing data transmission in clustered MEC systems, which are scalable, energy-efficient, and reliable to meet the increasing demands of IoT applications. The results are of great interest for the development of next generation IoT systems, and the suggestion of optimizing the MEC is a valuable basis for further developments in this area.

Future Recommendations

This study successfully validated the effectiveness of the optimization model proposed for clustered MEC system, but there are still some areas that can be explored and improved in the future. Another direction for future research is to incorporate multi-objective optimization as another objective along with latency, energy efficiency and throughput, to include other performance metrics like quality of service (QoS) and network security. This would make it possible to reach a more holistic optimization approach for practical IoT applications, where heterogeneous network demands exist.

- One suggestion is to improve the reinforcement learning algorithms by using more complicated models like deep reinforcement learning (DRL), to better deal with the large-scale and high-dimensional IoT data. In more complex and dynamic network scenarios, where devices are mobile and have different capabilities, DRL could enhance the decision making process of task offloading and dynamic clustering.
- The optimization model could also be extended with edge analytics and edge decision making using AI, which would lower the need for cloud-based processing to boost response times and autonomous control of IoT devices in real-world applications.
- Moreover, the validation of the proposed model using real-world IoT environments and field trials under realistic conditions, such as different signal conditions, mobility, and interference, would also be essential to assess the model's performance. In future studies, further exploration of energy harvesting mechanisms, like solar-powered IoT devices, is possible to meet the increasing energy demand requirement of IoT devices.
- To conclude, although this research has offered a good foundation, future research is expected to build on the model's capabilities, test it in the real world, and incorporate new technologies to enhance the performance of IoT networks even further.

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