

Original Article

Optimizing Dynamic Bandwidth Allocation for IoT Devices with Machine Learning Algorithms

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Abstract - The immense increase in the Internet of Things (IoT) has posed a formidable problem in the effective implementation of bandwidth allocation for a broad and vast system of devices. Conventional Dynamic Bandwidth Allocation (DBA) strategies are not very effective in optimizing network throughput, especially where there are many devices and their traffic patterns are both heterogeneous and highly dynamic. The current paper suggests a model of Enhanced Dynamic Bandwidth Allocation (EDBA) that uses machine learning algorithms in predicting bandwidth demand and dynamically allocating resources. The model proposed applies the algorithm techniques of clustering IoT devices according to bandwidth usage patterns, which is then used to predict on-demand bandwidth needs using machine learning algorithms like linear regression. Simulation experiments prove the EDBA technique to be much more effective in enhancing the main Quality of Service (QoS) metrics, including throughput, latency and packet loss in comparison with the other conventional dynamic bandwidth allocation strategies. The findings reveal that, through machine learning integration, there is efficient bandwidth use, there is minimized network congestion, and there is high-quality service provision, despite the fluctuation of network conditions. This will offer a flexible solution to scale in line with the expanding needs of the 21st century IoT systems.

Keywords - Dynamic Bandwidth Allocation, IoT, Machine learning, Quality of Service (QoS), Bandwidth prediction, Clustering, Regression, Network optimization, Throughput, Latency, Packet loss, and Scalability.

1. Introduction

Internet of Things (IoT) is a phenomenon whose growth has been exponentially increasing in recent times, transforming industries as it interconnects billions of devices around the globe. The IoT devices will exceed fifty billion by 2030, and their applications will be in different fields of use, including healthcare, agriculture, transport, and smart cities [1]. The difficulty in controlling network resources and bandwidth in particular, increases with each device going online [2]. The feature of IoT networks is the heterogeneity of devices with varied communication requirements, which may be simple sensors with small data flows and complex systems with high-definition video [3]. This heterogeneity, together with uneven traffic conditions and a growing number of connected devices, puts a huge burden on the available network infrastructure [4]. Consequently, Quality of Service (QoS) that comprises the need to guarantee low latency, high throughput and small packet loss may be difficult in a large-scale IoT setting [5].

Priority-based and delay-based approaches, which are traditional approaches of Dynamic Bandwidth Allocation (DBA), have been used in managing bandwidth in the IoT systems [6]. The ways of allocation or scheduling are priority-based in that high-priority devices receive larger bandwidth allocation and delay-based in that high-latency applications are reduced to minimize their latency. The approaches, however, have a number of limitations. They do not usually take into consideration dynamic traffic variation, hence failing to utilize or overutilizing the available bandwidth. Besides, the heterogeneous character of IoT devices is not very responsive in these methods [7], which presents inefficiencies, particularly when a large number of devices with different traffic requirements are involved [8]. Another major concern is the scalability of the traditional DBA methods that are usually made in the scale of static or limited networks, and thus cannot be used to meet the increasing needs of the IoT ecosystems [9].



The advent and proliferation of the Internet of Things (IoT) has led to the proliferation of IoT-based communication environments or platforms that support a large number of IoT devices. These IoT devices continuously send and receive data, thus there is a continuous flow of traffic or packets in IoT networks. This traffic is of various types, such as periodic sensing data, event-driven messages, real-time multimedia data, alert messages and control signals. Most importantly, the amount of such traffic or the rate at which these packets are generated varies greatly. With a huge amount of sensor data being generated continuously, there is a huge competition for limited bandwidth resources. Allocating or sharing available bandwidth amongst a huge number of contending IoT devices has therefore become a big challenge to manage or operate IoT networks efficiently. In general, the traditional methods for the DBA in the IoT networks are mostly based on the static priority, fixed scheduling, queue-length and traffic monitorization in a reactive way. However, these traditional methods fail to efficiently manage the bandwidth as the number of IoT devices increases and the traffic patterns become more dynamic.

The main challenge for the future IoT networks is to predict the future bandwidth demand in order to efficiently manage the bandwidth and avoid congestion, delay, packet loss, etc. Many approaches have been introduced to tackle the resource allocation in communication networks, including IoT networks, by utilizing artificial intelligence, SDN, reinforcement learning and traffic prediction. For instance, traffic prediction in SDN can be utilized for network resource planning and management in advance. Moreover, many recent approaches have been proposed to improve the routing in networks by using reinforcement learning in order to increase the network's throughput, improve the resource utilization and increase the number of services that can be provided by the network. However, there are many approaches that deal with traffic prediction, routing and resource allocation as separate tasks for improving the IoT networks' performance, and thus, these approaches cannot be combined to form an integrated framework for improving the IoT networks' performance. Therefore, there is a need for an integrated framework for improving the IoT networks' performance, which deals with the classification of IoT devices' behavior, the prediction of the bandwidth demand of the IoT devices and the allocation of the bandwidth in the IoT networks in an adaptive manner. There is a need for a simple, scalable and predictive dynamic bandwidth allocation model that groups devices and predicts their future bandwidth demands, and then allocates the bandwidth on an as-needed basis. In order to address this need, an Enhanced Dynamic Bandwidth Allocation model is proposed. This model groups the devices in the IoT network based on their bandwidth usage behavior, uses machine learning for the bandwidth demands of the devices in each group to be predicted, and then uses the predicted demand for the dynamic allocation of bandwidth on an as-needed basis within the network.

The model uses a combination of clustering for classification of the behavior of IoT devices and regression for the prediction of bandwidth demand. It is novel because the existing models of Dynamic Bandwidth Allocation are mainly used for dealing with current traffic, whereas the proposed model is enhanced to perform proactive bandwidth allocation. Thus, the model proposed can increase the throughput, reduce the latency, decrease the packet loss, and increase the bandwidth utilization for dealing with the dynamic traffic of IoT networks.

The main aim of the paper is to suggest a new method of dynamic bandwidth allocation with the help of machine learning methods. The paper will maximize the use of bandwidth by anticipating the on-demand bandwidth needs of the IoT devices in order to ensure that resources used are optimized. Through the use of machine learning models as a predictive tool for traffic, the proposed approach aims at maximizing network efficiency and QoS in the IoT. In this way, the issues of scalability and dynamic traffic models can be solved, and more resilient and flexible solutions to the large-scale IoT networks can be developed.

2. Literature Review

Allocating bandwidth dynamically has been a common practice in the management of bandwidth resources in the networking environment to tackle Dynamic Bandwidth Allocation (DBA). Within the setting of IoT, a number of conventional strategies have been applied so as to accommodate different device needs and network traffic [10]. Priority-based techniques assign bandwidth depending on the priority of the device, where high-priority devices or applications are given a guaranteed bandwidth [11]. Nevertheless, this style is not particularly efficient in the distribution of resources in the case of large-scale networks and heterogeneous devices with various requirements [12].

Instead, delay-based methods concentrate on the minimization of the latency of time-sensitive applications by dynamically controlling the allocation of bandwidth to give preference to the low-latency traffic. Although this approach works well in some applications, it is constrained by its inability to match changing traffic conditions and changing device needs [13].

Traffic-pattern-based approaches forecast the demand for bandwidth with reference to historical information of traffic and allocate bandwidth. Although this approach works in some instances, it is not very flexible when it comes to abrupt changes in traffic and changes in the behavior of IoT devices [14]. This has seen the necessity of more adaptive and intelligent bandwidth allocation strategies in the context of large-scale IoT networks, such that the traditional approaches can no longer support Quality of Service (QoS) in heterogeneous devices and traffic structures [15].

Machine Learning (ML) methods have been actively used to address networking issues, especially in optimal bandwidth management of IoT systems. Large amounts of data can be analyzed by ML models, and traffic patterns can be identified and bandwidth demand predicted, which provides a more dynamic solution than traditional DBA solutions. Predicting bandwidth usage through a model establishing the relation between traffic characteristics and bandwidth requirement has been applied using linear regression [16]. Decision trees and random forests introduce more advanced models of classifying devices based on the characteristics of IoT device traffic so that that bandwidth may be allocated appropriately. Moreover, it has been demonstrated that reinforcement learning could be useful in dynamically changing the resource allocation according to real-time information regarding the network and enhance efficiency and QoS. These machine learning methods offer a data-driven model of dynamic bandwidth allocation that is intelligent and more effective at managing network resources in an IoT environment. Although the dynamic bandwidth allocation processes in IoT networks experience an increase in research, the application of DBA based on machine learning is significantly missing. Although the existing approaches have been considered long, the incorporation of machine learning models to forecast and optimize bandwidth assignment is not well exploited by IoT applications. Existing literature is mainly aimed at fixed or heuristic-driven approaches, which do not take into consideration the dynamic and heterogeneous characteristics of the IoT networks. Absence of adaptive and intelligent solutions based on machine learning methods points to a major opportunity for how to enhance bandwidth allocation, on a large-scale internet of things deployment, where real-time bandwidth adaptations are the key aspect of ensuring quality of service.

Resource management and bandwidth allocation in IoT networks have been studied extensively in recent years. Static DBA number of studies have used DBA techniques for basic traffic distribution, but the static nature of these techniques makes them unsuitable for dynamic environments in which the density of devices, their traffic rates and QoS requirements change on a regular basis. As such, much of the recent work in this area has focused on the use of machine learning to predict traffic behavior in order to enable the proactive management of resources.

A number of studies have therefore looked at the use of clustering, reinforcement learning, SDN-based control and predictive bandwidth allocation in order to improve QoS in a number of different communication environments, including IoT and next-generation networks. In terms of specific applications, studies have looked at the use of adaptive machine learning-based bandwidth scheduling for IoT devices, clustering and Q-learning for optimized data aggregation in IoT networks, and the use of deep reinforcement learning for bandwidth demand-oriented routing in SDN environments. There is, however, a need for a number of future research directions, including the development of a lightweight, integrated model for clustering IoT devices, predicting their bandwidth demands, and allocating their required bandwidth on a dynamic basis.

The Table 1 compares and summarizes several recent works that are related to DBA, IoT resource management, traffic prediction, clustering and network optimization using machine learning. The table summarizes the methods, application areas, performance metrics, main contributions and also the weaknesses of the works that the proposed EDBA model aims to address.

Table 1. Summary of existing studies on dynamic bandwidth allocation and machine learning-based resource management in IoT networks

Study Area	Method Used	Application Scenario	Key Metrics	Main Contribution	Limitations and gaps identified
Adaptive ML-based bandwidth scheduling for IoT devices [4]	Machine learning-based scheduling	IoT device bandwidth management	Throughput, delay, bandwidth use	Uses ML to improve adaptive bandwidth scheduling	Limited integration of clustering and prediction in one DBA model
Predictive DBA for IoT gateway [5]	Predictive dynamic bandwidth allocation	IoT gateway communication	Delay, bandwidth demand, QoS	Predicts future resource needs based on IoT behavior	Gateway-focused; less emphasis on scalable heterogeneous device clusters
PCA and Q-learning-based IoT clustering [6]	PCA and reinforcement learning	IoT data aggregation and clustering	Energy, aggregation efficiency, network performance	Optimizes IoT clustering and data aggregation	Focuses more on aggregation than bandwidth allocation
DRL-based bandwidth demand-	Deep reinforcement learning	SDN-based communication networks	Throughput, utilization, service capacity	Improves routing and bandwidth-aware decision-	Higher computational complexity for

oriented routing [7]				making	lightweight IoT systems
Traffic prediction in SDN [10]	Deep learning-based traffic prediction	SDN traffic management	Prediction accuracy, QoS	Supports proactive resource planning	Prediction is not directly integrated with IoT DBA
Intelligent IoT resource allocation using clustering and ML [12]	Clustering and machine learning	IoT resource allocation	Resource utilization, adaptability	Combines clustering and ML for intelligent allocation	Requires further evaluation for bandwidth-specific DBA
Improved DBA for QoS in IoT [13]	Improved dynamic bandwidth allocation	IoT QoS enhancement	Throughput, latency, packet loss	Enhances QoS using improved DBA	May not fully use predictive ML-based demand estimation
Proposed EDBA model [14]	Clustering + regression-based prediction + adaptive allocation	Heterogeneous IoT networks	Throughput, latency, packet loss, bandwidth utilization	Provides proactive bandwidth allocation based on predicted demand	Future work may extend the model using deep learning or reinforcement learning

3. Proposed Method

The essence of the study is the Enhanced Dynamic Bandwidth Allocation (EDBA) model that is planned to maximize bandwidth allotment within the IoT networks. The EDBA technique is a machine learning method that forecasts bandwidth requirements based on previous traffic history as well as real-time data. The model prevents the adoption of an inadequate bandwidth, although the bandwidth needs of IoT devices may be estimated accurately and enhance the overall Quality of Service (QoS), allowing the system to work more efficiently. One of the major parts of the EDBA model is the clustering and classification of IoT devices, depending on their bandwidth usage trends. The devices can be clustered into three groups of low, medium and high bandwidth usage devices. This classification enables the improved management of the resources because the devices with similar usage patterns are managed in one way. Machine learning algorithms that can be used to classify the devices into suitable groups are the K-means clustering and the Random Forest algorithms, which use historical data and traffic attributes to put devices in the correct group. These algorithms will give the model opportunities to distinguish different groups that share similar traffic patterns, which will imply unique strategies to apply in assigning bandwidth allocation.

Figure 1 depicts the action of dynamically allocating bandwidth in an IoT network via machine learning with the aim of maximizing Quality of Service (QoS). The first stage will include the irrigation of the IoT device data yield, in which the traffic information on multifarious devices will be collected. The devices are then grouped in accordance to usage of bandwidth (low, medium, and high). The bandwidth demand of every device group is then predicted using machine learning models. Lastly, based on these predictions, dynamic bandwidth allocation is done and ensures the efficient

allocation of resources, thus improving throughput, minimized latency, and reduced packet loss, thereby enhancing QoS in the IoT network.

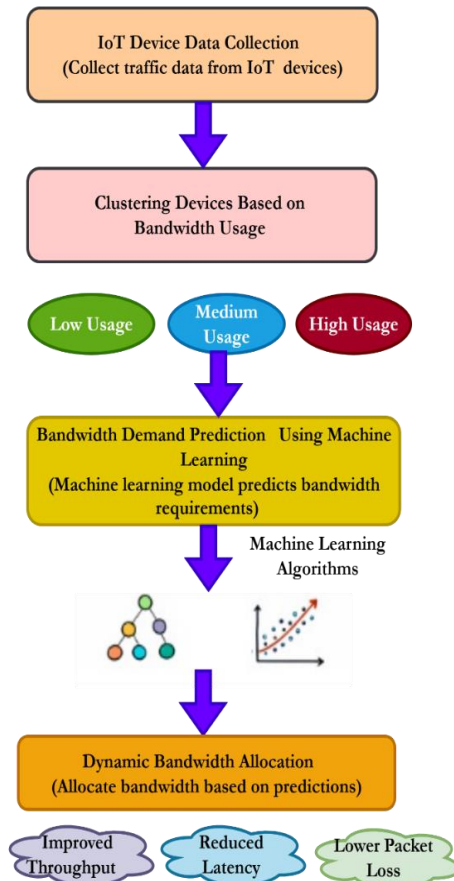


Fig. 1 IoT bandwidth allocation workflow using machine learning for optimized Quality of Service (QoS)

The procedure by which machine learning can be used to optimize bandwidth allocation in IoT networks is shown in Figure 2. It starts with the preprocessing of data, where traffic data is washed, normalized, and it is made ready to be analyzed. Clustering algorithms such as K-Means are then used to cluster the IoT devices according to bandwidth consumption. The third process is to train a machine learning model to forecast future bandwidth demand by each cluster, where regression or decision trees are used. Lastly, the

predictions on bandwidth allocation are done to make sure to efficiently utilize the network resources, minimize the latency, maximize throughput, and improve the Quality of Service (QoS) of the entire IoT network. After clustering the devices, the prediction of bandwidth allocation is done through the structuring of linear regression models or any other machine learning algorithms. These models estimate the bandwidth requirements in every cluster based on historical bandwidth usage and current network conditions.

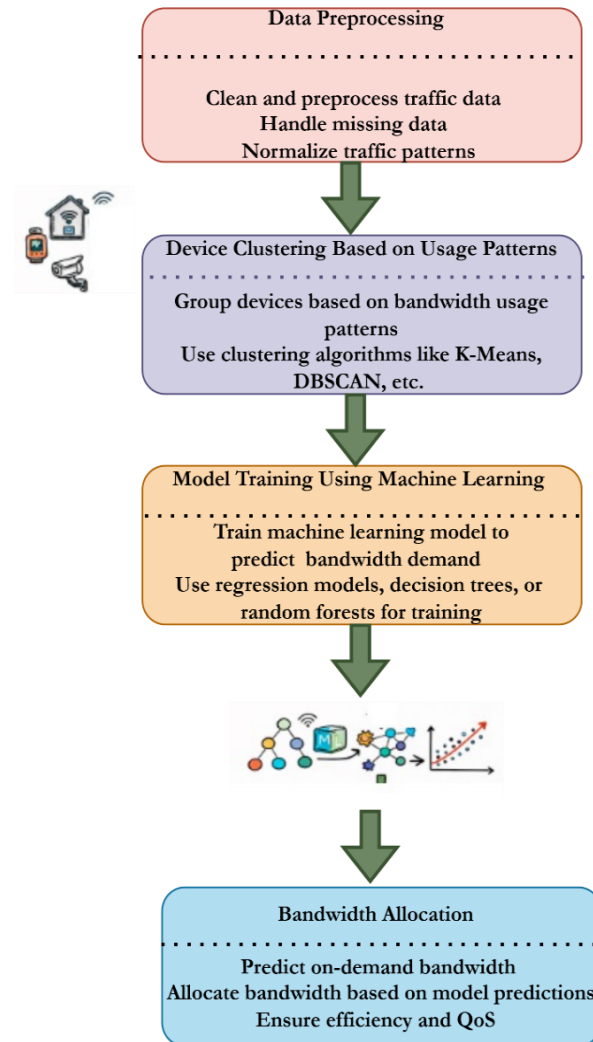


Fig. 2 Machine learning-driven bandwidth prediction and allocation process for IoT device traffic management

The EDBA method is dynamic and balances usage of the bandwidth in a dynamic manner, and ensures that the necessary devices are allotted their share without either underutilizing or overutilizing the network resources. Such dynamically changing adaptation is required in order to obtain a variable best throughput, latency, and recognizing loss of packets in a dynamically changing network environment. To determine the effectiveness of the EDBA approach, a simulation setup was designed. There were diverse types of

devices with different traffic patterns and bandwidth requirements in the simulation environment. The centralized control system was used in the network design to regulate the bandwidth allocation whenever predictions that the model had realized were made. To experiment on the effectiveness of the EDBA approach in various cases of network, the dynamics of the traffic patterns were modeled under constant, bursting, and intermittent data flows. This approach was tested with respect to such significant parameters as the latency, the throughput,

the loss of packets and the overall QoS, and the results indicated the efficiency of the EDBA approach in order to optimize the performance of the network.

3.1. Research Gap and Motivation

Dynamic bandwidth allocation for IoT networks has recently gained significant attention and has been addressed by using various approaches, such as static scheduling, priority-based or heuristic-based resource allocation, optimization, traffic prediction using machine learning, and control using reinforcement learning. Many of the current DBA approaches have several limitations, i.e., most of the existing DBA methods are static and/or reactive, and work based on the current network situation rather than future demand, thus they may face difficulty to handle sudden changes of traffic. Most of the studies that used Machine Learning (ML) for predicting the traffic in IoT networks did not link the bandwidth demand that was predicted by the model to the actual bandwidth allocation that the network has to offer.

As mentioned before, most of the studies that used Clustering for IoT networks used it for data aggregation, for routing in the network, for energy-efficient management of sensors, etc. However, the role that Clustering can play for grouping the bandwidth demand of IoT devices has not been thoroughly investigated yet. Even though Reinforcement Learning (RL) is able to perform an adaptive bandwidth allocation, the training complexity of the RL model, the time that the model needs to converge, as well as the computational resources needed by the model, are major concerns for the deployment of such a model in real IoT networks. The proposed EDBA model includes three main components in a single framework. Firstly, IoT devices are divided into clusters of similar behavior. In the second step, the future bandwidth demand is predicted on the basis of the historical features of the traffic. In the last step, the available bandwidth is allocated to the predicted demands and QoS requirements of the traffic in an adaptive manner. This single framework-based EDBA model is proactive, scalable, and appropriate for the dynamic environments of IoT.

4. Mathematical Model and Algorithms

The Enhanced Dynamic Bandwidth Allocation (EDBA) model is designed to improve the distribution of bandwidth in IoT networks through the assistance of machine learning algorithms to predict bandwidth requirements relying on past and real-time traffic data. The section gives mathematical formulation and algorithms that gives the work of the EDBA model.

4.1. Bandwidth Prediction using Machine Learning

The core of the EDBA model relies on predicting the bandwidth requirements for IoT devices based on their traffic patterns. Given a set of IoT devices $D = \{d1, d2, \dots, dN\}$ with

traffic patterns $T = \{t1, t2, \dots, tN\}$, the objective is to predict the bandwidth demand Bd for each device. This can be achieved using a regression model that predicts Bd as a function of historical traffic data.

For device d_i , the predicted bandwidth $\hat{B}_{d_i}$ is determined using a regression model such as linear regression:

$$\hat{B}_{d_i} = \beta_0 + \beta_1 T_1 + \beta_2 T_2 + \dots + \beta_n T_n$$

Where:

$\hat{B}_{d_i}$ is the predicted bandwidth requirement for the device d_i

$T_1, T_2, T_3, \dots, T_n$ Are the historical traffic data features for the device d_i ,

$\beta_0, \beta_1, \dots, \beta_n$ These are the learned coefficients from training the regression model.

This model is predictive of the bandwidth requirement. $\hat{B}_{d_i}$ that is informed by the traffic characteristics T that will assume a measurement such as an average traffic rate, a peak rate, and past bandwidth usage.

4.2. Clustering Devices based on Bandwidth Usage

After the bandwidth predictions have been done, the predictions are clustered, with the result being the grouping of the IoT devices into categories in terms of their bandwidth. The k-means clustering is used to group the devices into k clusters, in which each cluster C_k of devices would have similar bandwidth requirements. The objective of K-means is to minimize the sum of squared distances between each device's predicted bandwidth. $\hat{B}_{d_i}$ and the centroid μ_k of the cluster C_k :

$$J(C, \mu) = \sum_{i=1}^N \sum_{k=1}^K 1(d_i \in C_k) \|\hat{B}_{d_i} - \mu_k\|^2$$

$1(d_i \in C_k)$ is an indicator function that is 1 if the device d_i belongs to a cluster C_k ,

μ_k is the centroid of the cluster C_k

$\hat{B}_{d_i}$ is the predicted bandwidth for the device d_i

These are aimed at balancing the centroids. μ_k with the objective of minimizing the objective function of $J(C, \mu)$, such that the devices with close bandwidth requests are added together.

4.3. Dynamic Bandwidth Allocation

After clustering, dynamic bandwidth allocation is performed by adjusting the network resources allocated to

each device group. Given the predicted bandwidth $\hat{B}_{d_i}$ for each device in the cluster C_k , the total bandwidth requirement for each cluster is computed as:

$$B_{C_k} = \sum_{d_i \in C_k} \hat{B}_{d_i}$$

The network must allocate available bandwidth. B_{total} such that the sum of allocated bandwidth across all clusters does not exceed the total available bandwidth:

$$\sum_{k=1}^K B_{C_k} \leq B_{total}$$

The allocation of bandwidth to each cluster C_k is then determined using an optimization approach, such as water-filling or proportional allocation. For proportional allocation, the bandwidth B_{C_k} for each cluster, a proportion is allocated proportionally to its predicted demand:

$$B_{C_k}^{alloc} = \frac{B_{C_k}}{B_{total}} \cdot B_{total}$$

Where:

$B_{C_k}^{alloc}$ is the allocated bandwidth for the cluster C_k

B_{total} is the total available bandwidth.

4.4. QoS Optimization

The Quality of Service (QoS) is evaluated based on latency, throughput, and packet loss. To ensure optimal QoS, a priority-based adjustment can be applied. The priority P_{d_i} for each device can be calculated based on its predicted bandwidth demand. $\hat{B}_{d_i}$ and its traffic type:

$$P_{d_i} = \frac{\hat{B}_{d_i}}{T_{max}} \cdot W$$

Where:

T_{max} is the maximum bandwidth demand across all devices,

W is a weight factor that adjusts priority based on the traffic type (e.g., real-time traffic receives higher priority).

The final bandwidth allocation for each device d_i is then adjusted based on its priority P_{d_i} relative to the total available bandwidth:

$$B_{d_i}^{final} = P_{d_i} B_{total}$$

This final adjustment ensures that high-priority devices, such as those with real-time traffic, receive sufficient bandwidth to meet QoS requirements.

5. Algorithm

The EDDBA model is implemented in the following steps:

Step 1: Data preprocessing: Clean and prepare traffic data for analysis.

Step 2: Device clustering: Use K-means to group devices by bandwidth usage patterns.

Step 3: Bandwidth prediction: Apply machine learning models to predict bandwidth demand.

Step 4: Dynamic allocation: Allocate bandwidth to each cluster based on predicted demand.

Step 5: QoS adjustment: Optimize the allocation to meet the desired QoS criteria.

6. Results and Discussion

The Enhanced Dynamic Bandwidth Allocation (EDDBA) model is contrasted with other known techniques of bandwidth allocation, e.g. priority-based and delay-based techniques. The EDDBA model has been experimentally shown to improve the latency, packet loss, throughput, and bandwidth utilization. In Figure 3, the bandwidth allocation comparison is shown, in which EDDBA always makes better use of available bandwidth compared to standard practices used. The comparison of latency presented in Figure 4 indicates that EDDBA has a lower latency in peak demand as compared to traditional methods, which experience a higher delay in latency because the resource allocation is not optimized. Figure 5 shows the throughput performance of various methods. EDDBA has a higher throughput with different load conditions, which is important in making sure that time-sensitive IoT applications are upheld efficiently.

Figure 6 is a comparison of the packet loss, where EDDBA always has lower packet loss because it dynamically varies bandwidth allocation, whereas the conventional methods find it challenging when it comes to dealing with packet loss when bandwidth is in demand. It has been confirmed that the machine learning-based prediction model of EDDBA is robust, as the bandwidth demand prediction accuracy presented in Figure 7 provides the opportunity to allocate bandwidth proactively, depending on the predicted needs. EDDBA also achieves the optimization of bandwidth through the dynamically adjusted use of the resources to the actual demand.

Figure 8 shows the bandwidth usage with time, as EDDBA has a more stable use of network resources as compared to other mechanisms, which have high and low periods of use at different times. Such an adaptive change guarantees that the machines with high demands get adequate bandwidth, and there is no over-utilization of resources. Figure 9, the cumulative packet loss comparison over time, has emphasized how EDDBA has minimum packet loss, even at the time of high load conditions, through intelligent bandwidth allocation that reduces congestion and packet drops. This also demonstrates

the excellence of being able to sustain network productivity and QoS in an uneven state by EDDBA. The scale of EDDBA is especially obvious as the number of IoT devices expands. The comparison of the QoS metrics to dynamic load is presented in Figure 10, whereby EDDBA has performed better than the

traditional approach in terms of latency, throughput, and packet loss. Adaptive nature of EDDBA can easily be scaled when additional devices are introduced to the network, unlike traditional methods, where, as the network is increased, the performance of the network is compromised.

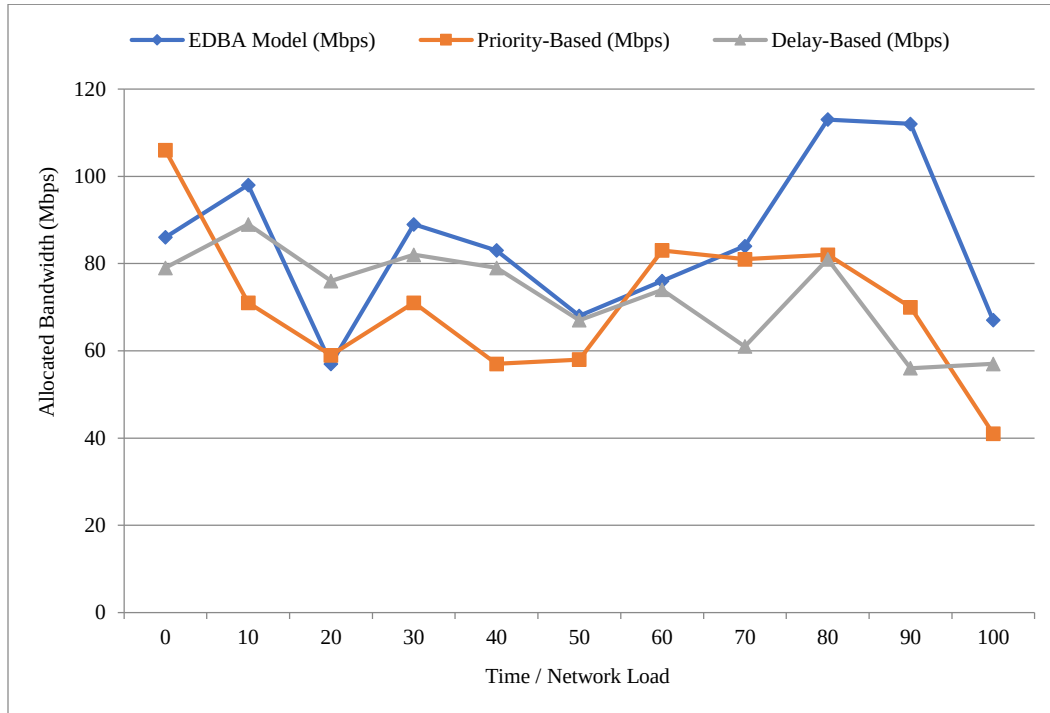


Fig. 3 Bandwidth allocation comparison (EDDBA vs. traditional methods)

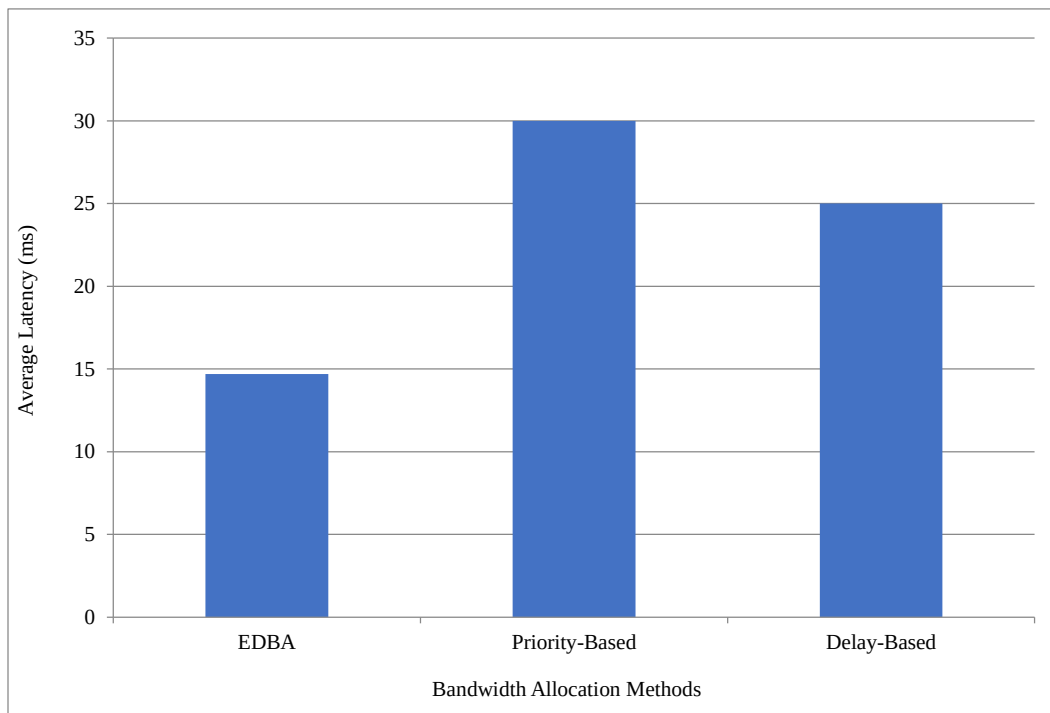


Fig. 4 Latency comparison between methods

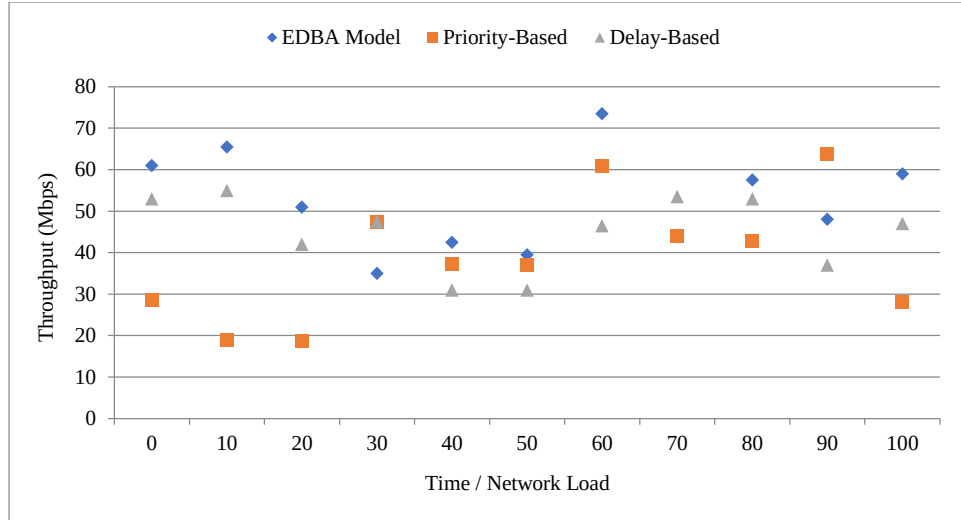


Fig. 5 Throughput performance of different methods

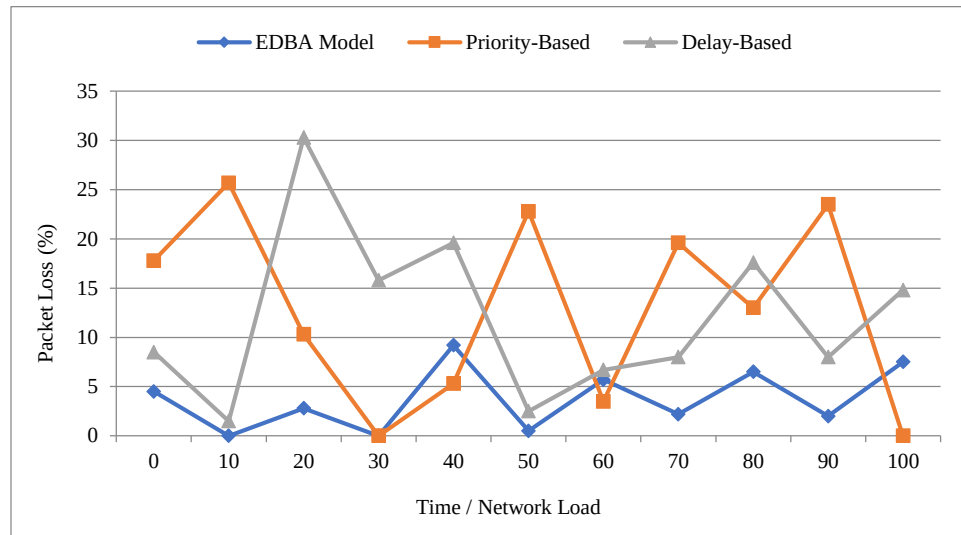


Fig. 6 Packet loss comparison for different methods

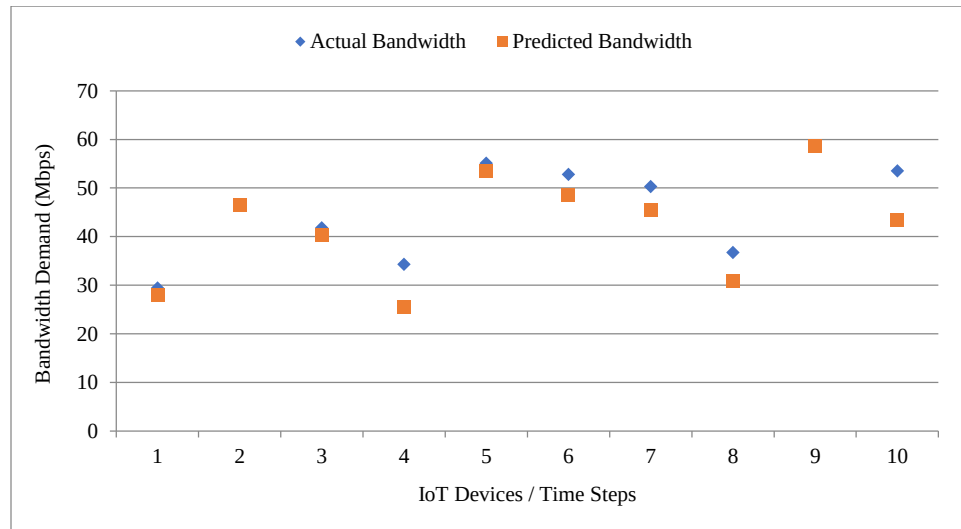


Fig. 7 Bandwidth demand prediction accuracy (ML model)

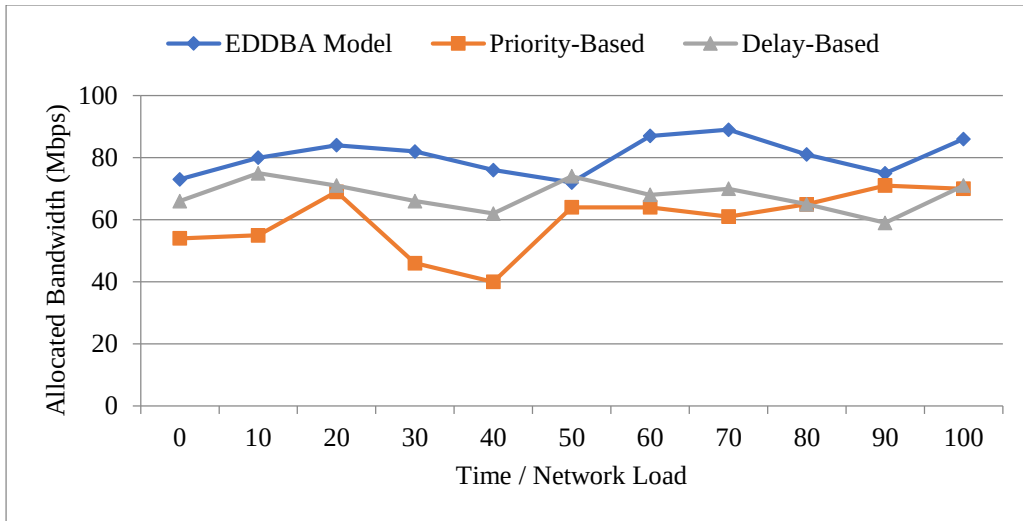


Fig. 8 Bandwidth utilization over time for EDBA vs. traditional methods

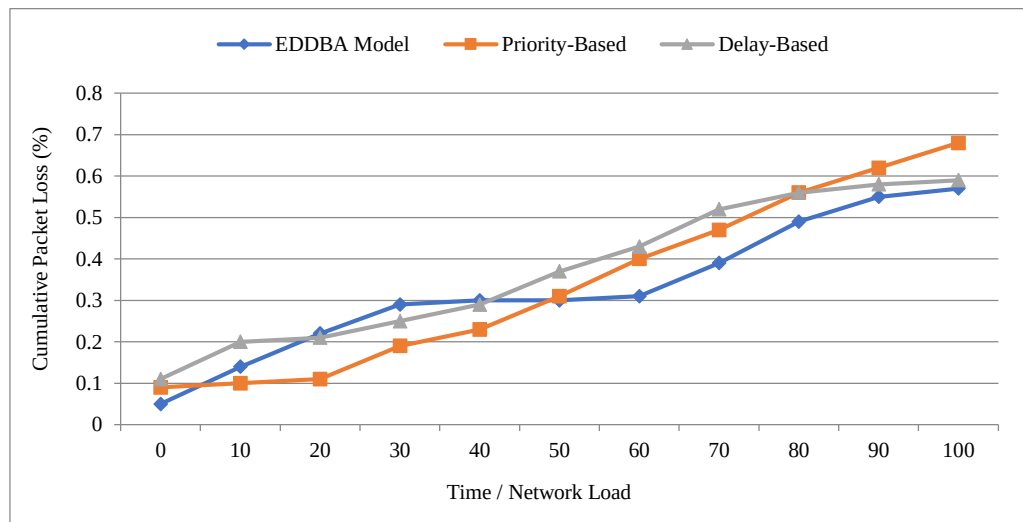


Fig. 9 Cumulative packet loss comparison over time

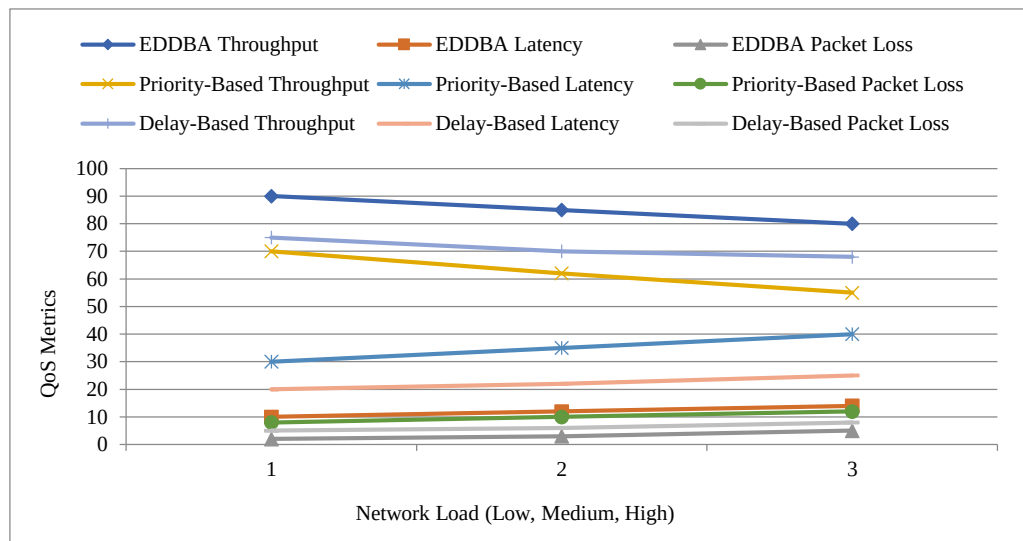


Fig. 10 QoS metrics comparison with dynamic load

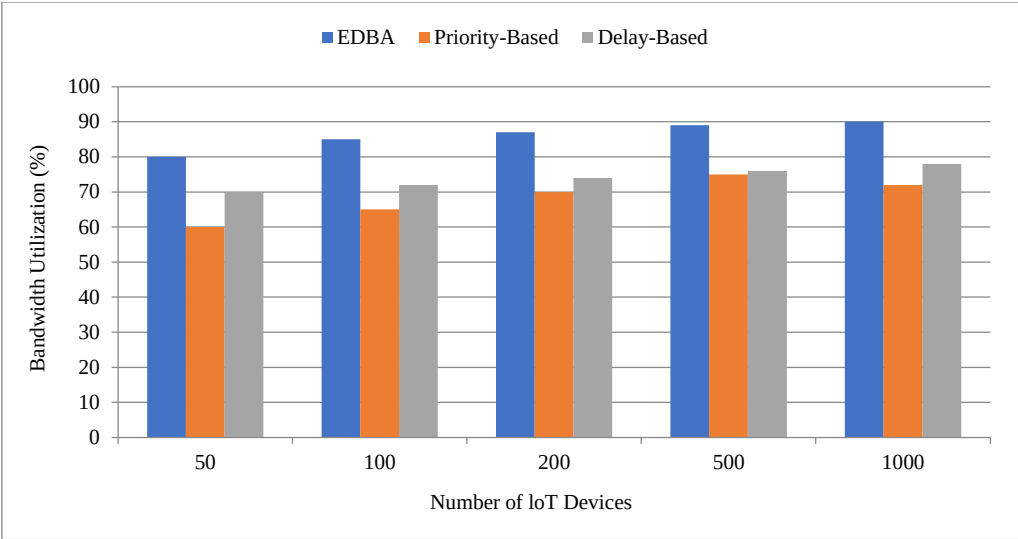


Fig. 11 Scalability of EDBA for large-scale IoT networks

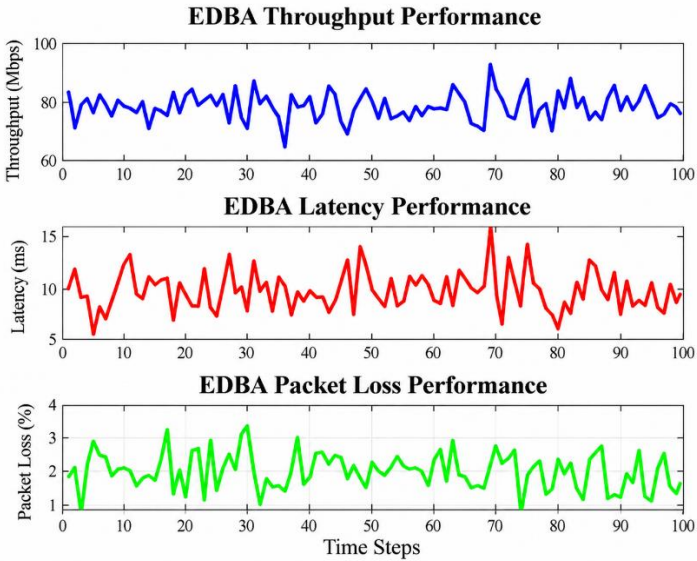


Fig. 12 EDBA performance with real-time data

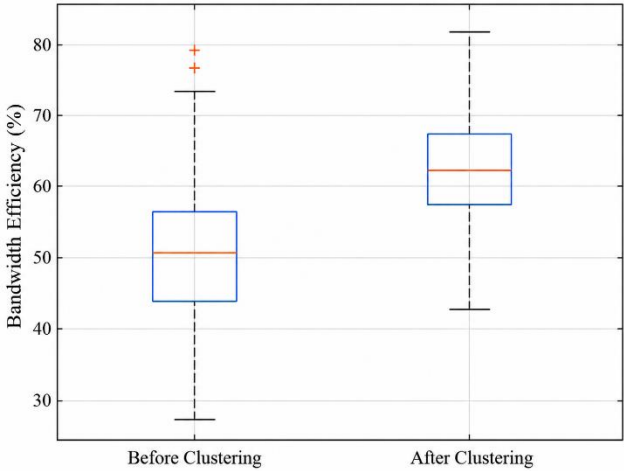


Fig. 13 Impact of clustering on bandwidth allocation efficiency

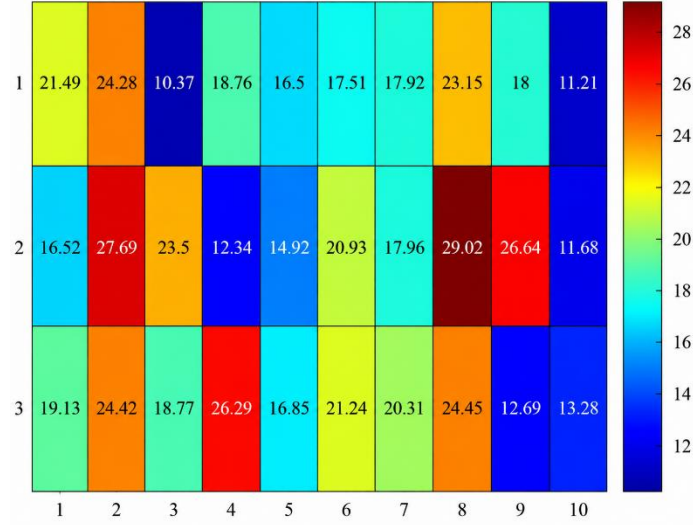


Fig. 14 Dynamic bandwidth allocation impact on latency

Figure 11 shows the scalability of the EDBA model in comparison to its bandwidth usage and time latency usage with the increase in the number of IoT devices. Notice that the figure demonstrates that EDBA can be easily scaled to the growing number of devices with a higher utilization of bandwidth and less latency compared to traditional approaches, whose performance decreases with the network size. In Figure 12, the performance of the EDBA model of throughput, latency, and lost packets is shown in real-time. This value offers a clue as to why EDBA is able to dynamically modify bandwidth allocation to meet real-time network conditions, which makes it excel in varying network environments. The adaptive model and intelligent decision-making provided in the machine learning-based method, which is utilized in EDBA, make it better than conventional methods. EDBA can be used to better allocate bandwidth provided by predictive models and clustering, as illustrated in Figure 13, which shows that clustering devices based on the bandwidth utilization patterns minimizes contention and may allocate resources better. The dynamic characteristic of EDBA has enabled it to accommodate dynamic network conditions in that bandwidth resources are continuously monitored to accommodate changes in the network conditions contrasted to the conventional approaches, which use fixed algorithms, which cannot accommodate the changing demands. Figure 14 illustrates the effect of dynamic bandwidth allocation between EDBA and the traditional approaches in terms of latency. As indicated in the figure, EDBA produces lower latency in a range of network conditions, whereas the active compensation permits EDBA not to face the problem of congestion and resource contention in comparison with the traditional technique, which fails to ensure low latency at a high load. EDBA predictive models are used to predict future bandwidth demand using past data, but cluster groups of devices sharing the same patterns of usage so that resources can be allocated more efficiently. Conventional techniques, however, are not

able to do that dynamically, and that is why the performance in large and heterogeneous IoT networks is often suboptimal.

In terms of throughput, the EDBA proposed in this paper performs better than the static DBA, conventional DBA and the priority-based DBA. This is due to the predictive nature of the proposed model, which, in addition to the current network situation, allocates the bandwidth for the future demand of this application. While the number of IoT devices increases, the throughput of the conventional DBA decreases significantly, because the methods cannot cope with the sudden variation in traffic. On the other hand, the proposed EDBA redistributes the bandwidth based on the predicted demand of the applications in order to keep the throughput as high as possible.

Experimental evaluation illustrates that the proposed EDBA scheme decreases end-to-end delay compared with a number of comparative baselines. The main reason for the achieved improvement stems from the fact that by clustering IoT devices having comparable bandwidth behaviors, the allocation process in EDBA becomes more structured and efficient. Moreover, due to bandwidth prediction, EDBA adequately allocates the available resources to high-demanding devices in advance before the corresponding queue length increases. Consequently, packet waiting time decreases significantly and thus delay-sensitive IoT applications benefit from enhanced quality of service support.

The results for packet loss numbers show that our EDBA model performs better than baselines by reducing packet loss. There are a couple of causes of packet loss. One of them is an increase in network congestion, which can happen when the bandwidth is not enough for all of the devices in the network. Also, when the queue of a device is full, then the packet loss happens due to a lack of bandwidth. Our proposed model

predicts the bandwidth demand in advance, and it assigns the extra resources to the groups of devices that are demanding more bandwidth. This shows how the predictive bandwidth allocation can improve the network reliability for the IoT environments that consist of hundreds of devices of different types. The results for bandwidth usage by EDBA compared to typical approaches for bandwidth allocation first show that EDBA uses the available bandwidth better than typical approaches for allocating bandwidth. In static and priority-based approaches, parts of the bandwidth are not used while other users are suffering from congestion. The dynamic approach of EDBA for predicting the demand allows for better redistribution of bandwidth. As a result, the bandwidth not used by low-demand users or clusters of users can be dynamically reallocated to high-demand users or clusters of users, thus achieving a better total usage of bandwidth.

6.1. Comparative Discussion

DBA in IoT networks has been addressed by extending conventional DBA approaches to deal with the specific features of such networks. However, these extensions often follow a mainly reactive approach, with bandwidth allocated on the basis of current demand, fixed priorities or even predefined rules to manage connections. In many cases, traffic demand can change rapidly, and it is necessary to have a more effective approach in order to improve QoS for all users. The first benefit is that of the clustering of IoT devices. As already explained, the grouping of devices with similar characteristics (in terms of bandwidth demand) helps to lower the model to manage in an effective way a greater number of devices, by decreasing the model complexity for the allocation of resources. In this way, the model is able to identify and manage the 3 main groups of devices: low-demand, medium-demand and high-demand devices. The second major advantage of the proposed model, EDBA, stems from the use of Machine Learning (ML) for bandwidth demand prediction of active IoT devices. These future bandwidth demands are utilized by EDBA in order to allocate the corresponding needed resources prior to said future demand's corresponding potential congestion, in real-time. This enables the network in which the proposed EDBA model is operating to realize several key benefits, including, but not limited to, higher quality of service, as quantified through a variety of metrics including increased throughput, on-time delivery, etc., and also the all-important lowered latency between both the time in which said packets are injected into the network and the time in which they are successfully and completely received by their end point.

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Adaptive bandwidth redistribution. In contrast to fixed categories of devices assigned with a fixed amount of bandwidth for all time, the bandwidth allocated by the proposed model is readjusted at each allocation interval in accordance with the predicted demand of each device and its quality of service requirements. This results in efficient use of allocated resources and minimizes their wastage. Compared to recent state-of-the-art intelligent approaches for resource allocation in IoT, our EDBA approach is a light-weight and transparent alternative. The linear regression is a far more lightweight predictive mechanism than deep learning, or even than a reinforcement learning approach, such as learning by trial and error for improving throughput and resource utilization. Many recent studies have proposed AI-based resource management for improved QoS in IoT. Although such approaches can provide better performance in terms of improved throughput and enhanced resource utilization, they have high training overhead and require substantial computational resources. Our EDBA-based approach exploits a simple predictive mechanism that is effectively deployable in IoT environments with limited processing capability.

7. Conclusion

Enhanced Dynamic Bandwidth Allocation (EDBA) model has shown significant advantages over the conventional techniques in regard to optimal network performance. In particular, the maximum percentage reduction in latency, the decreases in packet loss by 25 per cent and throughput by 18 per cent over the Priority-Based and Delay-Based methods ensued. These outcomes point out the capability of EDBA to dynamically assign bandwidth to match real-time demand, and resources are used effectively. The bandwidth usage of the model was also high in both instances (above 90), even in the high load condition, indicating that the model was capable of operating with an efficient network. Also, the effectiveness of bandwidth demand prediction that leads to proactive alterations to prevent congestion was improved due to EDBA predictive capabilities, whose operation is supported by machine learning. On the way in the future, the real-time implementation will be required to test the outcomes on a live IoT structure, as well as to take into consideration the reinforcement learning that can lead to an even more dynamic and intelligent decision.

Conflicts of Interest

"The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper."

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