Dynamic Big-Data Broadcast in Fat-Tree Data Center Networks with Mobile IoT Devices

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***Abstract*—In this paper, we study the problem of throughput and delay-optimal dynamic big-data broadcast in fat-tree Data Center Networks (DCNs) in the presence of mobile Internet-of-Things (IoT) devices, where one of the IoT devices acts as a source node. In existing literature, researchers studied that balanced traffic distribution in DCN is an NP-hard problem. With the integration of heterogeneous IoT devices in DCN, the difficulty in achieving balanced traffic distribution increases significantly. Hence, there is a need to design a throughput and delay-optimal big-data broadcast scheme in DCNs in the presence of IoT devices. In this work, we propose a Dynamic Big-Data Broadcasting scheme, named D2B, using single-leader-multiple-follower Stackelberg game for solving the aforementioned problem. Here, each switch acts as the leader, and the IoT devices act as the followers. We consider that the source node broadcasts the generated data in real-time. We represent bandwidth distribution as a pseudo-Cournot competition, where each follower decides the optimal downloading bandwidth. The existence of generalized Nash-Stackelberg equilibrium for D2B is evaluated theoretically. We observe that using D2B, the network throughput increases by 55.32%, while ensuring at least 33% increase in the average bandwidth allocation per IoT device, and the overall delay in broadcasting is reduced.**

***Index Terms*—Data Broadcasting, Big Data, Mobile IoT Devices, Switches, Data Center Networks, Stackelberg Game.**

I. INTRODUCTION

In the last two decades, the data generated by different applications and Internet-of-Things (IoT) devices increased significantly in terms of *Variety*, *Velocity*, and *Volume*, i.e., 3Vs, and named as '*big-data*' [1]–[3]. Traditionally, big-data is processed in Data Center Networks (DCNs) formed by inter-connecting multiple data centers. Hence, in order to design the backbone of big-data networks, i.e., the network infrastructure to handle big-data, there is a need to integrate the IoT devices into the DCN architecture. In existing literature, researchers focused on designing schemes for traffic distribution in DCNs. On the other hand, several existing works also focused on big-data analytics [4] and big-data computing performances [5] in the presence of IoT devices. Additionally, few works, viz. [6], [7], considered data broadcasting among IoT devices. However, there is a need for designing big-data broadcast schemes for DCNs in the presence of mobile IoT devices, while ensuring optimal throughput and delay among the IoT devices. In order to bisect the bandwidth and ensure high data-rate with path-multiplicity, DCNs follow fat-tree architecture, which is a multi-rooted tree structure and failure resilient and ensures a reduction in blocking probability [8]. Hence, in this work, we consider the fat-tree based DCN architecture while designing the big-data broadcast scheme.

In existing literature, most researchers consider the fat-tree architecture for DCNs, in order to ensure multiple paths having equal-cost between any pair of hosts [9] and high bandwidth inter-connectivity. However, unbalanced traffic distribution is one of the important problems in fat-tree DCNs. Uneven traffic load causes inefficient data parallelization, inferior network performance, and degradation of performance quality of the devices [10]. Therefore, there is a need for proper bandwidth distribution scheme for fat-tree DCN with mobile IoT devices. In existing literature, researchers proposed different scheduling techniques for data unicasting [11], [12] and multicasting [8] in fat-tree DCNs. However, there exists no scheme for throughput-optimal broadcasting in fat-tree DCNs. Additionally, in the presence of IoT devices [13], broadcasting big-data in real-time is a challenge [6], [7], which needs to be addressed in fat-tree DCNs. We consider that big-data generated by an IoT device needs to be broadcasted to the IoT devices and the servers at the edge-tier. Hence, considering that the core network is capable of handling the broadcasted data, proper bandwidth distribution and data parallelization for edge network are required for fat-tree DCN in the presence of mobile IoT devices. In this work, we consider that the control plane of each switch helps to improve the network performance while maximizing the network throughput and minimizing the network-delay.

In this paper, we introduce a game-theory-based scheme, named D2B, for broadcasting big-data in fat-tree DCNs with mobile IoT devices. The traffic distribution in the fat-tree DCNs follows a hierarchical architecture. The switches at the aggregation-tier are controlled by the routers at the core-tier, and the devices at the edge-tier are controlled by the switches at the aggregation-tier. Thereby, for the broadcasting of big-data, the bandwidth distribution among the devices at the edge-tier of the fat-tree DCN follows a leader-follower structure. Hence, we use a *single-leader-multiple-follower Stackelberg game* for designing the D2B scheme. In the fat-tree DCN, each switch broadcasts big-data among the IoT devices and the servers at the edge-tier, while ensuring data parallelization. In D2B, we focus on the bandwidth distribution at the edge-tier for achieving optimal throughput with optimal delay. Prior to deciding the amount of bandwidth to be allocated to each device, each switch makes the list of connected devices and the maximum link-capacity of the devices. Based on this information, each switch decides the amount of bandwidth

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to be allocated to each connected IoT device for ensuring balanced load-distribution in the fat-tree DCN. Consequently, optimal throughput and delay of the fat-tree DCN networks in big-data broadcasting are ensured. In summary, the specific contributions of this paper are as follows:

a) We present the D2B scheme for dynamic bandwidth allocation in real-time in fat-tree DCNs with mobile IoT devices at the edge-tier.

b) The single-leader-multiple-follower Stackelberg game theoretic approach is used to decide the optimum strategies of the switches for allocating bandwidth to the devices at the edge-tier, where optimal bandwidth allocation problem is visualized as a *pseudo-Cournot competition*.

c) We present three different algorithms. The first algorithm is used to register the devices with one of the available switches. Using the second algorithm, each device decides the optimal data-rate to download broadcasted big-data. Finally, using the third algorithm, each switch decides an optimal pseudo price coefficient in order to maximize the quality of service of the network.

II. Related Work

In recent years, a number of research works studied big-data processing and data broadcasting problems in DCNs. Some of the existing literature are discussed in this section. Chen *et al.* [14] surveyed the challenges in generation, acquisition, storage, and processing of data. They also mentioned the applications involving big-data such as — enterprise management, IoT, and social networks, while including different medical applications and smart grid. Muntean *et al.* [15] proposed a quality-oriented adaptation scheme for ensuring delivery of high bit-rate multimedia streams to the users using IP network efficiently. Liu *et al.* [6] proposed a neighbor-based probabilistic broadcast scheme for data distribution among the mobile IoT devices. The authors determine the re-broadcast probability while considering the neighborhood nodes and the adaptive connectivity factor. Lau *et al.* [16] proposed an Audience-Driven Live TV Scheduling (ADTVS) framework using 4G LTE broadcast in order to improve the traditional live television broadcasting system. Zarb and Debono [17] proposed a scalable free-viewpoint television broadcast architecture for long-term evolution cellular networks. Lakhlef *et al.* [7] proposed agent-based broadcast protocols for mobile IoT devices, while considering parallel data broadcasting with a limited channels. Based on the availability of communication channels, the network is partitioned into several groups, where each group has a group-leader, i.e., agent. Ahlgren *et al.* [18] surveyed data transfer in the context of Information-Centric Networking (ICN). Unlike DCN, in ICN, the data files are accessed by the user by their name or identifier in spite of the name of the host device. On the other hand, in DCN, the user accesses the data file by the host identifier. Hence, we argue that the schemes designed for ICN are not applicable to data broadcasting in DCN. In another review article, Jagadish *et al.* [1] cataloged different challenges for understanding big-data while citing case study about cleaning, analyzing, and interpretation of data or information. Trestian *et al.* [19] studied a network selection scheme, named E-PoFANS, for multimedia delivery in ad-hoc networks. Paul *et al.* [20] studied the optimal server provisioning problem in DCN and proposed two different schemes — for minimizing operational cost and for minimizing capital and operational cost, jointly, based on a discrete-time model. Wu *et al.* [21] proposed a big-data broadcasting scheme for distributed system. The authors considered that the source device has the maximum bandwidth or capacity, and modeled the network as a Lock-Step Broadcast Tree (LBST). Yu *et al.* [22] surveyed different networking aspect of big-data such as distributed and heterogeneous network. The authors also studied different schemes on big-data representation.

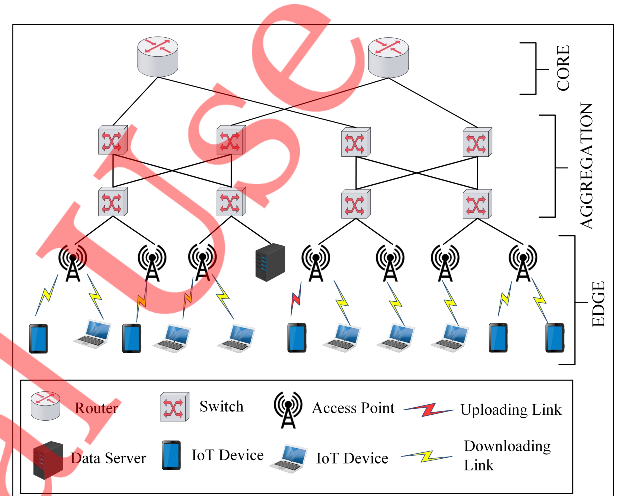

Fig. 1: Schematic Diagram for Fat-Tree DCN with IoT Devices

On the other hand, a few research works studied in data unicasting and multicasting in fat-tree based DCNs. Raiciu *et al.* [23] proposed a Multipath Transmission Control Protocol (MPTCP) in DCN for data unicasting. The authors observed that using MPTCP, the workload is balanced properly in fat-tree topology based DCNs. Chiu and Lau [24] proposed a scheme for efficient multicast broadcast services using transmitter-side channel state information. Al-Fares *et al.* [25] proposed a Dynamic Flow Scheduling (HEDERA) scheme for data multicasting, while aggregating network resources. In another work, Curtis *et al.* [26] studied the multicasting traffic pattern in DCNs. Guo and Yang [8] studied multicasting in DCNs with fat-tree topology. The authors claimed that their work is one of the pioneering work while exploring multicasting in fat-tree based DCNs. However, these works do not consider big-data broadcasting in fat-tree DCNs.

Synthesis: Thus, we infer that there exist a few works on big-data processing and data broadcast in DCN. Additionally, there are few works on data unicasting and multicasting in fat-tree DCN. Though there are few works on data broadcasting in mobile IoT devices, there is a need to design a data broadcast scheme for fat-tree DCN in the presence of mobile IoT devices. Additionally, using the general broadcasting approaches, optimal throughput with an optimal delay in the network cannot be ensured due to the presence of heterogeneous IoT devices. Moreover, there is a need for designing broadcasting scheme for proper utilization of available bandwidth in fat-tree

DCN, while maximizing network throughput and minimizing the network delay.

III. System Architecture

We consider a DCN with fat-tree topology [8] in the presence of mobile IoT devices. A fat-tree topology is a three-tier network architecture having three tiers — *core*, *aggregation*, and *edge*. In DCNs, fat-tree topology reduces blocking probability and is resilient to single-point failure due to the presence of multiple paths among any pair of nodes at the edge tier [8]. We consider that the mobile IoT devices are connected with switches at aggregation tier through Access Points (APs), as shown in Figure 1. In addition to the data-servers, each IoT device $n \in \mathcal{N}_s \subseteq \mathcal{N}$, where $\mathcal{N}$ and $\mathcal{N}_s$ denote the set of IoT devices available at the edge-tier and the set of IoT devices connected with switch s, respectively, at the edge-tier gets associated with a single switch $s \in \mathcal{S}$ at the aggregation-tier, where $\mathcal{S}$ represents the set of switches. We consider that the IoT devices are owned by the end-users. On the other hand, the servers at the edge-tier are deployed by the network operators. The servers are used as storage devices only. We consider that these switches are static in nature and connected to specific routers at the core-tier. Additionally, we consider that the routers and the switches are deployed in a grid fashion over the terrain. Moreover, we consider that the complete coverage of IoT devices is ensured by the APs and the switches in the fat-tree DCN.

Hence, to ensure throughput and delay-optimal big-data broadcast in the network from the source IoT device at the edge-tier, we need to allocate an optimal bandwidth to the IoT devices for downloading. Each IoT device $n \in \mathcal{N}_s$ is connected with switch s at time instant $t \in \mathcal{T}$, where $\mathcal{T}$ is the set of time slots in a day. Each device device n needs to decide the optimal data-rate $r_n(t)$ (in $Kbps$), while satisfying the following constraints:

$$r_n^{min} \leq r_n(t) \leq r_n^{max} \quad \text{and} \quad r_n(t) \leq \mathcal{C}_s - \sum \boldsymbol{r}_{-n} \tag{1}$$

where r_n^{max} and r_n^{min} denote the maximum and minimum data-rate requirement of device n; $\mathcal{C}_s$ defines the capacity of switch s (in $Kbps$), and $\boldsymbol{r}_{-n} \in \{r_1, \cdots, r_{n-1}, r_{n+1}, \cdots, r_{|\mathcal{N}_s|}\}$.

On the other hand, each switch s tries to ensure the use of its bandwidth $\mathcal{C}_s$ for optimal throughput, and allocates bandwidth to the connected devices $\mathcal{N}_s$, while satisfying the constraints in Equation (1). Thus, the main challenges faced to develop the D2B scheme are as follows:

(i) Modeling the D2B scheme, while considering the interaction between the IoT devices and the switches.

(ii) Developing algorithm for each device to decide the optimum downloading data-rate (in $Kbps$), while satisfying the constraints given in Equation (1).

(iii) Developing another algorithm for each switch s to decide the number of devices to serve at a time, while satisfying the constraint mentioned as — $\lim_{x \to 0^+} x < \epsilon$ and $\lim_{x \to 0^-} x = 0$, where $0 < \epsilon << \mathcal{C}_s$, and $x = [\mathcal{C}_s - \sum_{n \in \mathcal{N}_s} r_n]$. Hence, if switches s_1 and s_2 have the unused capacity x_{s_1} and x_{s_2}, respectively, $x_{s_1} < x_{s_2}$ signifies that $sf_{s_1} \prec sf_{s_2}$, where sf_{s_1} and sf_{s_2} signify the satisfaction factor of switches s_1 and s_2, respectively. We define the satisfaction factor of each switch s in Definition 1.

Definition 1. *We define the satisfaction factor sf_s of switch s as ratio of the optimal availed throughput and the maximum capacity of switch s. Mathematically,*

$$sf_s(t) = [\sum_{n \in \mathcal{N}_s} r_n(t)]/\mathcal{C}_s \tag{2}$$

Conjecture 1. *Based on Equation (1), we argue that sf_s of each switch s follows constraint — $sf_s \leq 1$.*

IV. Proposed D2B Broadcast Scheme

To study the interaction between the switches and the IoT devices, we use a single-leader-multiple-follower Stackelberg game. This is a non-cooperative game, where each follower decides his/her/its strategy, non-cooperatively while satisfying the constraints imposed by the leader. In this paper, we divide the entire network into multiple blocks. In each block, an individual switch acts as the *leader*, and the devices, which are connected to the switch, act as *followers*. The proposed D2B scheme is formulated as a *pseudo-Cournot competition*, where each IoT device and the switch choose strategies, non-cooperatively and distributively. On the other hand, each switch distributes the available capacity among the connected IoT devices in order to achieve high performance with optimal throughput and delay for big-data broadcast in fat-tree DCN. The components of the proposed scheme, D2B, are as follows:

(i) Each switch s, which acts as the leader, distributes the available bandwidth or capacity among the connected IoT devices, distributively.

(ii) Each IoT device n, which acts as a follower, decides its downloading data-rate r_n, while satisfying Equation (1).

(iii) Each switch s tries to maximize its satisfaction factor, while utilizing the bandwidth capacity $\mathcal{C}_s$.

(iv) There are $\mathcal{M}$ chunks of data to be broadcasted by the source IoT device, where size of each chunk is m kb.

(v) Each IoT device n and each switch s tries to maximize the payoffs of the utility functions $\mathcal{U}_n(\cdot)$ and $\mathcal{P}_s(\cdot)$, respectively, in order to achieve throughput and delay-optimal broadcast in fat-tree DCN.

Definition 2. *Pseudo cost coefficient $p_s(t)$ of switch s at time instant t is defined as follows:*

$$p_s(t) = \sigma sf_s(t) \tag{3}$$

where σ is a constant. σ acts as a scaling factor and defines the variance of throughput of the switches in fat-tree DCN.

A. Single-Leader-Multiple-Follower Stackelberg Game: The Justification

The fat-tree DCN follows a hierarchical architecture. In the fat-tree DCN, the routers at the core tier and the switches at the edge tier are connected with wired links and the capacity of the links are fixed. On the other hand, the switches at the aggregation-tier take lead over the IoT devices and the servers at the edge-tier. Hence, we consider that the fat-tree DCN follows a leader-follower architecture. Therefore, the IoT devices at the edge-tier behave non-cooperatively, and the fat-tree DCN architecture follows the *pseudo-Cournot competition*. Additionally, each leader, i.e., each switch, decides its optimum strategy, distributively. Thereby, the throughput and delay-optimal big-data broadcasting in fat-tree DCN in the presence of IoT devices is visualized as '*oligopolistic market*'. Hence, single-leader-multiple-follower Stackelberg game-theoretic approach is the most suitable approach for dynamic big-data broadcast in the presence of mobile IoT devices in fat-tree DCNs, where the IoT devices at the edge-tier act non-cooperatively.

B. Utility Function of Each IoT Device

Using the utility function $\mathcal{U}_n(\cdot)$, each IoT device $n \in \mathcal{N}$ finalizes the optimal data-rate $r_n^*(t)$ at time instant t. The data-rate $r_n(t)$ decided by each IoT device n depends on the data-rates $\boldsymbol{r}_{-n}(t)$ of the other IoT devices, indirectly. Thereby, each IoT device n decides data-rate $r_n(t)$, non-cooperatively. The utility function $\mathcal{U}_n(\cdot)$ of each IoT device n needs to ensure the following properties:

(i) Each IoT device n tries to download data with the maximum achievable data-rate. The utility function $\mathcal{U}_n(\cdot)$ is considered to be non-decreasing function.

(ii) The utility function $\mathcal{U}_n(\cdot)$ has a marginal value, which depends on $r_n(t)$. We represent the marginal condition of $\mathcal{U}_n(\cdot)$ as follows:

$$\frac{\partial^2 \mathcal{U}_n(\cdot)}{\partial [r_n(t)]^2} < 0 \tag{4}$$

(iii) The pseudo cost coefficient $p_s(t)$ has a negative influence on utility function $\mathcal{U}_n(\cdot)$. On the other hand, satisfaction factor $sf_s(t)$ of each switch s varies proportionally with $p_s(t)$.

Therefore, we design the utility function $\mathcal{U}_n(\cdot)$ as a concave function, which is represented as follows:

$$\mathcal{U}_n(\cdot) = \beta \tan^{-1}\left(e^{-\frac{r_n(t)-r_n(t-\delta)}{r_n(t-\delta)}}\right) - p_s(t) r_n(t) \tag{5}$$

where β is a constant and δ defines the time difference between two consecutive iterations. Each IoT device n tries to maximize its payoff value by deciding an optimal downloading data-rate, while satisfying constraints given in Equation (1). Hence, the objective of each device n is as follows:

$$\text{maximize} \quad \mathcal{U}_n(\cdot) \tag{6}$$

C. Utility Function of Each Switch

For each switch $s \in \mathcal{S}$, we formulate the utility function $\mathcal{P}_s(\cdot)$ for deciding the optimal throughput of the switch and minimize the network delay. Each switch s tries to maximize its satisfaction factor $sf_s(t)$, while utilizing the total capacity $\mathcal{C}_s$. The pseudo price coefficient $p_s(t)$ depends on $sf_s(t)$, as shown in Equation (3). Therefore, each switch s tries to maximize its payoff, while maximizing its utility function $\mathcal{P}_s(\cdot)$. Hence, the objective of each switch s is as follows:

$$\text{maximize} \quad \mathcal{P}_s(\cdot) \tag{7}$$

We define the utility function $\mathcal{P}_s(\cdot)$ of each switch s as multiplication of $p_s(t)$ and $sf_s(t)$, where $p_s(t)$ and $sf_s(t)$ are defined in Equations (2) and (3). Mathematically,

$$\mathcal{P}_s(\cdot) = p_s(t) sf_s(t) \tag{8}$$

where $p_s(t)$ and $sf_s(t)$ are defined in Equations (3) and (2), respectively. Hence, we observe that the utility function $\mathcal{P}_s(\cdot)$ of each switch s follows a concave hyperbolic curve.

D. Existence of Equilibrium

We define the generalized Stackelberg-Nash equilibrium of the proposed scheme, D2B, as follows:

Definition 3. *The tuple $< r_n^*(t), sf_s^*(t) >$ is considered as the generalized Stackelberg-Nash equilibrium solution of switch s, if it satisfies the following inequalities:*

$$\begin{aligned} &\mathcal{U}_n(r_n^*(t), \cdot, p_s^*(t)) \geq \mathcal{U}_n(r_n(t), \cdot, p_s^*(t)) \\ &\mathcal{P}_s(r_n^*(t), \boldsymbol{r}_{-n}^*(t), p_s^*(t), \mathcal{C}_s) \geq \mathcal{P}_s(r_n^*(t), \boldsymbol{r}_{-n}^*(t), p_s(t), \mathcal{C}_s) \end{aligned} \tag{9}$$

where $r_n^*(t)$ and $sf_s^*(t)$ are the optimum data-rate decided by each IoT device n and the optimum satisfaction factor of switch s, respectively.

We ensure the existence of generalized Stackelberg-Nash equilibrium by using Variational Inequality (VI), as shown in Theorem 1. Moreover, in Section IV-E, we get the optimum concave solution under constraints given in Equation (1).

Theorem 1. *Given a fixed price coefficient $p_s(t)$, there exists a generalized Stackelberg-Nash equilibrium, as there exists a VI for the utility function $\mathcal{U}_n(\cdot)$ of each IoT device n.*

Proof. In D2B, each IoT device $n \in \mathcal{N}_s(t)$ tries to maximize its payoff at time instant t. Therefore, for the $\mathcal{N}_s(t)$ set of IoT devices connected with the switch s, we define the overall utility function as follows:

$$\boldsymbol{\mathcal{U}}_s(\cdot) = \sum_{n \in \mathcal{N}_s(t)} \mathcal{U}_n(t) \tag{10}$$

where $\boldsymbol{\mathcal{U}}_s(\cdot)$ must satisfy the constraints given in Equation (1). We evaluate Jacobian of matrix $\mathcal{D}$, where $\mathcal{D} = \nabla \boldsymbol{\mathcal{U}}_s(\cdot)$, as follows:

$$\mathcal{D} = \begin{bmatrix} \vdots \\ -\frac{\beta}{\left[2+\left(\frac{r_n(t)}{r_n(t-\delta)}\right)^2\right] r_n(t-\delta)} - \frac{2r_n(t)}{\mathcal{C}_s} - \frac{\sum \boldsymbol{r}_{-n}(t)}{\mathcal{C}_s} \\ \vdots \end{bmatrix} \tag{11}$$

Thereafter, by neglecting $[\frac{r_n(t)}{r_n(t-\delta)}]^2$ as $[\frac{r_n(t)}{r_n(t-\delta)}]^2 << 1$, we get Hessian matrix $\nabla \mathcal{D}$ as follows:

$$\nabla \mathcal{D} = \begin{bmatrix} -\frac{2}{\mathcal{C}_s} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & -\frac{2}{\mathcal{C}_s} \end{bmatrix} \tag{12}$$

Here, we observe that $\nabla\mathcal{D}$ is a diagonal matrix, where each diagonal element is negative. Therefore, we conclude that the proposed scheme, D2B, ensures the existence of Stackelberg-Nash equilibrium. $\square$

E. Solution of Proposed D2B

For each IoT device n, by applying the KKT condition on utility function $\mathcal{U}_n(\cdot)$ individually, we equate:

$$-\frac{\beta}{r_n(t-\delta)\left[e^{\frac{\Delta r_n(t)}{r_n(t-\delta)}}\right]} - \frac{2r_n(t)+\sum \boldsymbol{r}_{-n}(t)}{\mathcal{C}_s} = 0 \tag{13}$$

where $\Delta r_n(t) = [r_n(t) - r_n(t-\delta)]$. Hence, we get:

$$[\beta\mathcal{C}_s - \sum \boldsymbol{r}_{-n}(t)]r_n(t-\delta) + 2r_n^2(t-\delta)\sum \boldsymbol{r}_{-n}(t) + r_n(t)\left[6r_n^2(t-\delta) + \sum \boldsymbol{r}_{-n}(t)\right] - 4r_n(t-\delta)r_n^2(t) + 2r_n^3(t) = 0 \tag{14}$$

Thereafter, using Cardano's method [27], we get:

$$r_n^*(t) = \sqrt[3]{-\frac{B}{2} + \sqrt{\frac{B^2}{2} + \frac{A^3}{27}}} - \sqrt[3]{\frac{B}{2} + \sqrt{\frac{B^2}{2} + \frac{A^3}{27}}} \tag{15}$$

where $A = (\frac{c}{a} - \frac{b^2}{3a^2})$ and $B = \frac{d}{a} + \frac{2b^3}{27a^3} - \frac{bc}{3a^2}$; $a = 2$, $b = -4r_n(t-\delta)$, $c = 6r_n^2(t-\delta) + \sum \boldsymbol{r}_{-n}(t)$, and $d = [\beta\mathcal{C}_s - \sum \boldsymbol{r}_{-n}(t)]r_n(t-\delta) + 2r_n^2(t-\delta)\sum \boldsymbol{r}_{-n}(t)$.

For simplicity, we consider that the IoT devices are *homogeneous* in nature, i.e., the maximum data-rate that can be supported by the IoT devices is fixed. Hence, we get $a = (|\mathcal{N}|+1)$, $b = -4r_n(t-\delta)$, $c = 2(|\mathcal{N}|+2)r_n^2(t-\delta) - (|\mathcal{N}|-1)r_n(t-\delta)$, and $d = \beta\mathcal{C}_s r_n(t-\delta)$.

V. Proposed Algorithms for D2B

In order to reach the equilibrium in D2B, each IoT device and each switch decide their respective strategies for throughput and delay optimal big-data broadcast in fat-tree DCN. Initially, each IoT device needs to be connected to a switch through an AP using Algorithm 1. Using Algorithm 1, each node selects the nearest switch and registers with that switch. This registration process needs to be repeated when that node comes to another region covered by a different switch. Thereafter, each IoT device decides and informs the optimum data-rate requirement to the concerned-switch using Algorithm 2 for downloading the broadcasted big-data. Using Algorithm 2, each IoT device initializes the downloading data rate to be minimum, and by maximizing its own utility function $\mathcal{U}_n(\cdot)$, IoT device n chooses an optimal downloading data-rate $r_n^*(t)$. On the other hand, using Algorithm 3, each switch decides an optimal pseudo price coefficient for maximizing the network throughput and minimizing the network delay. Based on the decided price coefficient, each IoT device tries to optimize the downloading data-rate, which indicates the throughput of the network. Moreover, the price coefficient depends proportionally on the number of IoT devices. Thereby, we argue that if less number of IoT devices are associated with a switch, the delay at the switch reduces and the throughput also decreases. On the other hand, if the number of IoT devices connected to a switch increases, the throughput increases, and the delay also increases. Hence, using Algorithms 2 and 3 sequentially, D2B tries to ensure a trade-off between the optimal network throughput and delay.

Algorithm 1 IoT Device Registration

INPUT: $d_{ns}, \forall n \in \mathcal{N}, \forall s \in \mathcal{S}$ ▷ Euclidean distance
OUTPUT: $\{<n, s>, n \in \mathcal{N}\}$
PROCEDURE:
for each $s \in \mathcal{S}$ **do**
  Form a tuple of $<n, s, d_{ns}>$;
end for
Select the tuple having minimum d_{ns} value;
return $\{<n, s>, n \in \mathcal{N}\}$;

Algorithm 2 Optimal Throughput for Each IoT Device n

INPUTS:
$r_n(t-\delta)$, $r_n(0) = 0$, $p_s^*(t)$, β
γ ▷ Data-rate increment factor in an iteration
OUTPUT: $r_n^*(t)$
PROCEDURE:
$r_n(t) = r_n^{min}$
while $\mathcal{U}_n(r_n^*(t), \cdot, p_s^*(t)) \geq \mathcal{U}_n(r_n(t), \cdot, p_s^*(t))$ **do**
  $r_n(t) = r_n^*(t)$;
  Evaluate the modified data-rate r_n^{mod} using Eq. (14)§;
  $r_n^*(t) = r_n^{mod}$;
  Call Algorithm 3;
end while
return $r_n^*(t)$;

Algorithm 3 Optimal $p_s(\cdot)$ for Each Switch s

INPUTS:
$\{r_n^*(t) | \forall n \in \mathcal{N}_s\}$, $\mathcal{C}_s(t)$
OUTPUT: $p_s^*(t)$
PROCEDURE:
$sf_s(t) = \sum_{n=1}^{\mathcal{N}_s} r_n^*(t)$;
Calculate $p_s^*(t)$ using Eq. (5)§;
return $p_s^*(t)$;

Complexity Analysis

In D2B, each IoT device registers with a switch using Algorithm 1. The computational complexity of Algorithm 1 is $O(|\mathcal{S}|)$. Thereafter, each IoT device n selects an optimal downloading data-rate using Algorithm 2. Considering that Algorithm 2 iterates K times before reaching Stackelberg equilibrium. Therefore, the computational complexity of Algorithm 2 is $O(K)$. For each iteration, Algorithm 3 having computational complexity of $O(1)$ is executed once. Therefore, the overall computational complexity of D2B is $O(|\mathcal{S}| + K)$.

VI. Performance Evaluation

A. Simulation Parameters

For the performance evaluation, we simulate using MATLAB simulation platform and deployed the IoT devices randomly over a terrain of 1000×1000 m^2 [28]. However, the switches and the routers are deployed in a grid fashion, while ensuring full coverage. We consider that the source IoT device generates 1000 number of data chunks, and the size of each data chunk is 800 Mb, as shown in Table I. Motivated by the device distribution of the Internet [21], [29], we consider that the distribution of IoT device capacities follows the distribution mentioned in Table II.

TABLE I: Simulation Parameters

Parameter	**Value**
Simulation Area	$1000\ m \times 1000\ m$ [28]
Number of Nodes	$100 - 50000$
Number of Switches	4
Number of Servers	3
Capacity of Nodes	128, 384, 1000, 5000 $Kbps$
Velocity of Source Node	5 m/s
Capacity of Switches	10 $Gbps$
Data chunks generated	1000
Size of each data chunk	800 Mb
Mobility model (MM)	Random Gauss-Markov [30] Random waypoint [31]

TABLE II: Node Capacity Distribution [29]

Capacity ($Kbps$)	**Nodes (%)**
128	20
384	40
1000	25
5000	15

B. Benchmarks

The performance of the proposed scheme, D2B, is evaluated while comparing with two existing schemes for DCNs — the Lock-Step Broadcast Tree based big-data broadcasting (LSBT) [21] and the Multicast Fat-Tree Data Center Networks (DCN_INFOCOM) [8] schemes.

In LSBT, Wu *et al.* [21] proposed a big-data broadcasting scheme, while forming a *Lock Step Broadcast Tree* which is considered as basic unit of upload bandwidth. The authors also considered that the source device, which has the maximum capacity in the network, is at the root of the tree. On the other hand, in DCN_INFOCOM, Guo and Yang [8] proposed a fat-tree based DCN. In DCN_INFOCOM, the authors tried to minimize the number of core switches needed to overcome the problem of over subscriptions. Additionally, the authors overlooked the problem of balanced bandwidth distribution. Moreover, these works do not consider the presence of the mobile IoT devices in fat-tree DCN. In the presence of IoT devices in fat-tree DCN, we improve the network performance

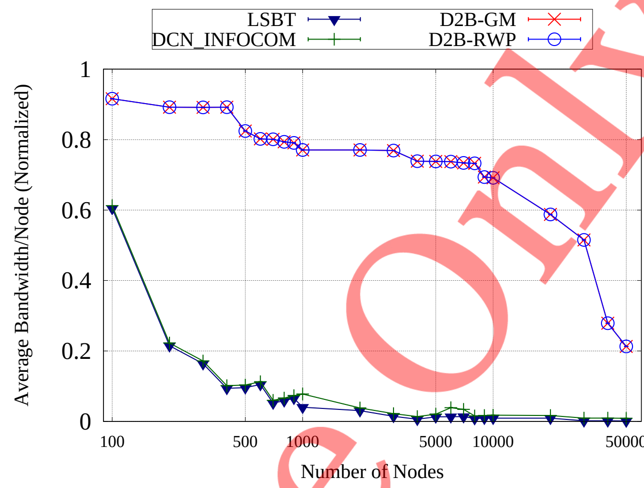

Fig. 2: Average Bandwidth Allocation per Node

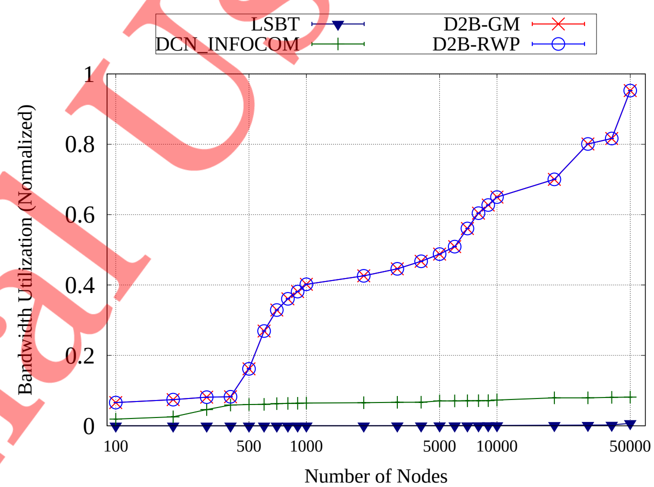

Fig. 3: Total Bandwidth Utilization

for big-data broadcast, while ensuring optimal throughput and delay of the network using D2B. Moreover, we simulated D2B with two mobility models — random Gauss-Markov [30] and random waypoint mobility [31], and named the schemes as D2B-GM and D2B-RWP, respectively.

C. Performance Metrics

We have evaluated the performance of the proposed scheme, D2B, using the following metrics:

Bandwidth Utilization: We consider that the IoT devices are heterogeneous in nature. Additionally, these devices are connected with the switches having limited bandwidth. Hence, we calculate the bandwidth utilization factor of each IoT device as a ratio of bandwidth usage for big-data broadcast and the maximum capacity of the IoT device.

Network Delay: We define network delay as the total time required to complete the big-data broadcast in the fat-tree DCN. Hence, the network delay is defined as the time duration needed for completion of data reception by all the IoT devices in the fat-tree DCN.

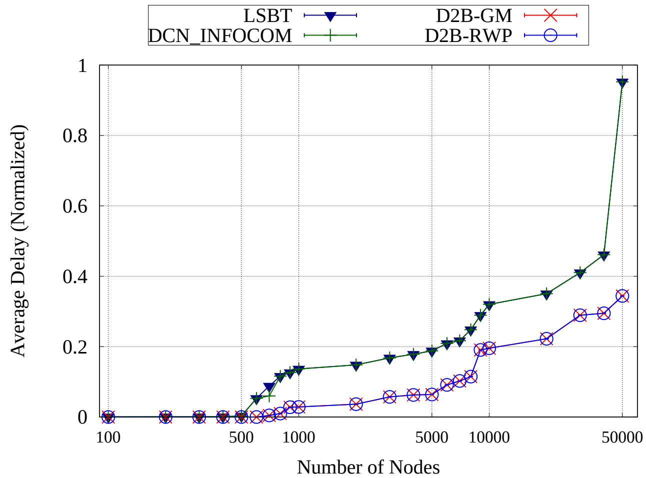

Fig. 4: Average Delay of the Network

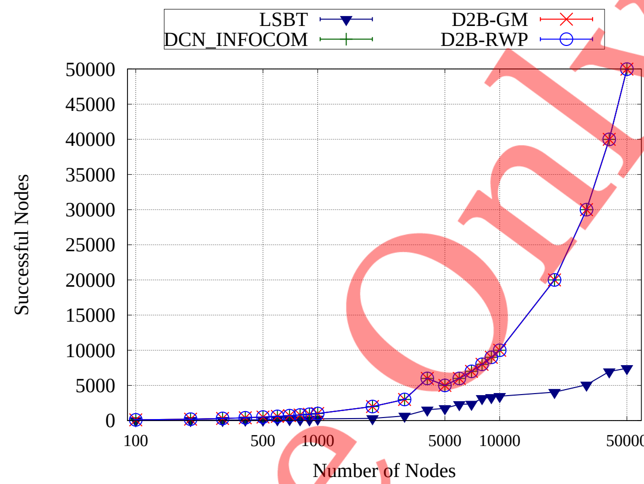

Fig. 6: Successful Nodes in Broadcasting

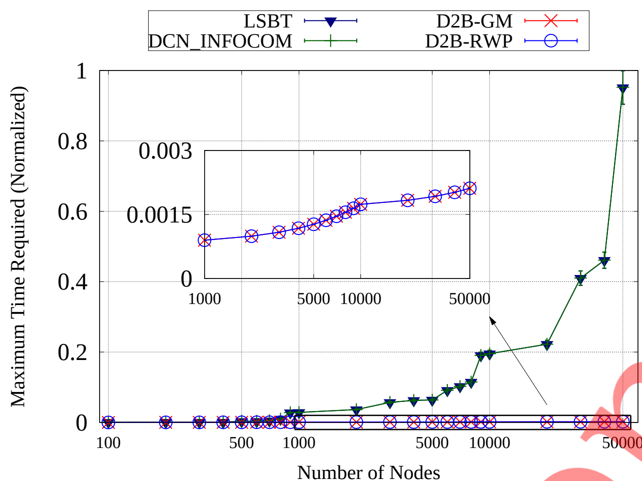

Fig. 5: Maximum Time Required for Broadcasting 100 Packets

Successful Nodes: We consider an IoT device as a successful node if that IoT device receives all the broadcasted data packets sent by the source IoT device, successfully.

D. Results and Discussions

Figures 2 and 3 show that the bandwidth utilization increases using D2B than using LSBT and DCN_INFOCOM. We observe that D2B yields 33-55$\%$ increase in the average amount of bandwidth allocated per IoT device. In LSBT, big-data is broadcasted from the main server having higher network capacity. In DCN_INFOCOM, the allocation of bandwidth is done sequentially. On the other hand, using D2B, the bandwidth is allocated per IoT device, distributively. Hence, using D2B, bandwidth utilization per IoT device is higher than using other schemes — LSBT and DCN_INFOCOM. Additionally, from Figure 3, we observe that the overall network bandwidth utilization increases by at least 55.32% using D2B than using LSBT and DCN_INFOCOM.

From Figure 4, we observe that using D2B, average delay decreases 25.83-62.4% than using LSBT and DCN_INFOCOM. In D2B, due to an increase in the average bandwidth allocated per IoT device, the overall network delay decreases. Moreover, from Figure 5, we observe that using D2B, with the increase in the number of devices, the total delay in data broadcasting increases linearly, whereas using LSBT and DCN_INFOCOM, the total time required to complete the process increases exponentially. From Figure 6, we observe that the number of IoT devices, which received broadcasted data packets successfully, is comparable using D2B and DCN_INFOCOM. However, using LSBT, the source IoT device is considered to be at the root of the tree. Hence, using LSBT, the IoT devices having a lesser capacity than the source IoT device form the subtree, which includes the successful nodes. Thereby, using LSBT, the number of IoT devices, which are successful in receiving the broadcasted packets, is lesser than using D2B and DCN_INFOCOM. Moreover, we argue that the bandwidth distribution using the proposed scheme, D2B, is temporal. Hence, we observe that in Figures 2-6, the results for D2B-GM and D2B-RWP are almost similar. Thereby, we conclude that D2B ensures efficient distribution of available bandwidth among the connected IoT devices. Hence, we conclude that D2B ensures dynamic big-data broadcast in fat-tree DCN in the presence of mobile IoT devices with optimal throughput and network delay.

VII. Conclusion

In this paper, we formulated a single-leader-multiple-follower Stackelberg game theory-based D2B scheme to ensure proper bandwidth utilization of the network for the dynamic big-data broadcast in fat-tree DCN in the presence of heterogeneous mobile IoT devices. We observe that the proposed scheme, D2B, ensures the reduction in network delay in the presence of the mobile IoT devices at the edge-tier of the fat-tree DCN. Moreover, from simulation, we observe that D2B outperforms the other existing schemes — LSBT and DCN_INFOCOM.

Future extension of this work includes an understanding of network bandwidth distribution in the presence of multiple source IoT devices at the edge-tier of fat-tree DCN. This work also can be extended to understand the optimal bandwidth distribution in the core and backhaul network. Additionally, this work can be extended to understand how network bandwidth is to be distributed while reducing the energy consumption of the network.

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