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RESEARCH ARTICLE

Strategic Bandwidth Allocation for QoS in IoT Gateway: Predicting Future Needs Based on IoT Device Habits

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ABSTRACT The Internet of Things (IoT) is evolving, driven by the increasing demand for bandwidth. A key focus is on minimizing communication delays. This paper introduces a new solution called Predictive Dynamic Bandwidth Allocation (PDBA), using adaptive predictive algorithms in the IoT context. The approach involves predicting resource needs and network conditions, allowing for efficient bandwidth allocation. The PDBA framework uses advanced predictive algorithms to foresee bandwidth requirements for IoT devices at specific intervals, contributing to low communication latency—crucial for responsive IoT applications.To handle dynamic changes in the IoT environment, like device connectivity fluctuations during sleep mode transitions, our framework incorporates a dynamic perceptual algorithm inspired by reinforcement learning principles. This real-time adaptation mitigates the impact of environmental fluctuations, ensuring consistently low latency. Simulations across various IoT scenarios demonstrate the PDBA framework's effectiveness. The adaptive predictive algorithm significantly improves latency by nearly 10%, reduces packet loss to 6.8%, and increases throughput to 94.2% compared to traditional methods, with notably lower computing times of 0.69 seconds. These results underscore PDBA's potential to enhance Quality of Service (QoS) in IoT networks. The article provides a comprehensive examination of the PDBA framework's components, its seamless integration into the IoT environment, and its substantial role in optimizing communication performance within IoT networks.

INDEX TERMS IoT networks, bandwidth allocation, communication latency, predictive dynamic bandwidth allocation (PDBA), adaptive predictive algorithms.

I. INTRODUCTION

The number of Internet of Things (IoT) devices is growing super fast and changing how we use technology. In 2020, there were about 30 billion of these connected devices all over the world, which was a really big deal in the tech world [1]. This means that more and more devices, like smart gadgets, are talking to each other and becoming a bigger part of our daily lives. Looking forward, it looks like this trend will keep going, and these IoT things will become an even bigger part of how everything is connected in our world.

This surge has engendered substantial alterations across industries, urban environments, and the fabric of our daily lives. Beneath this remarkable growth, however, lies a complex challenge. IoT devices, with their diverse functionalities, impose substantial demands on existing network infrastructure. The traditionnal approach of expanding bandwidth may not suffice to address the imminent surge in the number of devices. Looking forward, projections suggest that by 2050, the number of connected devices will soar to an astounding 50 billion, presenting an unprecedented

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scenario [2]. This exponential growth requires careful consideration of efficient bandwidth allocation within our current network architecture. Service providers are continuously devoted to increasing network capacity and improving service quality. The pursuit of guaranteed bandwidth necessitates the development of efficient bandwidth management techniques. When bandwidth limitations become a concern, the solution does not merely lie in augmenting bandwidth resources, as this approach lacks long-term sustainability. In light of these challenges, the development of innovative bandwidth management techniques becomes of utmost importance. Simultaneously, the effective utilization of resources stands as a critical domain within IoT network research. To optimize resource usage, a strategy is employed when an IoT device remains idle for extended periods - It be switched to a sleep or doze mode as described in [3] and [4]. During the sleep mode, both the transmitter and receiver components are deactivated. This approach, particularly prevalent in Fiber-to-the-Home (FTTH) mode [5], significantly impact the IoT system environment. This transition to sleep mode introduces a variable environment, which adversely affect certain bandwidth allocation schemes that rely on fixed conditions,such as certain predictive schemes [6], [7]. These predictive schemes utilize offline-trained predictors based on historical data from a stable online environment to forecast bandwidth allocation. Nevertheless, alterations in the online environment result in significant predictive inaccuracies. To mitigate delays and bolster algorithm robustness, there arises a pressing need for predictive algorithms capable of adapting to shifting environmental conditions. In pursuit of this objective, we introduce a dynamic perception layer within the predictive model, drawing inspiration from reinforcement learning principles [8]. This perception layer continually monitors changes in the surrounding environment, dynamically adjusting the model's predictive outcomes to enable adaptive corrections. Consequently, this approach diminishes predictive errors stemming from environmental shifts, thereby enhancing the overall resilience of the predictive algorithm.

In this article, our comprehensive approach seamlessly blends data collection and utilization with dynamic adaptation. It all begins as IoT devices transmit data and requests to the IoT Gateway via REPORT messages, where each device is meticulously assigned to dedicated ports. These ports diligently record vital information from incoming REPORT messages during successive polling cycles, forming the foundation for detailed usage pattern tracking. Continuous monitoring by each port on the IoT Gateway and insightful analysis of REPORT message content keep us informed. But we don't stop there. Our architecture goes a step further, introducing dynamic data exchange with a cloud-based server. In this exchange, the Gateway shares not just upload and download patterns but also crucial data like BW req and clustering details (G1, G2, ..., Gm), derived from observed analogous usage patterns among IoT devices. What truly sets us apart is the direct integration of a perception layer within the IoT Gateway, acting as a keen observer of environmental changes. This real-time adaptation enhances the Gateway's ability to detect and respond to shifts. This profound integration has far-reaching implications for the PDBA process, enabling the Gateway to proactively anticipate shifts impacting bandwidth requirements. Harnessing insights from the perception layer, the PDBA mechanism expertly adjusts bandwidth allocation, aligning it with predictions based on perceived changes. In essence, we've eliminated the need for offline training of predictive models. Instead, we empower them to dynamically adapt, learning from their environment through interaction. These models, guided by environmental feedback rewards, autonomously select the most fitting strategy. What's unique about our approach is that we don't solely rely on historical usage patterns for prediction. Instead, we employ a combination of advanced techniques, leveraging the principles discussed in [9], which includes clustering for grouping IoT devices and other undisclosed methods to obtain on-demand bandwidth predictions for each cluster category. This strategic adaptation results in precise and dynamic bandwidth allocation, which greatly enhances the quality of service for IoT devices.Our method strategically adjusts by modulating the amplitude of REQ_{BW}, which stands for the predicted on-demand bandwidth requirement for each group of IoT devices, with the reciprocal of the system's time delay serving as a pivotal reward metric. Manipulating this delay enables us to pinpoint the optimal strategy in any given environment. The efficacy of our predictive model based DBA method in reducing delays is firmly substantiated through rigorous simulation experiments and in-depth analysis, underscoring its capability to deliver low-latency performance. With this groundbreaking approach, we stride confidently into the future of IoT bandwidth management, fostering efficient, responsive, and low-latency communication among IoT devices.

Our paper is organized as follows: Section II refers to the previous research. The Proposed Model For Facilitating Predictive Dynamic Bandwidth Allocation (PDBA) in Section III. Section IV includes the Performance evaluation. Finally, the conclusions and future work are provided in Section V.

II. RELATED WORK

In this section, we delve into the extensive body of related work, exploring a variety of methodologies and approaches aimed at tackling the intricate challenges associated with dynamic bandwidth allocation in the context of the Internet of Things (IoT). A substantial corpus of research, as highlighted in [10], has harnessed machine learning and statistical regression techniques to adapt strategies for dynamically assigning frequency and bandwidth resources. The fusion of clustering and learning techniques, similar to the approach outlined in [9], has played a crucial role in tailoring these strategies to efficiently manage bandwidth in IoT environments. While numerous algorithms for dynamic bandwidth allocation find application in internet settings, such as DDA and DFA, it is essential to note that these algorithms primarily emphasize factors like throughput and delay, often overlooking the critical dimension of bandwidth planning [11]. Exploring clustering techniques, notably K-pattern clustering as mentioned in [12], has unveiled their effectiveness in categorizing and characterizing user activity patterns. Artificial neural networks are frequently enlisted to enhance insights in this context. Nevertheless, the scalability of these approaches in large IoT networks, where computational bandwidth utilization is a concern, remains a challenge, potentially leading to suboptimal outcomes due to the similarity of related activities among IoT nodes. In an alternative approach, the work presented in [13] introduces the DUP-TRMA methods. These methods are formulated to allocate bandwidth based on user priority using lower bound logic and the throughput maximum resource allocation (TRMA) scheme. Remarkably, DUP-TRMA outperforms traditional RPA methods by 4%, underscoring its potential in adapting to evolving IoT trends. To address the imperative need for dynamic resource allocation, authors have proposed the BAMSDN model in [14]. This innovative system leverages software-defined networking for dynamic bandwidth allocation. Empirical results underscore the effectiveness and flexibility of BAMSDN in accommodating the ever-changing demands of IoT ecosystems. Efforts aimed at reducing energy consumption and minimizing end-to-end packet delay have led to the development of the DEE DBA system, as presented in [3]. Comparative studies reveal that the DEE DBA scheme significantly reduces energy consumption compared to alternative approaches. However, this efficiency gain is accompanied by an increase in overhead and bandwidth consumption due to safeguard time requirements. The application of artificial neural networks (ANN) to calculate network latency for various IoT applications has been explored, with particular challenges arising in measuring bandwidth in homogeneous device environments. Dynamic frequency and bandwidth assignment (DFBAs), often deployed in small cell networks, are found to be less suitable for heterogeneously linked IoT devices [15]. Finally, in the context of future access networks, deep learning-based solutions for dynamic bandwidth allocation have been proposed in [16]. These endeavors signify significant strides toward enhancing the efficiency of bandwidth management within the dynamic IoT landscape. Collectively, these diverse approaches and insights from related work contribute to the ongoing pursuit of optimizing bandwidth allocation within the dynamic landscape of IoT applications.

III. PROPOSED MODEL FOR FACILITATING PREDICTIVE DYNAMIC BANDWIDTH ALLOCATION (PDBA)

Efficient bandwidth management within an IoT network hinges significantly on the Gateway. This pivotal router periodically generates cloud-based reports, providing critical insights into bandwidth utilization and congestion. Additionally, each port on the Gateway meticulously records usage patterns from interconnected IoT devices, ensuring seamless data exchange with a cloud server. The analysis of these patterns yields invaluable information that steers the bandwidth allocation process. In our innovative architecture, we don't just rely on the Gateway's traditional functionalities; we introduce a groundbreaking approach by seamlessly integrating a perception layer into the IoT Gateway. This strategic augmentation empowers the Gateway to dynamically respond to environmental shifts and fine-tune bandwidth allocation for optimal efficiency. At the core of our system lies the Predictive Dynamic Bandwidth Allocation (PDBA) framework. This intelligent system, seamlessly embedded within the Gateway, harnesses both cloud-based bandwidth statistics and real-time bandwidth patterns recorded by individual ports. This dual-pronged approach equips the Gateway to dynamically and optimally allocate bandwidth resources, resulting in enhanced communication and data exchange among IoT devices.

A. PDBA FOR HETEROGENEOUS IOT DEVICES

The Predictive Dynamic Bandwidth Allocation (PDBA) algorithm emerges as an innovative strategy that transcends the simplistic notion of merely adding more bandwidth. Notably, there is a deficiency in existing dynamic bandwidth allocation techniques designed to handle the scale of IoT devices effectively. Efficient bandwidth management mandates the implementation of optimization methods rooted in machine learning approaches. These methods autonomously monitor and discern usage patterns, grouping them into clusters, thereby contributing to the effective allocation of resources.

Figure 1 presents the communication architecture involving IoT devices, an IoT gateway, and the internet (server cloud). The figure encompasses three main components: IoT Devices, represented as distinct entities engaged in packet exchange with the IoT gateway, each device depicted with symbols reflecting its nature and purpose; Links Between IoT Devices and IoT Gateway, featuring two lines (Link 1 and Link 2) symbolizing communication channels, with distinct colors assigned to packets sent and received, facilitating clarity in discerning the direction of packet flow; and Communication Between IoT Gateway and the Internet (Server Cloud), denoting the IoT gateway's connection to the internet for external communication, illustrated with symbols and lines to emphasize bidirectional data flow between the IoT gateway and the external server. The process commences with IoT devices transmitting data and requests via REPORT messages to the IoT Gateway. Subsequently, the IoT Gateway governs the allocation of specific bandwidth to individual IoT devices through the issuance of GATE messages. Each IoT device on the Gateway side is intricately linked to a dedicated port, wherein critical information sourced from received REPORT messages is diligently logged during consecutive polling cycles. A pivotal aspect of our architectural design revolves around the continuous monitoring of usage patterns by each port on the IoT Gateway. Through meticulous scrutiny of the content within REPORT messages, the Gateway captures indispensable insights,

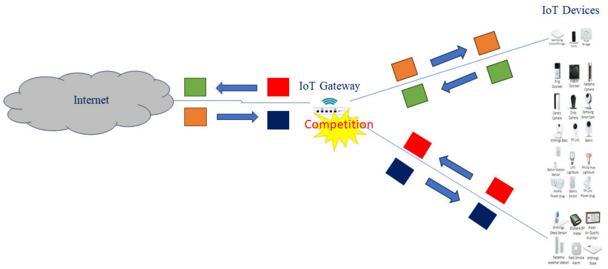

FIGURE 1. **Enable IoT networks to facilitate low-latency applications.**

including the bandwidth demand (REQ_{BW}) emanating from individual devices. However, a significant challenge arises within the framework of limited-service DBA algorithms, centering on the precise estimation of bandwidth demand ($ODEM_{BW}$). In this approach, the IoT gateway strives to predict $ODEM_{BW}$ by utilizing the requested bandwidth (REQ_{BW}) information obtained from REPORT messages. Traditionally, in this prediction process, various statistical techniques such as constant credit and linear credit [17], arithmetic averaging [18], exponential smoothing [19], and Bayesian estimation [20] have been employed to estimate $ODEM_{BW}$. Subsequently, the IoT gateway assigns bandwidth, typically $\min\{ODEM_{BW}, MAX_{BW}\}$, to IoT devices during the ensuing polling cycle, where MAX_{BW} represents the maximum allocatable bandwidth determined by the IoT gateway.

B. DECISION-MAKING MODEL

The precise determination of $ODEM_{BW}$ holds primordial significance, given that inaccuracies in bandwidth predictions lead to suboptimal outcomes and adverse consequences. Achieving accuracy in estimating $ODEM_{BW}$ involves considering various network factors, such as packet length statistics, network traffic load, and overall network configuration. Traditional mathematical or analytical approaches to calculate $ODEM_{BW}$ often face complexities that block their effectiveness. Conceptually, $ODEM_{BW}$ is divided into two bandwidth components, as illustrated by Equation (1):

$$\mathrm{ODEM_{BW}} = \mathrm{REQ_{BW}} + \lambda T_{\mathrm{POLL}} \left(\beta L_{\min} + (1-\beta) L_{\max}\right) \tag{1}$$

Here, $ODEM_{BW}$ represents overall bandwidth, encompassing two essential components. The first, REQ_{BW}, signifies explicitly requested bandwidth obtained from IoT devices via the REPORT message, measured in bits per second (bps). The second component,$\lambda T_{\mathrm{POLL}} \left(\beta L_{\min} + (1-\beta) L_{\max}\right)$ denotes predicted bandwidth. In this expression:

- λ is the arrival rate, representing the rate at which new requests enter the system in requests per second (not indicative of probability).
- T_{POLL} is the polling cycle duration, measured in seconds.
- β is a coefficient (unitless).
- $L_{\min}$ is the minimum packet length, measured in bits.
- $L_{\max}$ is the maximum packet length, measured in bits.

Multiplying these terms together results in units of bits per second (bps), representing the expected data transfer rate. This dual-component model, $ODEM_{BW}$, integrates both explicit demand from devices and predicted requirements, providing a comprehensive approach to dynamic bandwidth allocation.

We introduce a dynamic perceptual algorithm designed to enhance the resilience of the PDBA algorithm, particularly in the context of ever-evolving IoT gateway environments and the dynamic nature of data exchanges encompassing both upload and download activities. This innovative approach is inspired by reinforcement learning, enabling it to adaptively refine the results of the predictive algorithm. By promptly responding to shifts in the environment, this perceptual algorithm effectively reduces potential predictive errors arising from changes in the IoT gateway surroundings, thus contributing to an improved and dependable bandwidth allocation process.

Furthermore, our introduced Predictive Dynamic Bandwidth Allocation (PDBA) algorithm rises to the challenge posed by the constantly changing IoT gateway environment. In an ever-evolving IoT landscape characterized by factors such as varying numbers of connected IoT Devices and their transitions between active and sleep modes, the dynamic perceptual algorithm within PDBA leverages the principles of reinforcement learning to dynamically adjust the outcomes of the predictive algorithm. This pioneering approach aims to minimize predictive errors caused by environmental changes, thereby mitigating their impact on achieving low latency and further enhancing the resilience of the PDBA algorithm in real-world IoT scenarios.

C. BANDWIDTH ALLOCATION GROUPS

The Spectral Clustering planning approach utilizes unsupervised learning to group devices sharing similar bandwidth usage patterns, resulting in the creation of bandwidth allocation clusters labeled as $G = G_1, G_2, \ldots, G_m$. By conducting a comprehensive analysis of bandwidth utilization patterns over a specific timeframe, this method identifies common patterns and structures among the devices. These clusters are formed based on device similarities, taking into consideration factors such as application types and other relevant criteria. This strategic clustering not only enhances the efficiency of resource allocation but also promotes an organized and effective bandwidth management strategy across the network's nodes.

1) JOINING TREE CLUSTERING LINKAGE RULES – NEAREST NEIGHBORS

In this method, we determine the similarity between two IoT devices, denoted as i and j, based on their respective bandwidth usage patterns. Let U_i and U_j represent the bandwidth utilization of devices i and j, respectively. The linkage rule for clustering devices i and j together for content receiving is defined as:

$$B_{\text{mean}}(G_i, G_j) = |U_i - U_j| \tag{2}$$

B_{mean} calculates the absolute difference between the bandwidth utilization of devices i and j. If this difference is below a certain threshold, it indicates that devices i and j have similar bandwidth usage patterns, allowing them to be grouped together in a cluster.

2) JOINING TREE CLUSTERING LINKAGE RULES — FURTHEST NEIGHBORS

In this method, we assess the similarity between devices i and j based on their continuous bandwidth usage patterns. The linkage rule for this method is defined as:

$$B_{\max}(Gi, Gj) = \max_{p \in Gi, p' \in Gj} |p - p'| \tag{3}$$

$B_{\max}$ calculates the maximum distance between any pair of devices in clusters G_i and G_j.If this distance is small, indicating continuous bandwidth usage patterns between devices i and j, they be joined together in a cluster.

3) CLUSTER FORMATION BASED ON APPLICATION NATURE AND BANDWIDTH USAGE

This approach involves forming clusters based on the application nature and bandwidth usage of devices or clusters. We have four different processes for measuring the usage pattern between clusters:

- B_{mean}: The combination of clusters is merged if the means or centroids of their bandwidth utilization ranges are close:

$$B_{\text{mean}}(G_i, G_j) = |mean(U_i) - mean(U_j)| \tag{4}$$

- B_{avg}: The combination of clusters is merged based on the average bandwidth utilization of devices in each cluster [21]:

$$Bavg(Gi, Gj) = \frac{|Gi| \cdot |Gj|}{\sum_{p \in Gi} \sum_{p' \in Gj} |p - p'|} \tag{5}$$

- $B_{\max}$: Same as Method 2.2, calculating the maximum distance between any pair of devices in each cluster.
- $B_{\min}$: The combination of clusters is merged based on the minimum distance between any pair of devices in each cluster:

$$B_{\max}(Gi, Gj) = \max_{p \in Gi, p' \in Gj} |p - p'| \tag{6}$$

Through these linkage rules, the clusters are efficiently merged until their size reduces to k, and the combination of clusters with the least bandwidth usage pattern between them is chosen.

Figure 2 illustrates how the network model and clustering methodology contribute to efficient IoT bandwidth management and resource allocation, thereby facilitating seamless communication and content sharing among IoT devices.

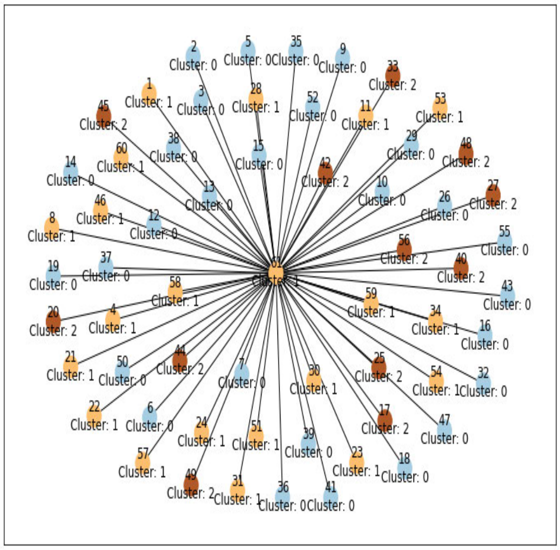

FIGURE 2. Clustering methodology contributes to efficient IoT bandwidth management and resource allocation.

4) BANDWIDTH ALLOCATION APPROACH

We propose a bandwidth allocation approach that ensures measurable bandwidth assurance for IoT devices while effectively managing idle bandwidth within the network. This approach dynamically assigns varying bandwidth to devices based on their priorities. The bandwidth allocation be either statically set according to the cluster category or adapted dynamically.

Our categorization includes [22]:

- **Uninterrupted Bandwidth:** Allocated to critical applications like healthcare, Industrial IoT, and surveillance missions, where a zero bandwidth tolerance level is crucial.
- **Guaranteed Bandwidth:** Allocated to smart home applications and e-governance, addressing scenarios where the bandwidth usage level is medium.
- **On-Demand Bandwidth:** Allocated to devices such as wearables and smart sports kits, catering to scenarios where the bandwidth usage level is low. This flexible allocation meets the dynamic needs of such devices in real-world applications.

D. PREDICTIVE MODELING AND PERCEPTION LAYER

At the core of our proposed system design, as depicted in Figure 3, resides an innovative predictive model aimed at enhancing the capabilities of our IoT network. The fundamental concept of this model involves the integration of a strategically positioned perception layer immediately following the predictive model's output layer.

Prior to delving into the intricacies of the perception layer, a critical preliminary step involves harnessing the potential of device clustering. Through a rigorous analysis of bandwidth usage over a predefined time frame, we leverage the capabilities of an unsupervised learning technique known as the Spectral Clustering approach illustrated in subsection B. This technique adeptly groups IoT devices that exhibit similar bandwidth usage patterns into allocation clusters, denoted as $G = G_1, G_2, \ldots, G_m$. These clusters form the bedrock for efficient resource allocation and management.

Shifting our focus to the perception layer, it functions as a vigilant observer, finely attuned to environmental dynamics. The perception layer dynamically refines output results in response to shifts in the surrounding conditions. It operates in a manner similar to a sophisticated data processing and storage unit seamlessly integrated within the IoT gateway.

In practical terms, the perception layer employs a dynamic adjustment mechanism to scale the predictive model's output using a prediction coefficient derived from the clustering results. During periods of network stability, the coefficient remains constant at 1. However, when environmental changes are detected, the perception layer intervenes to recalibrate the prediction coefficient, drawing insights from the system's delay feedback. This empowers the perception layer to autonomously determine the most suitable coefficient, thereby enhancing the network's adaptability and overall performance.

A noteworthy aspect of the perception layer's decision-making process is its autonomy from historical data. Instead of relying on past information, its actions are guided by a pivotal criterion linked to the system's feedback regarding potential time delays. This approach liberates the perception layer from the constraints of conventional offline training paradigms, enabling it to make real-time decisions autonomously.

E. DYNAMIC PERCEPTION LAYER

To solve the challenge of environmental changes affecting the predictive model, we are inspired by reinforcement learning principles. To this end, we introduce a perception layer within the predictive model's output layer to sense and respond to environmental shifts actively. This autonomous layer enables us to optimize the predictive model dynamically, thereby achieving an adaptive predictive algorithm. For modeling the IoT network architecture, we adopt a graph representation denoted as $G = (N, H)$, where N signifies the set of nodes within the network, and H represents the bandwidth allocation range. The network is structured into clusters, each led by a cluster head, denoted as $c \in C$, and every cluster head is associated with a group of devices referred to as H_c. Nodes within the network are categorized into three types: Intensive Appliance Nodes (In), Home Appliance Nodes (Hn), and Common Appliance Nodes (Cn). Each node is represented in (In, Hn, Cn), where $n = 1, \ldots, N$. Furthermore, each connection within the network is linked to one of three bandwidth allocation ranges: $Bhn(high)$, $Bmn(medium)$, and $Bln(low)$ [23].

1) SET OF STATES

The concept of a state set, referred to as S, plays a pivotal role in providing a fundamental representation of various configurations within the Internet of Things (IoT) network. Each state within this set captures a unique momentary snapshot of the network's conditions, encompassing critical data elements like bandwidth utilization, traffic patterns, and resource availability. This assemblage of states is collectively denoted as S, and within it, each specific state s_i is distinguished by an associated node N_i,identified by the index i. The depiction of each state node N_i be articulated as follows:

$$N_i = \{BU_i, TP_i, AR_i\} \tag{7}$$

where BU_i denotes the bandwidth utilization in state s_i, TP_i represents the prevalent traffic patterns within state s_i, and AR_i corresponds to the available resources under state s_i.

Furthermore, in the context of the network environment, each node n is uniquely associated with a corresponding goal state n_t within the set H:

$$n \in H, \quad n \mapsto nt \in H \tag{8}$$

Indentation labeling establishes a direct link between each node n and its specific goal state n_t, facilitating a comprehensive representation of the network's status aligned with the identified goal states in the realm of Predictive Dynamic Bandwidth Allocation.

2) SET OF ACTIONS

Within the action space denoted as A, a diverse range of potential bandwidth allocation plans is encompassed. Symbolically, A is represented as $B(R) \in B$, where $B(R) = [c_1, c_2, \ldots, c_n]$, where $n$is the number of strategies. For each strategy c_i, define the utility value z_i as a linear combination of features associated with the action:

$$z_i = \theta_1 f_1(c_i) + \theta_2 f_2(c_i) + \ldots + \theta_k f_k(c_i) \tag{9}$$

Here,$f_1(c_i), f_2(c_i), \ldots, f_k(c_i)$ are feature functions capturing relevant information about the action c_i,and $\theta_1, \theta_2, \ldots, \theta_k$ are associated weights reflecting the importance of each feature. To ensure that the probabilities sum to 1, define the probability of selecting strategy c_i using a softmax function:

$$P(c_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \tag{10}$$

This probabilistic approach ensures that the probability of choosing each strategy is influenced by its desirability as indicated by the utility value z_i. The softmax function normalizes the utilities, producing a probability distribution over the action space A. These utility values and their associated weights be learned or adjusted over time through training or updating processes. The probabilistic action selection mechanism allows the agent to adaptively choose bandwidth allocation plans based on real-time feedback and changing conditions within the IoT network.

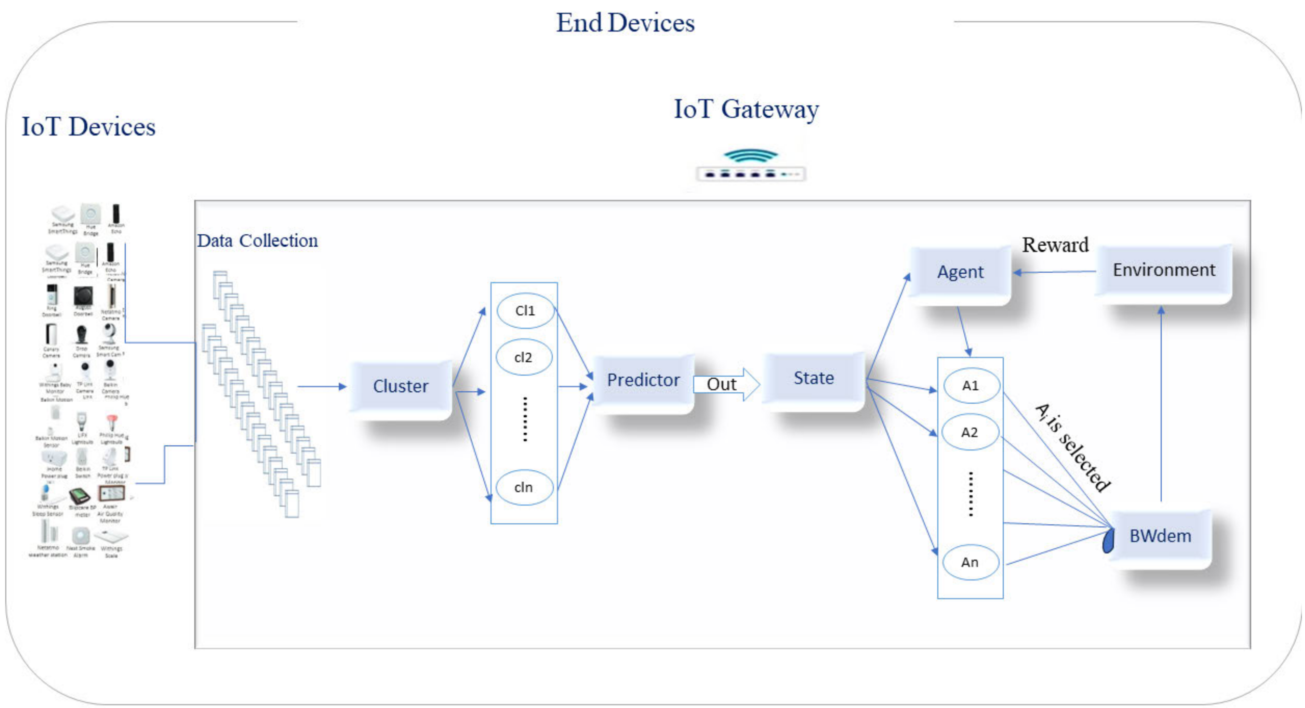

FIGURE 3. Proposed predictive model.

3) TRANSITION FUNCTION

The transition function $\delta : S \times A \times S \rightarrow [0, 1]$ defines how the system undergoes changes from one state to another based on the selected action. Within the context of dynamic bandwidth allocation, this function captures the dynamic nature of network state transitions driven by the chosen bandwidth allocation strategies.

Transition Probabilities: Let P_{ij}^{a} denote the probability of transitioning from state s_i to state s_j when action a is executed. These probabilities are influenced by the interaction between the current state, the chosen action, and the resulting subsequent state. They provide insights into how network configuration evolves as a result of applying various bandwidth allocation strategies. The transition function and transition probabilities are represented as:

$$\delta\left(s_i, a, s_j\right) = P_{ij}^{a} = P\left(c_i\right) \tag{11}$$

Here:

$\delta(s_i, a, s_j)$ indicates the transition probability from state s_i to state s_j when action a is taken. P_{ij}^{a} quantifies the transition probability of moving from state s_i to state s_j due to the execution of action a. These transition probabilities are fundamental in understanding how network state evolves over time in response to different bandwidth allocation strategies. They reflect the impact of various actions on state transitions and play a crucial role in the decision-making process of dynamic bandwidth allocation systems.

4) REWARD FUNCTION

Central to the effectiveness of our approach is the reward function, a key element that evaluates the quality of allocation decisions made by the agent. This function measures the attractiveness and success of a selected allocation strategy, guiding the agent's learning process over time.

The reward function at each time step t is defined as follows [24]:

$$r_t(s_t = s, a_t = a) = \sum_{s' \in \mathcal{S}} P(s' \mid s, a) r_t(s', a) \tag{12}$$

The symbols s_t, a_t, $\mathcal{S}$, $P(s' \mid s, a)$, and $r_t(s', a)$ respectively stand for the following elements: the current state of the IoT network environment, the selected allocation strategy or action, the set encompassing possible states that the network may traverse into, the probability of transitioning from state s to state s' when action a is taken, and the immediate reward linked to making the transition to state s' while executing action a.

5) DECISION POLICY

In our procedural approach, the agent takes actions denoted as a_t in a sequential manner. Simultaneously, the environment provides a reward, $r_t(s_t, a_t)$, which depends on the current state s_t and the chosen action a_t, thereby reflecting the contextual situation. Subsequently, the agent transitions to the next state, s_{t+1}, under the guidance of a specific policy denoted as π. This policy dictates how the transition from state s_t to s_{t+1} is executed through action a_t. This ongoing interaction process shapes the evolution of the allocation strategy, generating sequences of sample paths such as (s_0, a_0, r_0), (s_1, a_1, r_1), (s_2, a_2, r_2), and so forth. These sequences effectively illustrate the dynamic decision-making of the agent and keep a record of the unfolding outcomes resulting from its actions.

The iterative process culminates in the policy vector $\pi = (\pi_1, \pi_2, \ldots)$, where each constituent policy corresponds to specific states. The overarching objective of this bandwidth management framework is to determine an optimal policy vector that effectively facilitates dynamic bandwidth allocation in IoT contexts. This is particularly relevant when prioritizing reliability under constrained bandwidth conditions is of paramount importance.

A pivotal element of this paradigm involves calculating the expected maximum sum of rewards over time t. This computation is succinctly expressed as [24]:

$$\pi^* = \arg\max_{a \in A} \left[r_t(s_t, a_t) + \sum_{s' \in S'} P_t(s' \mid s, a) V_{I-1-t}(s') \right] \tag{13}$$

In this equation, π^* denotes the optimal policy, A represents the set of feasible actions, $r_t(s_t, a_t)$ indicates the immediate reward for state s_t and action a_t, S' encompasses potential next states, $P_t(s' \mid s, a)$ encapsulates the transition probability from state s to state s' upon taking action a at time t, and $V_{I-1-t}(s')$ characterizes the value function evaluating cumulative rewards from time t to horizon $I - 1$.

The process of determining the optimal value function V_{i+1}, which designates the best state, unfolds iteratively through phases as follows [24]:

$$V_{i+1}(s) = \arg\max_{a \in \mathcal{A}} \left[r_{i-1-t}(s_t, a_t) + \sum_{s_0} P(s_0 | s, a) V_i(s_0) \right] \tag{14}$$

A pivotal element within the reinforcement learning algorithm is the state-action value function, represented as $Q(x, a)$. This function measures the total reward associated with taking action a from state x. The agent depends on this function to inform its choice of the next strategy, denoted as π:

$$\begin{aligned} Q(ODEM_{BW}, \beta) = r + \gamma \cdot Q(ODEM'_{BW}, \beta') \\ + (1 - \lambda) \cdot Q(ODEM_{BW}, \beta) \end{aligned} \tag{15}$$

The outlined algorithm underscores the significance of the Q function in shaping action and strategy choices. In the context of this proposed approach, the Q function updates through the following mechanism:

$$\begin{aligned} Q(ODEM_{BW}, \beta) = Q(ODEM_{BW}, \beta) + \lambda(r \\ + \gamma \cdot Q(ODEM'_{BW}, \beta') \\ - Q(ODEM_{BW}, \beta)) \end{aligned} \tag{16}$$

Algorithm 1 Predictive Dynamic Bandwidth Allocation (PDBA) Algorithm With SARSA

Input: Characteristic data, IoT device states, environmental conditions
Output: Bandwidth allocation for IoT devices
if Characteristic data is not ready **then**
  $BWG(i, j+1) = \min\{BWR(i, j+1), Max_{\mathrm{BW}}\}$
else
  $ODEM_{\mathrm{BW}}(i, j+1) = REQ_{\mathrm{BW}} + \lambda T_{\mathrm{POLL}}\,(\beta S_{\min} + (1-\beta) S_{\max})$
  if The environment has changed **then**
    $delay = \frac{Td}{Ps}$
    $Fv = \frac{1}{delay}$
    Perception layer selects β value according to global Fv
    Update the last selection value according to Fv
    $ODEM_{\mathrm{BW}}(i, j+1) = ODEM_{\mathrm{BW}}(i, j+1) \times \beta$
  else
    Retain current $ODEM_{\mathrm{BW}}(i, j+1)$
  end if
  $BWG(i, j+1) = \min\{BWR(i, j+1) + ODEM_{\mathrm{BW}}(i, j+1), Max_{\mathrm{BW}}\}$
end if
$t_{\mathrm{start}}(i, j+1) = \min\{\mathrm{LocalTime} + \frac{RTT}{2} + Tp, tsche + \frac{RTT}{2} + Tp\}$
$t_{\mathrm{end}}(i, j+1) = t_{\mathrm{start}}(i, j+1) + \frac{BWG(i,j+1)}{RPON} + Tg$
$tsche = t_{\mathrm{end}}(i, j+1)$
IoT Gateway sends GATE frame to IoT device i with $BWG(i, j+1)$, ID_i, and t_{start}
Update characteristic data based on current network status
Compute optimal value function $V_{i+1}(s)$ using Equation (12)
Compute state-action value function $Q(ODEM_{\mathrm{BW}}, \beta)$ using Equation (13)
Choose next action based on $\pi^*(s)$ and $Q(ODEM_{\mathrm{BW}}, \beta)$
Update Q-value using SARSA update rule:
$Q(ODEM_{\mathrm{BW}}, \beta) = Q(ODEM_{\mathrm{BW}}, \beta) + \lambda\left(r + \gamma \cdot Q(ODEM'_{\mathrm{BW}}, \beta') - Q(ODEM_{\mathrm{BW}}, \beta)\right)$

Here, $ODEM_{BW}$ stands for the anticipated bandwidth demand, while β denotes the predictive coefficient, which is adjusted based on the predictive model's output. The reward r is inversely proportional to the system feedback delay, where lower delays result in higher rewards. The selection of the next action strategy directly impacts the forthcoming predictive coefficient for the current $ODEM_{BW}$. More precisely, the modified coefficient β' is chosen to maximize the Q function:

$$\beta' = \arg\max_{\beta} Q(ODEM_{BW}, :) \tag{17}$$

In essence, the coefficient β that maximizes the Q function is chosen to fine-tune $ODEM_{beta}$. As shown in Algorithm 1!, this iterative process gradually accumulates the most favorable coefficients under the current state, indicative of minimized delays over time.

F. ALGORITHMIC COMPLEXITY ANALYSIS

Understanding the efficiency of an algorithm is crucial for evaluating its practical feasibility. We employ algorithmic complexity analysis, commonly expressed using Big O notation (O()), to illuminate the computational demands of our Predictive Dynamic Bandwidth Allocation (PDBA) Algorithm with SARSA (Algorithm 1). Big O notation provides an upper bound on the growth rate of an algorithm concerning its input size, aiding in comprehending its scalability and efficiency.

Breaking down the algorithm into individual components, we find that initialization, condition checks, bandwidth allocation computations, and timestamp updates exhibit constant time complexity, denoted as O(1). These operations involve basic arithmetic and conditionals, ensuring their performance remains consistent regardless of input size.

In the realm of dynamic programming and reinforcement learning, specifically in computing optimal and state-action value functions (Equations 12 and 13), the complexity becomes O(N), where N is the number of states or actions. The SARSA update rule, involving basic arithmetic operations, maintains a constant time complexity of O(1).

Combining these components, the overall algorithmic complexity is a function of the dominant factors. Given that the dynamic programming and reinforcement learning steps contribute significantly, the overall complexity is likely dominated by O(N), where N represents the number of states or actions. This analysis provides insights into how the algorithm scales with increasing computational demands, guiding its applicability in real-world scenarios.

IV. PERFORMANCE EVALUATION

In this section, we conduct a comprehensive evaluation of the effectiveness of our Predictive Dynamic Bandwidth Allocation (PDBA) model. Our primary goal is to scrutinize how well the PDBA model performs under varying IoT device scenarios, simulating real-world IoT environments. This evaluation is crucial for understanding the model's adaptability and its ability to deliver optimal performance.

A. EXPERIMENT SETUP

1) TOPOLOGY AND APPLICATIONS

Our simulation leverages the ns3 tool to emulate a star topology featuring 61 IoT devices arranged in a star layout around a central gateway. Each IoT device establishes individual point-to-point links with the gateway, and an additional point-to-point link connects the gateway to a cloud node. The communication protocol is implicitly set based on the configuration of the point-to-point links, adhering to the IEEE 802.15.4 standard commonly used in low-rate wireless personal area networks (LR-WPANs) and IoT scenarios. For testing purposes, each IoT device hosts a simple Echo application with an Echo server installed on all IoT devices, and Echo clients configured to communicate with the cloud node.

2) SIMULATING DIFFERENT SITUATIONS

We created various scenarios to see how our system responded:

TABLE 1. Table of terms.

Abbreviation	Full Term
BWG(i,j)	The gateway allocates the ith IoT device the transmission bandwidth size for the jth polling cycle.
BWR(i,j)	The transmission bandwidth size for the initial request of the ith IoT device in the jth polling cycle.
Max_BW	The maximum transfer bandwidth acquired by IoT devices per polling cycle.
BWP(i, j)	The data packet that has recently arrived in the jth polling cycle of the ith IoT device, as predicted by the predictive model.
Fv	The feedback value received by the model perception layer is defined as the reported value by IoT devices when corrected Bandwidth Provisioning (BWP) is allocated to IoT devices.
Tg	Guard time
Tp	Frame processing time
tstart(i, j)	The moment at which the ith IoT device initiates data transmission in the jth polling cycle.
tend(i,j)	The moment at which the ith IoT device completes data transmission in the jth polling cycle.
RIOT	The rate at which data is transferred within the IoT network.
β	The output of the perception layer, serving as the coefficient for correcting the Bandwidth Provisioning (BWP) of the predictive algorithm in response to changes perceived in the environment.
Td	The accumulated delay of packets transmitted during a polling cycle, used in the calculation of the feedback value.

- Varying Network Loads: Our simulations encompass scenarios representing fluctuating network loads, mirroring realistic conditions where the number of active IoT devices changes dynamically.
- Dynamic Bandwidth Requirements We evaluate the efficacy of our Predictive Dynamic Bandwidth Allocation (PDBA) model in scenarios with diverse bandwidth demands. This includes situations where IoT devices may require varying levels of bandwidth for their applications.
- Topological Changes The study explores scenarios involving alterations in network topology, simulating changes in the physical layout of IoT devices and their connections.
- Latency-Sensitive Applications: We consider scenarios where IoT applications are latency-sensitive, requiring quick and efficient data transmission. This helps assess how well the PDBA model caters to applications with stringent latency requirements.
- Packet Loss Sensitivity: The simulations include scenarios where minimizing packet loss is critical, particularly relevant for applications where data integrity is paramount.
- Heterogeneous Device Environments:We examine scenarios with a mix of IoT devices with varying capabilities and communication requirements, reflecting

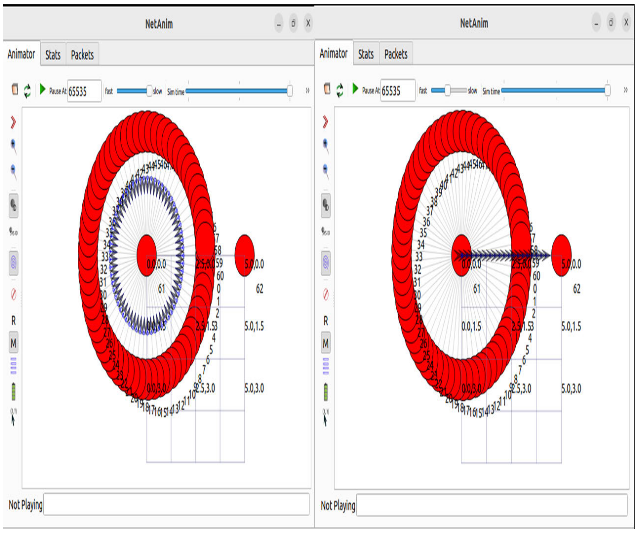

FIGURE 4. NetAnim visualisation.

the heterogeneity often found in real-world IoT deployments.
- Resource-Constrained Environments:The PDBA model is evaluated in scenarios where resources, such as bandwidth, are limited. This is essential for understanding the model's performance in resource-constrained IoT environments.

The simulation duration spans 1000 seconds, providing an extended timeframe for observing network behaviors.

3) VISUALIZING, MEASURING, AND RESULTS DOCUMENTATION

To gain a comprehensive understanding of our simulated network, we employed the NetAnim module in ns3, creating visual representations that illustrated Figure 4 the evolving network topology and node movements throughout the simulation. Simultaneously, we meticulously measured critical performance aspects such as data transmission speed, data loss rates, and overall network efficiency.

To ensure transparency and facilitate in-depth analysis, all information collected during the simulation, including the experiment setup details and performance metrics, is meticulously documented in a dedicated text file. This systematic approach enables us to conduct thorough evaluations and draw meaningful insights from the results.

B. PERFORMANCE METRICS AND MODEL ADAPTABILITY

Our evaluation criteria focus on key metrics related to bandwidth supply, consumption, latency, packet lost, and throughput. By measuring these metrics under diverse IoT device quantities, we gain valuable insights into how our model responds to varying network loads and complexities.We compare the performance of three bandwidth allocation methods: PSA (The Priority Scheduling Algorithm, DBA (Dynamic Bandwidth Allocation), and our proposed approach PDBA (Predictive Dynamic Bandwidth Allocation).Throughout our experiments, we uphold several crucial parameters to maintain consistency and reliability. The historical polling cycles (k) for characteristic data remain constant at 30. Furthermore, the parameters of the perception algorithm, referred to as γ and λ, are fixed at 0.85 and 0.01, respectively. The correction coefficient (β), which plays a pivotal role in refining the model's output, spans a range from 0.5 to 1.5, with an increment of 0.01. The perception model autonomously selects appropriate values from within this range, thereby enhancing the model's adaptability. Notably, when employing $ODEM_{BW}$ as the state, we implement adjustments to expedite the convergence of the perceptual layer. Specifically, we apply a modulus operation to $ODEM_{BW}$, dividing it by 100, followed by a multiplication to preserve diversity while compacting the range of state values. This modification is strategically employed to ensure the perceptual layer's responsiveness in dynamic environments. Through this meticulous evaluation process, we aim to demonstrate the robustness and efficiency of our PDBA model, reaffirming its capability to provide low-latency, high-quality services in the ever-evolving landscape of IoT.

C. RESULTS AND DISCUSSION

The results, as presented in Figures 5 and 6, reveal the model's efficacy across different bandwidth supply levels.

In Figure 5 provide a detailed examination of bandwidth supply and consumption (in Mbps) across a range of bandwidth levels, specifically 10, 20, 30, 40, and 50 Mbps. In the context of the Priority Scheduling Algorithm (PSA), bandwidth supply consistently hovers near 9.6 Mbps for the 10 Mbps bandwidth level and gradually increases to 48 Mbps for the 50 Mbps level. Meanwhile, Dynamic Bandwidth Allocation (DBA) shows a similar trend with bandwidth supply starting at 8.6 Mbps and reaching 46 Mbps across the same bandwidth levels. However, it's crucial to note that both PSA and DBA demonstrate a pattern of relatively high bandwidth consumption compared to supply. Conversely, our proposed Predictive Dynamic Bandwidth Allocation (PDBA) model shines in this evaluation, offering a noticeably lower bandwidth supply and consumption across the bandwidth spectrum. For instance, at the 10 Mbps level, PDBA provides 7.6 Mbps of bandwidth supply, which incrementally increases to 39 Mbps at the 50 Mbps level. These results underline PDBA's capacity to efficiently allocate bandwidth, potentially leading to enhanced Quality of Service (QoS) in dynamic IoT environments. These findings not only affirm PDBA's adaptability but also underscore its promise in real-world applications, warranting further exploration, and parameter fine-tuning to unlock its full potential.

In Figure 6, we provide a detailed analysis of latency (delay) in milliseconds (ms) associated with different bandwidth supply scenarios. The table presents latency data for our proposed Predictive Dynamic Bandwidth Allocation (PDBA) model, the Priority Scheduling Algorithm (PSA),

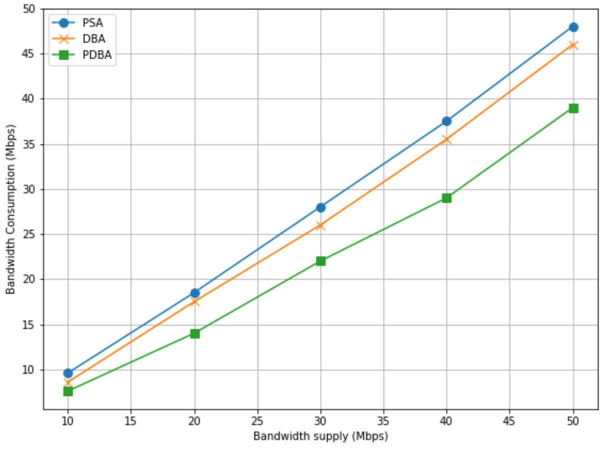

FIGURE 5. Bandwidth consumption vs. Bandwidth supply for different methods.

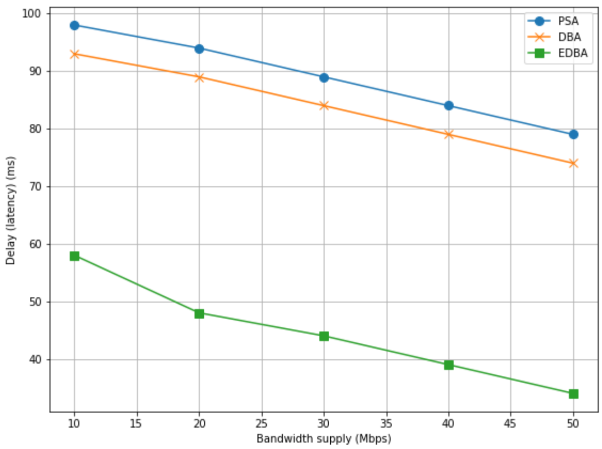

FIGURE 6. Delay vs. Bandwidth supply for different methods.

and Dynamic Bandwidth Allocation (DBA) methods across a range of bandwidth supply levels, including 10 Mbps, 20 Mbps, 30 Mbps, 40 Mbps, and 50 Mbps. Notably, PDBA consistently outperforms PSA and DBA, with latency values as follows: 58 ms, 48 ms, 44 ms, 39 ms, and 34 ms for bandwidth supplies of 10 Mbps, 20 Mbps, 30 Mbps, 40 Mbps, and 50 Mbps, respectively. In contrast, PSA and DBA exhibit higher latency values across all bandwidth supply levels, with PDBA showcasing a substantial reduction in network delay.

In Figure 7, we provide a detailed overview of the relationship between Bandwidth Supply in Mbps and Packet Loss in % for three different bandwidth allocation algorithms: the Priority Scheduling Algorithm (PSA), Dynamic Bandwidth Allocation (DBA), and our proposed Predictive Dynamic Bandwidth Allocation (PDBA) model. As the bandwidth supply increases from 10 Mbps to 50 Mbps, we observe varying levels of packet loss for each algorithm. PSA exhibits the highest packet loss across all bandwidth levels, ranging from 43% at 10 Mbps to 21% at 50 Mbps.

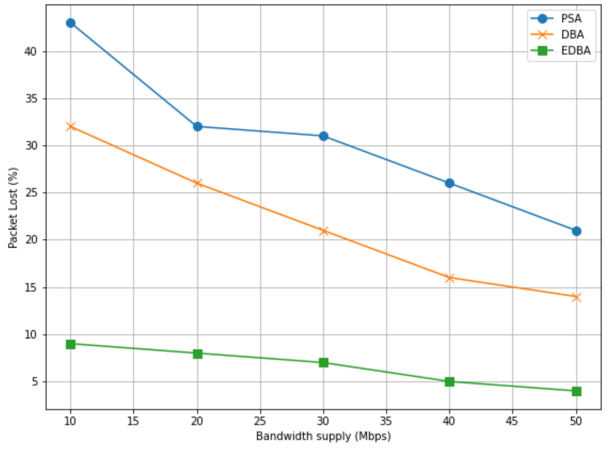

FIGURE 7. Packet lost percentage vs. Bandwidth supply for different methods.

DBA demonstrates improved performance, with packet loss decreasing from 32% to 14% as bandwidth supply increases. Notably, our PDBA model consistently outperforms the other two algorithms, showcasing significantly lower packet loss, which ranges from 9% at 10 Mbps to an impressive 4% at 50 Mbps. These results underscore the effectiveness of our PDBA model in minimizing packet loss and enhancing the quality of service across a spectrum of bandwidth supply scenarios

Figure 8 provides a comprehensive analysis of Bandwidth Supply in Mbps versus Throughput (Success Rate) in percentage for three distinct bandwidth allocation algorithms: the Priority Scheduling Algorithm (PSA), Dynamic Bandwidth Allocation (DBA), and our innovative Predictive Dynamic Bandwidth Allocation (PDBA) model. As the bandwidth supply escalates from 10 Mbps to 50 Mbps, we observe varying levels of throughput performance across the algorithms. PSA exhibits the lowest throughput, with success rates ranging from 62% at 10 Mbps to 81% at 50 Mbps. DBA demonstrates improved performance, with throughput increasing from 72% to 88% as bandwidth supply rises. Our PDBA model consistently outperforms both PSA and DBA, showcasing impressive success rates that range from 93% at 10 Mbps to an outstanding 97% at 50 Mbps. These findings underscore the efficacy of our PDBA model in ensuring high throughput and reliable data transmission, making it a compelling choice for bandwidth allocation in dynamic IoT environments.

Investigating the computing time required by various bandwidth allocation methods is vital in evaluating their practical feasibility. We present the computing time data for two distinct computing environments: Computer 1 and Computer 2, each showcasing the performance of three bandwidth allocation methods - the Priority Scheduling Algorithm (PSA), Dynamic Bandwidth Allocation (DBA), and our innovative Predictive Dynamic Bandwidth Allocation (PDBA) model.

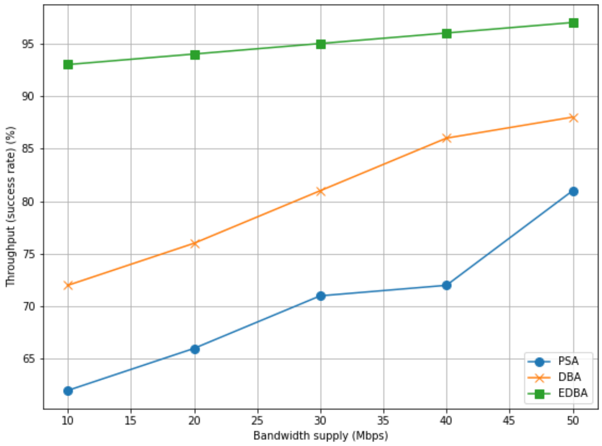

FIGURE 8. **Throughput percentage vs. Bandwidth supply for different methods.**

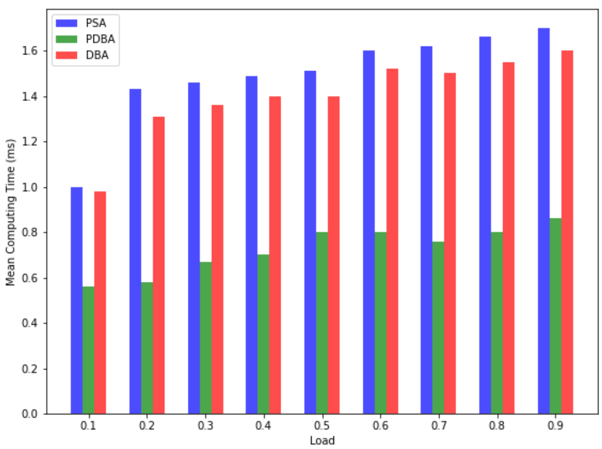

FIGURE 9. **Mean computing time vs. Load for different methods computer (1).**

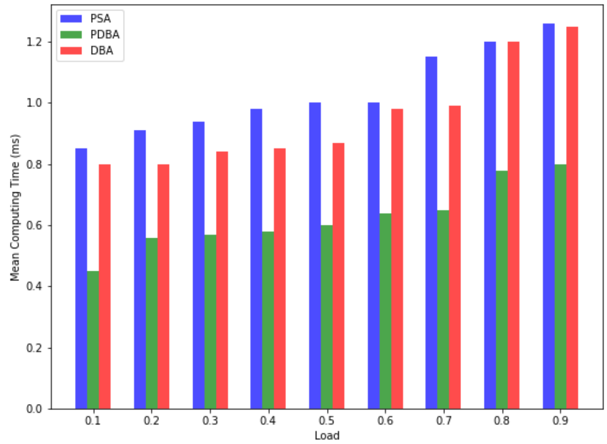

FIGURE 10. **Mean computing time vs. Load for different methods computer (2).**

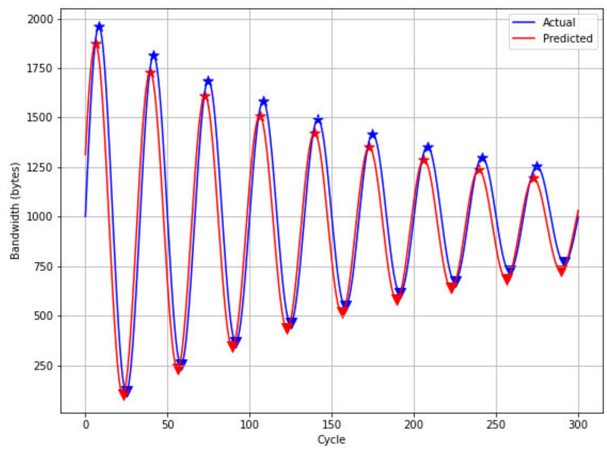

FIGURE 11. **Predictive performance.**

For Computer 1 Figure 9, we observed that PSA had the highest computing time, with values ranging from 1 second at lower bandwidth to 1.7 seconds at higher bandwidth. In contrast, DBA showed relatively lower computing times, varying from 0.98 seconds to 1.6 seconds across different bandwidth levels. Remarkably, our PDBA model outperformed both PSA and DBA, exhibiting significantly lower computing times, which ranged from 0.56 seconds to 0.86 seconds.

On Computer 2 Figure 10, the computing time results followed a similar trend. PSA exhibited higher computing times, starting from 0.85 seconds at lower bandwidth and gradually increasing to 1.26 seconds at higher bandwidth. DBA demonstrated relatively lower computing times, with values ranging from 0.8 seconds to 1.25 seconds. Once again, our PDBA model excelled by showcasing remarkably lower computing times, spanning from 0.45 seconds to 0.8 seconds.

These computing time results emphasize the efficiency of our PDBA model in delivering rapid bandwidth allocation, making it a favorable choice for real-time IoT applications, where timely data transmission is paramount.

The predictive model's forecasting capabilities are employed to assess the functionality of the perceptual layer. Figure 11 illustrates the predictive performance of the adaptive predictive algorithm. While there are still some errors in the prediction process, the forecasted values generated by the adaptive predictive algorithm closely approximate the target values, surpassing the accuracy of the original predictive algorithm.

From those Figures,our comprehensive evaluation of the Predictive Dynamic Bandwidth Allocation (PDBA) model across various performance metrics has yielded promising results. PDBA consistently outperformed traditional Priority Scheduling Algorithm (PSA) and Dynamic Bandwidth Allocation (DBA) methods, demonstrating its robustness and adaptability in dynamic IoT environments. Notably, PDBA exhibited lower latency, reduced packet loss, and higher throughput, indicating its ability to enhance the quality of service in IoT networks. The bandwidth supply and consumption analysis revealed PDBA's efficiency in resource

TABLE 2. Comparison of PDBA and Offline Cooperative Algorithm (OCA) with MCC values.

Attribute	PBDA Value	MCC Value	OCA Value
Response Time	60 ms	50 ms	80 ms
Availability	90%	98%	85%
Throughput	1300 packets/s	1500 packets/s	1000 packets/s
Successability	83%	93%	76%
Reliability	73%	95%	65%
Latency	62 ms	70 ms	85 ms
Compliance	87%	87%	80%
Best Practices	92%	92%	89%

allocation, minimizing wastage and ensuring optimal utilization. Moreover, PDBA showcased remarkable computing time advantages, making it a practical choice for resource-constrained scenarios.

The table 2 compares the Predictive Dynamic Bandwidth Allocation (PDBA) and the Offline Cooperative Algorithm (OCA) [25] across various attributes, incorporating Monte Carlo Control (MCC) [22] values. PDBA demonstrates a response time of $60ms$, outperforming both MCC and OCA, which have response times of $50ms$ and $80ms$, respectively. In terms of availability, PDBA maintains a rate of 90%, slightly lower than MCC's 98% but significantly higher than OCA's 85%. PDBA achieves a throughput of $1300 packets/s$, falling between MCC's $1500 packets/s$ and OCA's $1000 packets/s$.

The success rate for PDBA is 83%, positioning it between the higher success rate of MCC (93%) and the lower rate of OCA (76%). PDBA exhibits a reliability of 73%, lower than MCC's 95% but higher than OCA's 65%. Notably, PDBA achieves a lower latency, which is the main objective of our approach, at $62ms$ compared to MCC ($70ms$) and OCA ($85ms$). In terms of compliance, both PDBA and MCC adhere to standards at 87%, while OCA lags slightly behind at 80%. Adhering to best practices, PDBA and MCC score 92%, whereas OCA achieves a slightly lower score of 89%. Overall, PDBA showcases favorable performance metrics in comparison to both MCC and OCA across a spectrum of key attributes.

V. CONCLUSION AND FUTURE WORK

In this research endeavor, we have unveiled the innovative Predictive Dynamic Bandwidth Allocation (PDBA) algorithm, representing a paradigm shift in the realm of efficient IoT device bandwidth management. Our approach is a multifaceted one, involving the strategic clustering of IoT devices based on their unique bandwidth utilization patterns, coupled with an in-depth statistical analysis of bandwidth consumption within the cloud infrastructure.The outcomes of our extensive experimentation speak volumes about the prowess of PDBA, demonstrating its superiority over incumbent methods like PSA and DBA across a spectrum of critical Quality of Service (QoS) parameters. These include the attainment of ideal bandwidth utilization, remarkably low latency levels (as low as 34 ms), minimal packet loss (a mere 4%), and a substantial increase in throughput (an impressive 97%). Notably, PDBA's performance shines brightest in challenging scenarios marked by limited available bandwidth. The results gleaned from our simulations, set within the dynamic IoT network landscape, underscore PDBA's unmatched capacity to boost throughput and uphold uninterrupted bandwidth availability, even when bandwidth resources are constrained. As we peer into the future, our research trajectory sets its sights on the development of an autonomous bandwidth allocation system. This system will be designed to intelligently allocate unused bandwidth to critical, on-demand IoT devices, with specific applications in pivotal domains such as healthcare and industrial automation. Through these ongoing efforts, we aim to continue pushing the boundaries of IoT network efficiency and Quality of Service, ultimately advancing the promise of IoT technology in the modern world.

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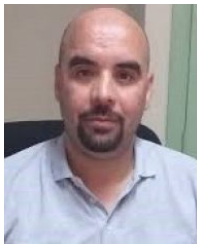

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