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An Intelligent Dynamic Bandwidth Allocation Method to Support Quality of Service in Internet of Things

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ABSTRACT Worldwide, Internet of Things (IoT) devices will surpass a range of five billion by 2025 and developed countries will extend to advance by supplying almost two-thirds of such connections. With existing infrastructure, allocating bandwidth to billions of IoT devices is going to be cumbersome. This paper addresses the problem of Dynamic bandwidth allocation in IoT devices. We enhanced the dynamic bandwidth allocation algorithms to support QoS in different bandwidth ranges. Our Proposed innovative Machine learning-based Intelligent Dynamic Bandwidth Allocation (IDBA) algorithm allocates the bandwidth effectively between IoT devices based on utilization patterns observed through machine learning methods. Moreover, we showed that an IDBA algorithm results in supporting quality of service in terms of ensuring uninterrupted bandwidth to critical IoT application where bandwidth tolerance is zero percent, along with that IDBA increasing the network throughput correlated to other dynamic bandwidth allocation algorithms. We demonstrate simulations in different applications. The results show that IDBA achieves better throughput even in low bandwidth range.

KEYWORDS Dynamic bandwidth allocation; Reinforcement Learning; Machine learning models; Quality of Service

I. INTRODUCTION

In recent years, the Internet of things applications have been rapidly growing in size and are expected to reach 30 billion mark by 2020 [1]. A number of devices going from millions to a billion, supporting quality based service with existing infrastructure will be challenging. Moreover, IoT devices are heterogeneous and loosely coupled, which further increases the complexity of IoT networks. Implementation of IoT in smart cities, transport and industry is growing rapidly, blockchain technology is becoming inevitable in supporting IoT [2]. Companies are endlessly pursuing to enhance the network capacity and quality of service. To meet the requirement of guaranteed bandwidth there is a need for efficient bandwidth management technique. When bandwidth scarcity occurs, simply adding more bandwidth does not provide permanent solutions. An efficient Intelligent Dynamic Bandwidth Allocation (IDBA) algorithm is an innovative strategy than simply added additional bandwidth. There ia a lack of existing dynamic bandwidth allocation techniques for handling massive IoT devices. For efficient bandwidth management, there is a requirement for optimization methods adopting machine-learning approaches to study automatically observe usage patterns and group them to cluster. Several machine learning and statistical regression techniques discussed in [3], to adapt dynamic frequency and bandwidth allocation, such a composite of clustering and learning helped to acclimate the efficient bandwidth management strategies to the requirements of the massive IoT applications. Many dynamic bandwidth allocation algorithms are used on the internet such as DDA and DFA. However, such algorithms focus only on throughput and delay, and are not connected to the bandwidth planning mechanism [4]. Some devices on IoT very often send few bytes of data in a day, for example, in smart parking, parking sensors send a signal when parking slot becomes free. These IoT devices do not use conventional services such as SMS, voice not even duplex data transmission [5]. In this scenario our proposed method automatically allocates the unused bandwidth to on-demand critical devices such as health care and industrial automation. The objective is the smart allocation of network bandwidth seeing bandwidth demands of IoT applications, along with measuring bandwidth utilization pattern in clustered devices. This method supports the efficient dynamic bandwidth management techniques observed through a machine learning process over IoT devices. The performance of our IDBA is evaluated by simulation over different types of applications. Simulation results show that our proposed method achieves better performance than other dynamic bandwidth allocation algorithms in terms of throughput and reliability.

2. GROUPING THE DEVICES THROUGH CLUSTERING METHODS

The Spectral Clustering planning approach using unsupervised learning is targeted to group similar bandwidth utilization devices for bandwidth allocation in the standard rate. The unsupervised learning observes the bandwidth usage over the period with the utilization pattern, the cluster range can be formed then the nodes that have a close identity with the cluster range can be added together based on the type of application, severe care and using a pattern of such an idea. Clusters type can be built in the midst of nodes N [6].

2.1 Joining tree clustering linkage rules nearest neighbors: In this method similarity between two devices is determined by the less bandwidth usage pattern in different IoT devices such as parking sensors, wearable and home appliances. This instruction will string devices together to form a cluster, the resultant cluster tends to denote cluster heads.

2.2 Joining tree clustering linkage rules furthest neighbors:

In this method similarity between two devices is determined by continuous bandwidth usage among different IoT devices such as Healthcare and Industrial IoT devices.

2.3 Cluster formation is based on application nature and bandwidth usage couple of devices or clusters that then are efficiently merged, till then clusters size reduces to k, the combination of clusters merged are the ones between which the bandwidth usage is the least. Widely used processes for usage pattern between clusters are as follows (Ui is the mean for cluster Gi and Ti is the number of nodes

$$B_{mean}(G_i, G_j) = | U_i - U_j |$$
$$B_{avg}(G_i, G_j) = 1 / (T_i, T_j) \sum_{P \in Gi} \sum_{P' \in Gj} \|p-p'\|$$
$$B_{max}(G_i, G_j) = max\ p \in Gi, p' \in Gj \| p - p' \|$$
$$B_{min}(G_i, G_j) = min\ p \in Gi, p' \in Gj \| p - p' \|.$$

Example B_{mean} as the bandwidth measure at each cycle, the combination of clusters are merged whose means or centroids ranges are the closest. Contrarily, with B_{min}, the combination of clusters merged are the ones comprising the closest range of minimal points [7].

3. IOT SERVICE MODEL AND DYNAMIC DELIVERY ARCHITECTURE

A. Service model

A service model proposed that, primarily, offers a measurable bandwidth assurance to devices and then maneuvers the idle bandwidth, indicating regularly in the network to offer additional bandwidth. In this method, diverse bandwidth can be allocated to IoT devices based on priorities; such load can be set statically based on the cluster category or adapted dynamically. Our service model is characterized as:

Uninterrupted bandwidth: allocated to critical applications such as healthcare, Industrial IoT and surveillance mission where bandwidth tolerance level zero.

Guaranteed bandwidth: allocated to smart home applications and e-governance where bandwidth usage level is medium.

On-demand bandwidth: allocated to devices such as wearables, smart sports kits where bandwidth usage level is low [8].

B. Dynamic Delivery Architecture

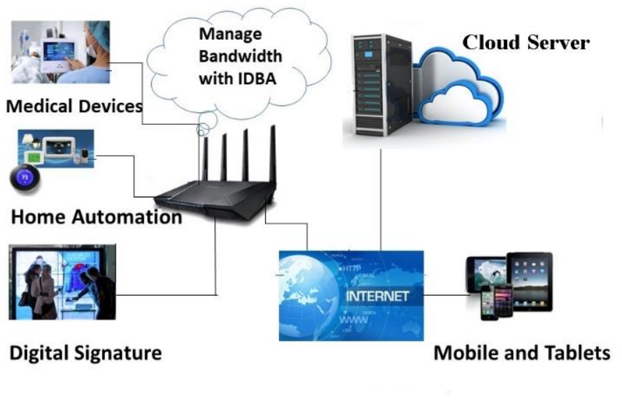

Figure 1. The proposed architecture that supports Dynamic Bandwidth Allocation

The Gateway router in the IoT network periodically updates in the clouds to report bandwidth utilization or congestion situation. Each port in router collects the usage pattern performed by connected IoT devices and periodically exchanges the upload and download pattern with cloud server to analyze via machine learning algorithms In addition, “IDBA” implemented in gateway routers takes the account bandwidth statistics performed in the cloud server and the bandwidth pattern reported by ports making the Gateway routers to allocate bandwidth in a dynamic and efficient way.

4. ENHANCED DYNAMIC BANDWIDTH ALLOCATION METHOD

A. Dynamic Bandwidth Allocation Based on Reinforcement Learning

RL based bandwidth planning is aimed to find the ideal policy for dynamic bandwidth management in the IoT environment, which considers reliability in a lower bandwidth environment. The Operation of RL is possible because various categories traffic loads are using the same supply channel, the development of allocating source is based on resource reservation observed in various applications [9], in particular, the interval-based reservation request permits resilience of allocation indefinite interval, in the view of optimizing the cost and efficient resource utilization towards QoS [10].

Reinforcement Learning Problem Design

RL problem for ideal bandwidth allocation is proposed to increase the throughput for all the time. The scheduling with RL was observed broadly in [11]. A set of nodes n ∈ H labeling the environment with a goal state $n_t \in H$.

A set of bandwidth allocation plan *B* with $B(R) \in B$, $B(R) = [c_1, c_2, \ldots. c_n]$, and operation for resource allocation c_j are operated at time sequence *t*, where $t = 0 \ldots T$.

An unidentified transformation function δ: $H \times B \text{ -> } H$.

An unidentified real value premium function *p*: $H \times B \text{ -> } P$.

An unknown real-valued Asset a bandwidth schedule $B(P)$: $B \text{ -> } H$ that increases a flow rate $F^*(B_t)$

$$n_t \in H, \text{where } F *= E(\textstyle\sum_{t=1}^{T} pt).$$

The flow F^* is based on collective bandwidth availability for the bandwidth schedule $B(p)$ achieved for the target state n_t.

4.2 Artificial Intelligence Enabled Bandwidth Allocation model

We demonstrate here, an Artificial Intelligence Enabled Bandwidth allocation method to show how OD_{BW} can be predicted with a high degree of precision by machine intelligence, as shown below OD_{BW} can be solved in two bandwidth components

$$OD_{BW} = OD_{req} + \lambda U_{poll} (\beta T_{min} + (1\text{-} \beta) T_{max}).$$

The term on the right side, OD_{req} is a bandwidth demand for each cluster based on the request message and the second term is the forecasted bandwidth U_{poll} which examines round period of the cluster category. T_{min} and T_{max} are the minimum and maximum packet length. λ and β parameters are used to measure arrival rate distinct forecast coefficient [12]. Our AIE bandwidth allocation model furcates the second term and thus OD_{BW}. An AIE composes an input layer in between some hidden layer and learns to change the weight and bias iterating to achieve the desired output by changing neurons in each layer.

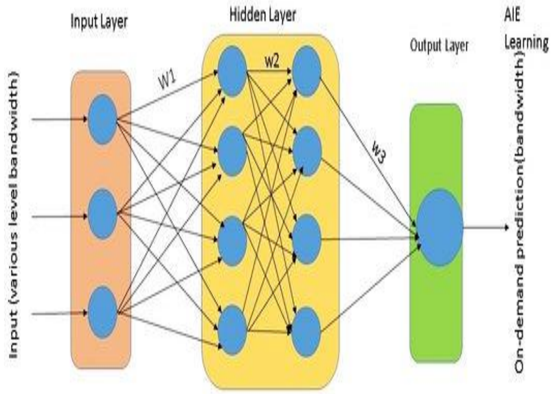

Figure 2. The Sketch of the AIE learning and bandwidth allocation model

An AIE establishes dynamic non-linear interactions between the features and achieves a target output. The goal is to increase bandwidth efficiency. Therefore, we train an AIE to learn the efficiency of various OD_{BW} decisions by using different β. When the supervised learning is complete, the AIE estimates the average on-demand bandwidth for every possible β value. It permits β to be resolved and provides minimal latency. The *Co* then assigns the OD_{BW} solution corresponding to the assigned β. In this section; we demonstrate how supervised training can be carried out with an IDBA algorithm driven by the trained AIE learning model. The proposed Intelligent Dynamic Bandwidth Allocation (IDBA) algorithm that allocates bandwidth efficiently is based on traffic statistics observed by machine learning models. Bandwidth allocation is done by Gateway routers systematically and is imposed using traffic conditioners. Besides, Gateway router observes bandwidth usage in each node, if any node faces bandwidth interruption, IDBA is instantly fixing the situation. IDBA policy is presented as bandwidth range allocated to nodes based on comes under which cluster heads. In [13], it was revealed that routers maintain flow state and attach label into each header based on priority.

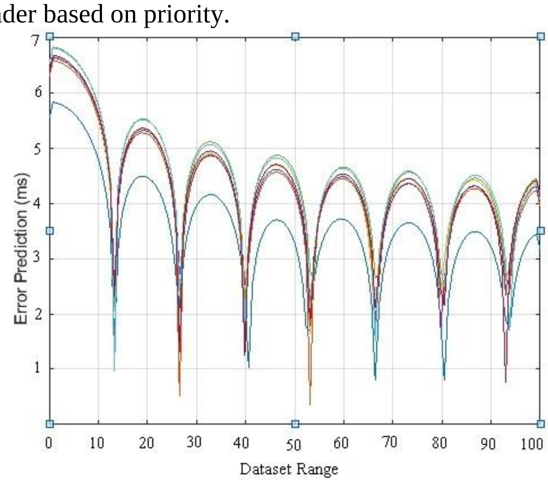

Figure 3. Error Prediction of the trained AIE with 100 samples

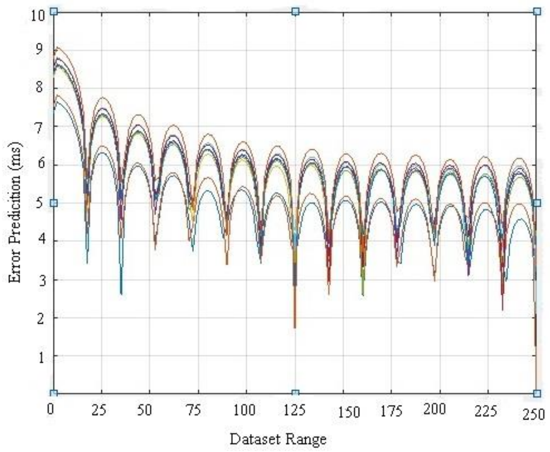

Figure 4. Error Prediction of the trained AIE with 250 samples

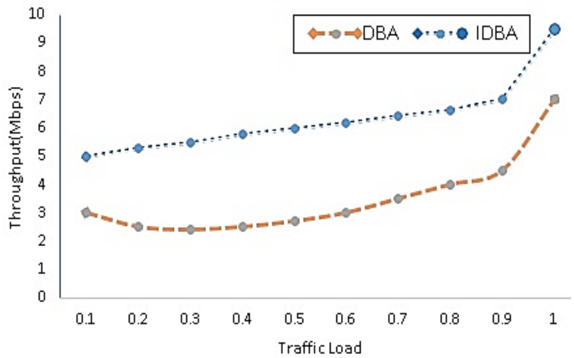

Figure 5. Throughput performance comparison

Here we present bandwidth allocation scheme in detail, that fall in three steps:

In the first step- all IoT devices in the network connected to internet work simultaneously and bandwidth usage for each device is observed by gateway router over the period.

Near term bandwidth requirement for the connected device predicted is based on statistics compiled by machine learning models at cloud sever.

In the second step, additional bandwidth along with unused idle bandwidth and inactive connections is identified on each link.

In the third step, such surplus bandwidth is additionally allocated to exclusive intensive nodes, where bandwidth tolerance is zero percent. This additional bandwidth provides an on-demand basis to meet the requirement of high priority nodes [14].

According to the demonstrated IDBA algorithm, considered network model proposed in [15], we model the architecture of IoT graph $G = (N, H)$, where N represents the number of nodes and H represents the bandwidth allocation range. Each cluster head $c \in C$ has an associated group of device H_c. A group of n devices is connected with the network. Each node is represented by characters (I_n, H_n, C_n) for $n=1,\ldots N$, where I_n, H_n and C_n represent the Intensive, Home and Common appliance nodes respectively, in addition to each connection are associated with Bh_n, Bm_n, Bl_n which represent bandwidth allocation ranges such as high, medium and low [16].

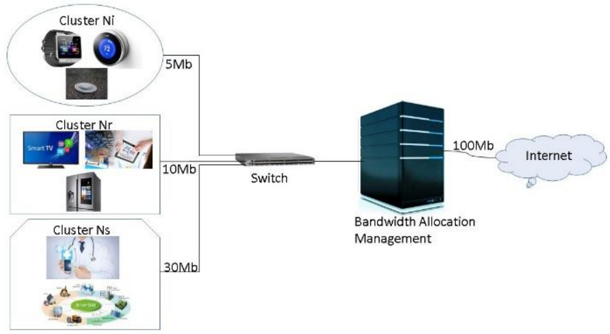

Figure 6. Bandwidth Allocation Management as per IDBA

N_i, N_r, N_s are denoted as the sets of idle, severe and regular clusters respectively.

Normal wearable devices (N_i) are allocated with their minimum required bandwidth rate, i.e $u_n^{\,t} = u\text{-}min_n$, $\forall n \in Ni$.

Regular appliances (N_r) are allocated with standard bandwidth range based on guideline value obtained from ML statistics: $u_n^{\,t} = \min(2.\ u_n^{\,t-1}, avg_n)$, $\forall n \in Nr$.

Severe applications (N_s) allotted with guaranteed bandwidth and based on demand offer additional bandwidth from N_i clusters idle nodes [17].

Second method: The IDBA identifies on each node N the residual bandwidth Rn, i.e, unused bandwidth in N_r along with idle bandwidth in N_i. Hence R_n is expressed as follows:

$$R_n = C_n - \left(\sum_{n \varepsilon Ni \cup Nr} u_n^{\,t} . a_n^{\,t} + \sum_{n \in Ns} avgn.\ a_n^{\,t} \right) \forall t \in T.$$

Summation one represents the complete bandwidth allocated in the first step to N_i idle and N_r regular connections, whereas the second summation represents the bandwidth allocated to N_s severe connection. Table 1 depicts the way additional bandwidth allocated exclusively to N_s severe connections; this is the development of the dynamic bandwidth allocation algorithm proposed in [18].

The set of N_S Severe connection input is given in this algorithm, the cluster set C_s with residual capacity on nodes in each cluster C, Rl and the dynamic allocation technique $d_n^{\,m}$, all produce extra bandwidth amount as output $d_n^{\,m}$, $n \in Ns$ allocated to each node in the severe category during i^{th} restore delay, decisively

$$u_n^{\,t} = avgn + d_n^{\,m}.$$

Pseudo-code specification of the Intelligent Dynamic Bandwidth Allocation algorithm

1. *Setup entire* $d_n^{\,m} = 0$, $\forall n \in Ns$
2. *extract from cluster set N all nodes* $t \in T$, *where the number of connections exceeds* n_t *is equal to 0*
3. *for each node* $t \in T$ *measure* $D_t = R_t / n_t$

4. categorize the node β that reduce D_β, i.e., β / D_β, = min_n (D_n)
5. Fix $d_n^m = D_{\beta'}$ $n \in N\beta$, where $N\beta \cup N_s$ is the number of severe connection that exceeds the node limit β
6. In each cluster C, restore the residual size exceeding severe connections

Such this way

$$R_t = R_t - \sum_{n\in N\beta} d_n^m .\ a_n^t$$

$$n_t = n_t - \sum_{n\in N\beta} a_n^t$$

7. extract from cluster N, node β and the particular bear n_t =0
8. if C is void then break otherwise, drive to step3.
9. Repeat the steps until N_i, N_r and N_s bandwidth range $\geq$ set range.

Intelligent Dynamic Bandwidth Allocation (IDBA) computation

Let us take the Scenario Channel/ Link capacity – 125Mb/s

Cluster N_i: Assured bandwidth – 5 Mb, Peak use bandwidth – 20 Mb, Importance Level – 3

Application: wearable devices, Remote control appliances, parking sensor

Cluster N_r: Assured bandwidth – 10 Mb, Peak use bandwidth – 36 Mb, Importance Level – 2

Application: smart home appliances, intelligent shopping appliances, vehicle auto diagnosis

Cluster N_s: Assured bandwidth – 15 Mb, Peak use bandwidth – 56 Mb, Importance Level – 1

Industrial automation, Patients surveillance and smart grid.

Computation method

Surplus link Bandwidth (1) = Surplus link Bandwidth (2) – Assured bandwidth

Assured Burstable bandwidth = Nodes Burstable bandwidth -Assured bandwidth

Surplus link Bandwidth (2) = Surplus link Bandwidth (1) – Assured Burstable bandwidth [19].

Actual capacity [20] is the duo of operative bandwidth and it states the greatest stable bandwidth level that can be the rate that backed by the system based on availability α, where α available bandwidth level obtained through dynamic bandwidth policy is referred to QoS booster as in [21].

In IoT applications, sensors generate enormous amounts of data in a repetitive manner [22], bandwidth allocation challenges encountered in IoT application to handle massive data [23]. Intelligent Dynamic Bandwidth Allocation [IDBA] method handles on-demand bandwidth in the IoT devices with this Bandwidth allocation scheme.

Table 1. Bandwidth allocation scheme

Cluster / Application	Bandwidth required by nodes	Assured bandwidth	Surplus link Bandwidth (1)	Assured Burstable bandwidth	Surplus link Bandwidth (2)
-	-	-	125 Mb	-	125Mb
Cluster N_i	20Mb	5Mb	120Mb	15Mb	105Mb
Cluster N_r	36Mb	10Mb	95Mb	26Mb	69Mb
Cluster N_s	56Mb	28Mb	41Mb	28Mb	0Mb
Final bandwidth allocation (assured + burstable)	Cluster N_i – 12Mb (5Mb + 7 Mb) Cluster N_r – 30Mb (10Mb + 20Mb) Cluster N_s – 56Mb (28Mb + 28Mb) As the Important level of Cluster N_s is high, its necessity will be achieved by taking away 6 Mb from Cluster N_r and 8Mb from Cluster N_i as they have the lowest Important level.				

5. SIMULATION RESULTS

Comparison of IDBA with PSA and DBA methods.

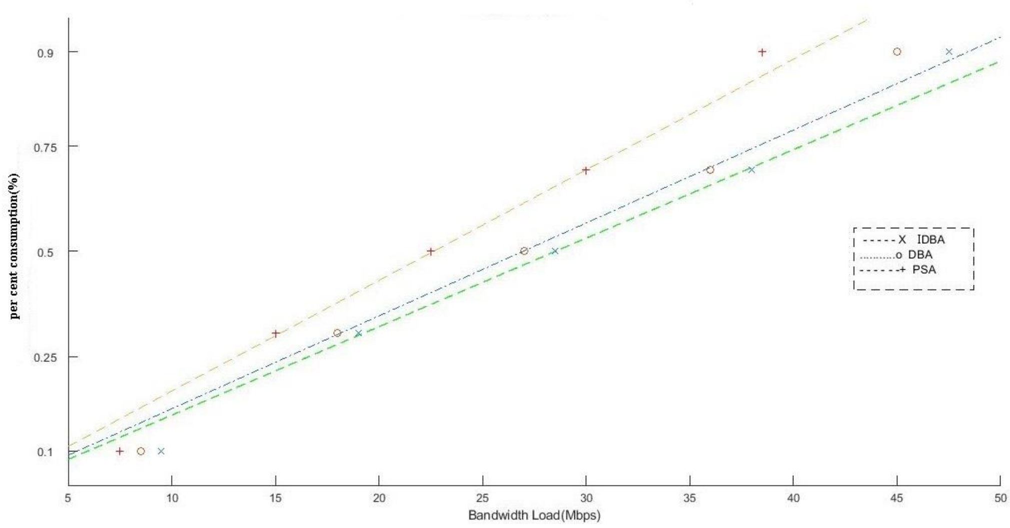

Figure 7. Ideal Bandwidth consumption (PSA, DBA and IDBA)

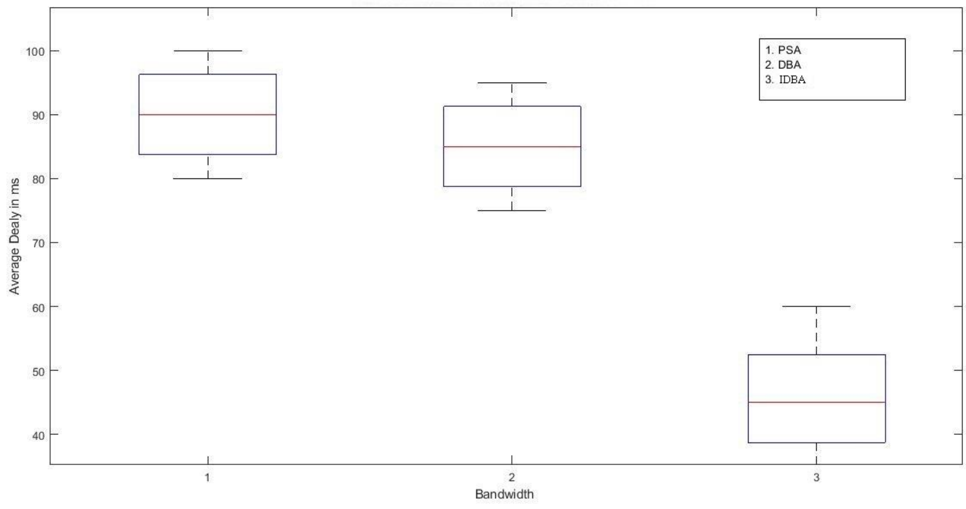

Figure 8. Packet delivery delay (PSA, DBA and IDBA)

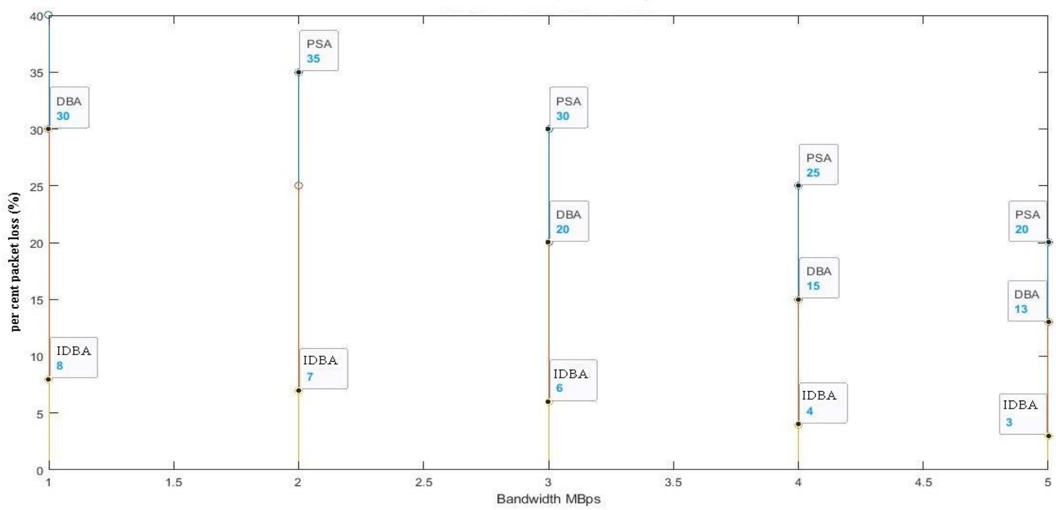

Figure 9. Packet loss (PSA, DBA and IDBA)

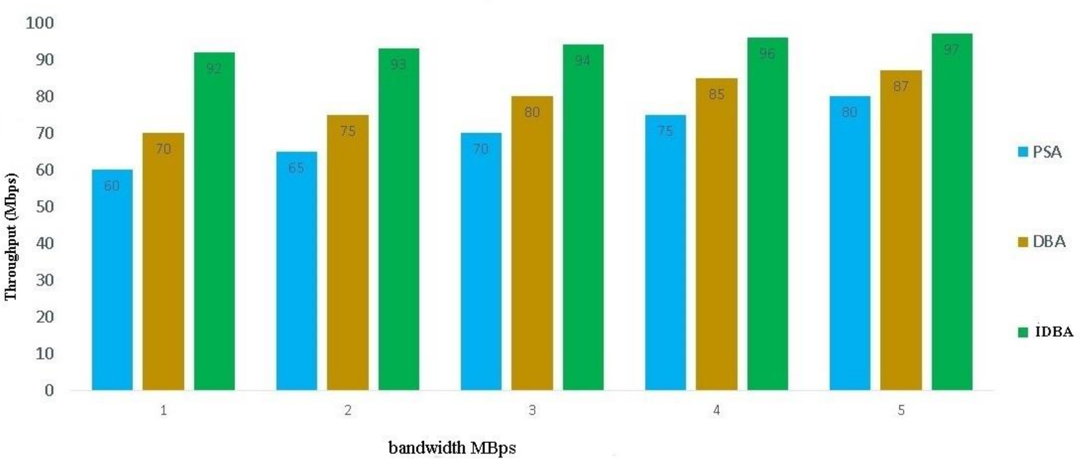

Figure 10. Throughput (PSA, DBA and IDBA)

Table 2. Results of Comparison of QoS factors with reference to PSA, DBA and EDBA

Bandwidth supply in Mbps	Bandwidth Consumption in Mbps			Delay (Latency) in ms			Packet lost in percentage			Throughput (success rate) in percentage		
Bandwidth Allocation Method	PSA	DBA	EDBA	PSA	DBA	EDBA	PSA	DBA	EDBA	PSA	DBA	EDBA
10	9.6	8.6	7.6	98	93	58	43	32	9	62	72	93
20	18.5	17.5	14	94	89	48	32	26	8	66	76	94
30	28	26	22	89	84	44	31	21	7	71	81	95
40	37.5	35.5	29	84	79	39	26	16	5	72	86	96
50	48	46	39	79	74	34	21	14	4	81	88	97

6. CONCLUSION

In this paper, an Intelligent Dynamic Bandwidth Allocation (IDBA) algorithm is proposed to manage efficient bandwidth management provisioning in IoT devices. We described joining tree clustering linkage rules to categories of IoT devices based on bandwidth utilization besides that bandwidth usage is statisticaly analyzed at cloud. An Intelligent Dynamic Bandwidth Allocation (IDBA) algorithm is designed with the ability to learn a policy that matches to adapt dynamic bandwidth allocation to ensure guaranteed bandwidth and increase throughput to IoT devices. IDBA method performs better than PSA and DBA methods in terms of Improving Quality of Service factors such as Ideal Bandwidth usage, low delay (34 ms) and less packet loss (4%) and Increasing throughput (97%) even in low bandwidth range. The simulation results measured in the IoT network scenario show that IDBA is able to increase throughput along with improving QoS in terms of providing uninterrupted bandwidth even in low bandwidth range. In the future, the machine learning algorithms can be enhanced to achieve efficient dynamic bandwidth allocation over non-clustered IoT devices as well.

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