Concurrent Data Collection Trees for IoT Applications

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***Abstract*—Internet of Things (IoT) systems comprise massive volumes of smart devices. Through exchanges of information, smart objects are capable of reasoning and generate higher level of intelligence. The effectiveness of data collection processes is a key factor to the success of IoT systems as it can seriously affect the freshness of the captured data. Efficient data collection processes have been well-studied on sensory systems with static topologies and single data extraction point. Smart devices in IoT systems are often shared by different parties, therefore concurrent data collection processes are always expected. Such a unique characteristic of IoT systems has imposed new challenges to the designs of efficient data collection processes. In this paper, concurrent data collection trees specifically designed for IoT applications are proposed. It is shown that, comparing with an existing single-user data collection structure, systems with the proposed tree structures can significantly shorten their concurrent data collection processes.**

***Index Terms*—Internet of things, concurrent transmissions, data collection processes, tree topology**

I. Introduction

By 2050, 70% of the worlds' population is expected to live in cities. To support such a rapid growth, it is important for cities to deliver up-to-date information to its residents in a timely manner by adopting modern information and communications technologies. Among the technologies, Internet of Things (IoT) is well recognized as a promising solution [1], [2]. Currently, most existing smart cities are equipped with non-interoperable isolated IoT infrastructures [3]. To maximize the effectiveness and fully unleash the potential of smart cities, IoT devices installed on different assets should be interconnected instead of forming multiple discrete closed-form systems [4]. Furthermore, to avoid over- provision and unnecessary redundancy, public and private sectors should share their IoT infrastructures.

Therefore, it is safe to assume that for future IoT systems, a set of sensors and middleware will be owned and shared by multiple users. Users or even IoT devices may submit their queries simultaneously, which trigger multiple parallel data streams in the same network. The effectiveness of data collection processes is always an important issue for IoT systems as it can seriously affect the freshness of the captured data and ultimately affect the decision-making process behind [5]. Parallel data streams introduce new challenges to the delay optimization in IoT systems. In this paper, concurrent data collection trees are proposed to keep the overall data collection duration short. Simulation results show that the proposed idea can greatly reduce delays in concurrent data collection processes. The rest of the paper is organized as follows. Section II presents the related work of this project. Section III introduces the characteristics of the proposed data collection trees structure. Detailed mathematical analyses on the performance of the proposed data collection trees and the delay-aware data collection network structure (DADCNS) in [6] are provided in Section IV. Practical procedures for achieving feasible transmission schedules under the proposed tree structure are introduced and elaborated in Section V. Results are presented and analyzed in Section VI. Concluding remarks are given in Section VII.

II. Related Work

The problem of data collection in large-scale sensory systems has been studied in the early work of Cheng *et al.* [7]. In their work, they considered collecting data from a large volume of individuals to a single data extraction point. Based on the fact that all the nodes in a sensory system are owned by the same party, the authors in [7] have provided a new insight to the well-studied routing problem in computer networks. That is,

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instead of avoiding congested links, one should maximize the utilization of his network resources by means of having a coordinated transmission schedule. In [8], Florens *et al.* provided a framework for evaluating the time performance of data collection and data distribution tasks in sensory systems. In their work, they derived low bounds for networks with various topologies and given their corresponding optimal transmission schedule. Ji *et al.* are the pioneers studying the problem of continuous data collection in sensory systems. In their work [9], they derived the lower bounds for single-snapshot data collections and continuous data collections. They also showed that a data collection process can be significantly shortened by employing devices with multiple transceivers. The above works provided the foundations for the development of delay-aware data collection network structures in [6], [10], [11]. In [6], Cheng *et al.* introduced a delay minimized network structure for fusible data and its corresponding formation algorithms for centralized and distributed systems. In [10], Cheng *et al.* introduced another network structure to facilitate opportunistic in-network data fusion, which the upper bound will never exceed that of a star network. For sensory systems that require consecutive data collection processes, a delay-aware network structure and its formation algorithm have been proposed in [11] to resolve conflicts among transmission schedules. The data collection problem has been further investigated with the consideration of channel models by Chen *et al.* in [12]. In their work, they provided the upper and lower bounds for data collection processes in networks that data fusion is not applicable. In [13], Durmaz Incel *et al.* proposed a fast data aggregation tree for single-snapshot data collection in wireless sensor networks. In their tree construction process, interferences among sensor nodes are taken into account. Wang *et al.* was taking the approach of obtaining an approximate data collection by selectively sampling some of the nodes [14]. Their proposed idea is highly efficient and reliable for scenarios with data showing a high degree of correlation geographically. Recently, studies in [15] have considered optimizing transmission schedules in sensory systems with dynamic traffic patterns. Sensory systems with a probabilistic network model have been investigated in [16] and [17]. Data collection processes in sensory systems with mobility have been studied in [18]. Nevertheless, the works done by Kapoor *et al.* in [19], [20] considered the task scheduling problem in wireless sensor networks (WSNs), which may show the highest similarity to the problem considered in this work. It is noted that machine-to-machine (M2M) communication is the key enabling technology that differentiates IoT from conventional sensory systems [21].

In ordinary WSNs, sensor nodes are normally owned and managed by a single party. In IoT applications, however, IoT devices can be jointly owned by multiple users or applications, who may trigger concurrent data aggregations simultaneously on the same set of nodes. Unfortunately, none of the above works consider concurrent data collection processes and the existence of multiple data extraction points. Data collection in real-world IoT systems have drawn much attention in recent years [1], [22]. In [23], Kawamoto *et al.* suggested to realize a global-scaled IoT federation by utilizing satellite data links to connect remote IoT fragments together. In IoT systems, while an average packet loss rate of around 25% is expected, delays due to retransmissions can be shortened by compressing data and avoiding packet fragmentations [24]. Wu *et al.* stated that data collection systems based on the ordinary IEEE 802.11 standard can suffer from performance degradations when devices are sharing a single channel [25]. They proposed an adaptive channel allocation mechanism and an energy-aware access control protocol for achieving efficient data collection in large-scale IoT systems. Bellavista *et al.* are the very first in the area who bring mobility into IoT by integrating mobile ad hoc networks (MANETs) with WSNs [26].

III. Concurrent Data Collection Trees

In this section, properties of the proposed trees structure will be elaborated. An expression for the duration of a data collection process under the proposed structure will be given, followed by a working example.

Consider an IoT network $N = \{n_1, n_2, \cdots, n_{|N|}\}$ and a set of base stations $S = \{s_1, s_2, \cdots, s_{|S|}\}$. It is assumed that all these $|N|$ IoT nodes can communicate with each other and reach the base stations. Data collected from different IoT devices are assumed to be perfectly fusible, such that multiple received data packets can be fused into one before forwarding to one's parent node [6]. Transmission of a single unit of data will last for 1 time-slot and the duration of a data fusion process is assumed to be negligible. Each concurrent data aggregation process will use a different base station (BS) to access the IoT network and the total number of concurrent data streams is k. To maintain fairness among these users, all concurrent data stream should begin and end at the same time-slot. Nevertheless, parallel data streams should utilize the same number of nodes at each time-slots. To shorten the overall data collection process, each data stream should utilize the maximum possible number of nodes at each time-slot. In a network N with k concurrent data aggregation processes, such that

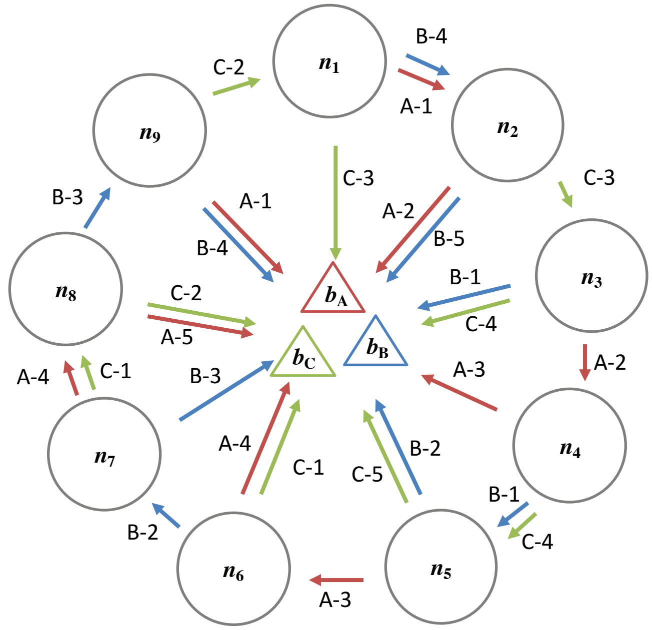

Fig. 1. Data collection in a network N with $|N| = 9$ nodes and $k = 3$ concurrent data streams. Circles and triangles are representing IoT nodes and base stations, respectively. Arrows are indicating the flow of data streams. The text next to an arrow is indicating its data stream (i.e. A, B, C) and the time-slot number (i.e. $1, \cdots, 5$).

$|N| \geq k$, the maximum possible number of nodes that can be utilized by a single data stream at the first time-slot is expressed as

$$u_{\max} = \lfloor \frac{|N|}{k} \rfloor. \tag{1}$$

Here, $\lfloor x \rfloor$ represents the largest integer smaller than or equal to x. Let u_i be the number of nodes utilized by a data stream in the i^{th} time-slot, such that $u_i \leq u_{\max}, \forall i$. If u_i is an odd number, it indicates one of the nodes is involved in a node-to-BS (N2BS) transmission, while the other nodes are paired up and involved in node-to-node (N2N) transmissions. In contrast, if u_i is an even number, it indicates all u_i nodes are involved in N2N transmissions. In general, u_i can be expressed as

$$u_i = \min[u_{\max}, |N| - \sum_{j=1}^{i-1} \hat{u_j}], \tag{2}$$

where $\hat{u_j}$ represents the number of nodes that have finished their transmissions after the j^{th} time-slot and it is expressed as

$$\hat{u_j} = \lceil \frac{u_j}{2} \rceil. \tag{3}$$

Here, $\lceil x \rceil$ represents the smallest integer greater than or equal to x. According to (2), a data stream in the proposed data collection tree will utilize $u_{\max}$ nodes in the first τ_1 time-slots consecutively, where τ_1 is expressed as

$$\tau_1 = \begin{cases} \lfloor \frac{2(|N| - u_{\max})}{(u_{\max}+1)} + 1 \rfloor, & \text{if } u_{\max} \text{ is odd,} \\ \lfloor \frac{2(|N| - u_{\max})}{u_{\max}} + 1 \rfloor, & \text{if } u_{\max} \text{ is even.} \end{cases} \tag{4}$$

There will be $|N| - \tau_1 \lceil \frac{u_{\max}}{2} \rceil$ nodes waiting for transmission at the $(\tau_1 + 1)^{\text{th}}$ time-slot. These nodes will take τ_2 time-slots to finish the remaining data collection process of the current data stream by using DADCNS in [6]. Therefore, τ_2 of the proposed data collection tree is expressed as

$$\begin{cases} \lfloor \log_2(|N| - \tau_1 \lceil \frac{u_{\max}}{2} \rceil) \rfloor + 1, & \text{if } |N| - \tau_1 \lceil \frac{u_{\max}}{2} \rceil > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

By considering cases with $u_{\max}$ being odd or even numbers, τ_2 can be further elaborated as

$$\begin{cases} \lfloor \log_2(|N| - \tau_1 \frac{u_{\max}+1}{2}) \rfloor + 1, & \text{if } |N| - \tau_1 \frac{u_{\max}+1}{2} > 0 \\ & \text{and } u_{\max} \text{ is odd,} \\ \lfloor \log_2(|N| - \tau_1 \frac{u_{\max}}{2}) \rfloor + 1, & \text{if } |N| - \tau_1 \frac{u_{\max}}{2} > 0 \\ & \text{and } u_{\max} \text{ is even,} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Therefore, the overall duration of k concurrent data collection processes in a network N is expressed as

$$T = \tau_1 + \tau_2. \tag{7}$$

Example 1: Consider a network N with $|N| = 9$ nodes and $k = 3$ concurrent data streams. The maximum possible number of nodes that can be utilized by a single data stream is $u_{\text{max}} = \lfloor 9/3 \rfloor = 3$. Using (4), (6), and (7), the overall duration of the 3 concurrent data collection processes in the network is expressed as

$$\begin{aligned} T &= \lfloor \tfrac{2(|N|-u_{\text{max}})}{u_{\text{max}}+1} + 1 \rfloor \\ &\quad + \lfloor \log_2 (|N| - \lfloor \tfrac{2(|N|-u_{\text{max}})}{u_{\text{max}}+1} + 1 \rfloor \tfrac{u_{\text{max}}+1}{2}) \rfloor + 1 \\ &= \lfloor 4 \rfloor + \lfloor \log_2(1) \rfloor + 1 = 5. \end{aligned}$$

According to (2), a data stream will utilize 3, 3, 3, 3, and 1 nodes in the 1st to the 5th time-slot, respectively. A feasible data transmission schedule is illustrated in Fig. 1. Procedures for obtaining such transmission schedule will be elaborated in Section V.

Comparatively, if only DADCNS in [6] is employed, as all the nodes will be utilized by one data stream in the first time-slot, concurrent data collection processes are not feasible. Multiple data collection processes on the same set of nodes can only be carried out sequentially and thus the overall duration of k data collection processes in a network N is expressed as

$$T = k(\lfloor \log_2(|N|) \rfloor + 1). \tag{8}$$

IV. Performance Analyses

In this section, analytical proofs will be used to verify the improvements, in terms of delays in data collection processes, brought by the proposed structure over DADCNS.

Lemma 1: For $k \geq 2$, $|N| - \tau_1 \lceil \frac{u_{\text{max}}}{2} \rceil \leq \frac{|N|}{2}$ is true.

Proof: First consider cases when u_{max} is odd, it can be shown that

$$\begin{aligned} |N| - \tau_1 \lceil \tfrac{u_{\text{max}}}{2} \rceil &= |N| - \tau_1 \tfrac{u_{\text{max}}+1}{2} \\ &\leq |N| - \tfrac{2(|N|-u_{\text{max}})}{u_{\text{max}}+1} \tfrac{u_{\text{max}}+1}{2} \\ &= u_{\text{max}} \leq \tfrac{|N|}{k} \leq \tfrac{|N|}{2}. \end{aligned} \tag{9}$$

Now consider cases when u_{max} is even, it can be shown that

$$\begin{aligned} |N| - \tau_1 \lceil \tfrac{u_{\text{max}}}{2} \rceil &= |N| - \tau_1 \tfrac{u_{\text{max}}}{2} \\ &\leq |N| - \tfrac{2(|N|-u_{\text{max}})}{u_{\text{max}}} \tfrac{u_{\text{max}}}{2} \\ &= u_{\text{max}} \leq \tfrac{|N|}{k} \leq \tfrac{|N|}{2}. \end{aligned} \tag{10}$$

The lemma is proven. ∎

Lemma 2: For $k \geq 2$ and $|N| \geq 4$, then $k \lfloor \log_2(|N|) \rfloor \geq k + \lfloor \log_2(|N|) \rfloor$ is true.

Proof: Consider the inequality $ab \geq a + b$, which holds when $b \geq \frac{a}{a-1}$ and $a \geq 2$. Together with (1), it can be show that

$$\lfloor \frac{|N|}{u_{\text{max}}} \rfloor = k \geq 2 \geq \frac{\lfloor \log_2(|N|) \rfloor}{\lfloor \log_2(|N|) \rfloor - 1}, \tag{11}$$

and therefore

$$k \lfloor \log_2(|N|) \rfloor \geq k + \lfloor \log_2(|N|) \rfloor. \tag{12}$$

The lemma is proven. ∎

Theorem 1: With the proposed arrangement, the overall duration of k data collection processes in a network N with $|N| \geq 4$ is always lower or equal to that of a network with the DADCNS proposed in [6].

Proof: Denote T_{p} and T_{o} as the overall durations of k data collection processes in a network N with the proposed arrangement and the DADCNS, respectively. When $k = 1$, $|N| = u_{\text{max}}$. Therefore,

$$\begin{aligned} T_{\text{p}} &= \tau_1 + \lfloor \log_2(|N| - \tau_1 \lceil \tfrac{u_{\text{max}}}{2} \rceil) \rfloor + 1 \\ &= \lfloor 2(|N| - u_{\text{max}})/u_{\text{max}} + 1 \rfloor \\ &\quad + \lfloor \log_2(|N| - \tau_1 \lceil \tfrac{u_{\text{max}}}{2} \rceil) \rfloor + 1 \\ &= 1 + \lfloor \log_2(|N| - \lceil \tfrac{|N|}{2} \rceil) \rfloor + 1 \\ &\leq 1 + \lfloor \log_2(|N| - \tfrac{|N|}{2}) \rfloor + 1 \\ &= \lfloor \log_2(|N|) \rfloor + 1 \\ &= T_{\text{o}}. \end{aligned} \tag{13}$$

For cases with $k \geq 2$ and u_{max} is odd, it can be shown that

$$\begin{aligned} T_{\text{p}} &= \tau_1 + \lfloor \log_2(|N| - \tau_1 \tfrac{u_{\text{max}}+1}{2}) \rfloor + 1 \\ &= \lfloor \tfrac{2*(|N|-u_{\text{max}})}{u_{\text{max}}+1} + 1 \rfloor \\ &\quad + \lfloor \log_2(|N| - \tau_1 \tfrac{u_{\text{max}}+1}{2}) \rfloor + 1 \\ &\leq \lfloor \tfrac{2*(|N|-u_{\text{max}})}{u_{\text{max}}+1} + 1 \rfloor \\ &\quad + \lfloor \log_2(\tfrac{|N|}{2}) \rfloor + 1 \qquad \because \textit{Lemma } 1 \\ &\leq \lfloor \tfrac{2*(|N|-u_{\text{max}})}{u_{\text{max}}} + 1 \rfloor \\ &\quad + \lfloor \log_2(\tfrac{|N|}{2}) \rfloor + 1 \\ &= \lfloor \tfrac{2|N|}{u_{\text{max}}} \rfloor + \lfloor \log_2(\tfrac{|N|}{2}) \rfloor \\ &\leq 2 \lfloor \tfrac{|N|}{u_{\text{max}}} \rfloor + 1 + \lfloor \log_2(\tfrac{|N|}{2}) \rfloor \\ &= 2k + \lfloor \log_2(|N|) \rfloor \\ &\leq k + k \lfloor \log_2(|N|) \rfloor = T_{\text{o}} \qquad \because \textit{Lemma } 2. \end{aligned} \tag{14}$$

For cases with $k \geq 2$ and u_{max} is even, it can be shown that

$$\begin{aligned} T_{\text{p}} &= \tau_1 + \lfloor \log_2(|N| - \tau_1 \tfrac{u_{\text{max}}}{2}) \rfloor + 1 \\ &= \lfloor \tfrac{2*(|N|-u_{\text{max}})}{u_{\text{max}}} + 1 \rfloor \\ &\quad + \lfloor \log_2(|N| - \tau_1 \tfrac{u_{\text{max}}}{2}) \rfloor + 1 \\ &\leq \lfloor \tfrac{2|N|}{u_{\text{max}}} \rfloor + \lfloor \log_2(\tfrac{|N|}{2}) \rfloor \qquad \because \textit{Lemma } 1 \\ &\leq 2 \lfloor \tfrac{|N|}{u_{\text{max}}} \rfloor + 1 + \lfloor \log_2(\tfrac{|N|}{2}) \rfloor \\ &= 2k + \lfloor \log_2(|N|) \rfloor \\ &\leq k + k \lfloor \log_2(|N|) \rfloor = T_{\text{o}} \qquad \because \textit{Lemma } 2. \end{aligned} \tag{15}$$

The theorem is proven. ∎

V. Feasible Transmission Schedules

In this section, two special network topologies, known as α-ring and β-ring are proposed to obtain the aforementioned performance in data collection processes. It

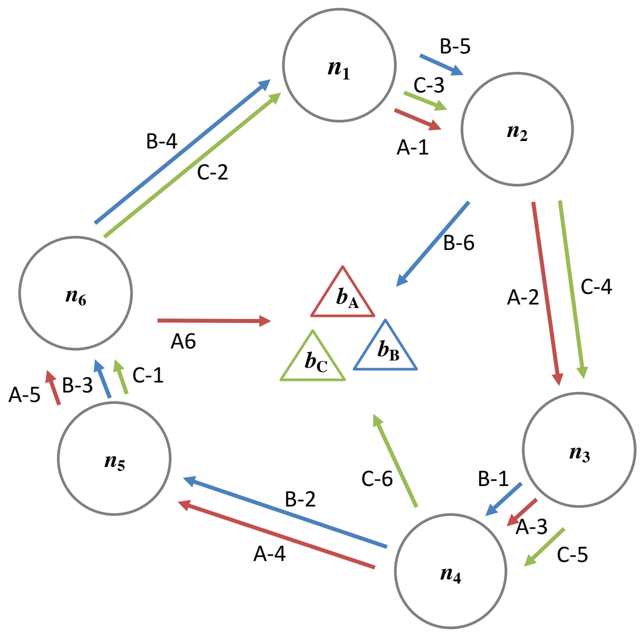

Fig. 2. Data collection in a network N with $|N| = 6$ nodes and $k = 3$ concurrent data collection processes. Circles and triangles are representing IoT nodes and base stations, respectively. Arrows are indicating the flow of data streams. The text next to an arrow is indicating its data stream (i.e. A, B, C) and the time-slot number (i.e. $1, \cdots, 6$).

will be shown that the transmission schedules derived from the proposed structures can fulfill (7) for different values of $|N|$ and k. For scenarios with $u_{\text{max}} = 1$, the BS of each data stream can collect data from $|N|$ IoT nodes using star topologies (i.e. $T = |N|$). For networks with $u_{\text{max}} = 2$ and $u_{\text{max}} = 3$, data aggregation processes with durations equal to (7) can be achieved by arranging the nodes into an α-ring and a β-ring, correspondingly.

A. The α-ring

An α-ring is a ring structure with $|N_\alpha|$ nodes, which $|N_\alpha| \geq 2k$. Consider a case with $u_{\text{max}} = 2$, each data stream will utilize a maximum of 2 nodes in a time-slot. A data stream in an α-ring N_α will need τ_1 time-slots to aggregate data from $|N_\alpha| - 1$ nodes onto a single node. Such node will take one time-slot to report the fused data to the BS. Such result concurs with (7) for cases with $u_{\text{max}} = 2$ and $|N'| \geq 2k$.

Suppose nodes in an α-ring are assigned with arbitrary node numbers, i.e. $n_1, \cdots, n_{|N_\alpha|}$. At time-slot $0 < t \leq \tau_1$, node n_{c_1} in the κ^{th} data collection process will transmit its data to node n_{c_2}, where

$$\begin{aligned} c_1 &= (1 + \text{mod}(2(\kappa - 1) + t - 1, |N_\alpha|)), \\ c_2 &= (1 + \text{mod}(2(\kappa - 1) + t, |N_\alpha|)). \end{aligned} \tag{16}$$

Node n_{c_2} will fuse the incoming data with its own data. Concurrent data collection processes will cycle around the ring structure. At time-slot $t = \tau_1 + 1$, $|N_\alpha| - \tau_1$ nodes in an α-ring will be waiting to transmit their data. Data from these $|N_\alpha| - \tau_1$ nodes will then be collected using the DADCNS, which will last for τ_2 time-slots (6). An example of an α-ring with $|N_\alpha| = 6$ and $k = 3$ is shown in Fig. 2, which has $T = \tau_1 + \tau_2 = 5 + 1 = 6$.

B. The β-ring

Consider another case with $u_{\text{max}} = 3$, following the same logic, the network N_β should have $|N_\beta| \geq 3k$ nodes. When 3 nodes are being utilized at the same time-slot, 2 of them will be involved in an N2N communication and the remaining node will be involved in an N2BS communication. Suppose the nodes in an β-ring is assigned with arbitrary node numbers, i.e. $n_1, \cdots, n_{|N_\beta|}$. At time-slot $0 < t \leq \tau_1$, node n_{c_3} in the κ^{th} data collection process will be involved in a N2BS communication. At the same time, node n_{c_4} in the κ^{th} data collection process will transmit its data to node n_{c_5}, where

$$\begin{aligned} c_3 &= (1 + \text{mod}(3(\kappa - 1) + 2(t - 1), |N_\beta|)), \\ c_4 &= (1 + \text{mod}(3(\kappa - 1) + 2(t - 1) + 1, |N_\beta|)), \\ c_5 &= (1 + \text{mod}(3(\kappa - 1) + 2(t - 1) + 2, |N_\beta|)). \end{aligned} \tag{17}$$

Node n_{c_5} will fuse the incoming data with its own data. At time-slot $t = \tau_1 + 1$, $|N_\beta| - 2\tau_1$ nodes in a β-ring will be waiting to transmit their data. Data from these $|N_\beta| - 2\tau_1$ nodes will then be collected using the DADCNS, which will last for τ_2 time-slots (6). The example shown earlier in Fig. 1 is a β-ring with $|N_\beta| = 9$ and $k = 3$, which has $T = \tau_1 + \tau_2 = 4 + 1 = 5$.

C. Multiple rings

For scenarios with $u_{\text{max}} > 3$, multiple α and β rings of different sizes are needed to ensure the data aggregation duration as suggested in (7).

1) u_{max} is an even number ≥ 4: For u_{max} being an even number ≥ 4, an $n_\alpha = \frac{u_{\text{max}}}{2}$ number of α-rings are formed, i.e. $|N_{\alpha 1}|, |N_{\alpha 2}|, \cdots, |N_{\alpha n_\alpha}|$. Each of these α-ring will first be allocated with $2k$ nodes. The remaining $|N| - n_\alpha(2k)$ nodes will then be allocated to those n_α rings one by one. The difference in ring size between 2 arbitrary α-rings will therefore be less than or equal to 1. Nodes in each α ring will operate according to the rules in Section V-A. In each of the first τ_1 time-slots, a data stream will utilize 2 nodes in every α-ring. Therefore, $2n_\alpha = u_{\text{max}}$ nodes are utilized in each of the first τ_1 time-slots. At time-slot $\tau_1 + 1$, the remaining $|N| - \tau_1 u_{\text{max}}$ will be ready to report their data. Data from these nodes can be collected using the DADCNS using τ_2 time-slots (6).

2) u_{max} is an odd number ≥ 5: For u_{max} being an odd number ≥ 5, a single β-ring together with an $n'_\alpha = \frac{u_{\text{max}} - 3}{2}$ number of α-rings are formed, i.e. $|N_\beta|, |N_{\alpha 1}|, |N_{\alpha 2}|, \cdots, |N_{\alpha n'_\alpha}|$. Initially, the β-ring will be allocated with $3k$ nodes, while each α-ring will be allocated with $2k$ nodes. The remaining $|N| - 3k_{\text{BS}} - n'_\alpha(2k_{\text{BS}})$ node will be allocated to the β-ring until $|N_\beta| = 2\tau_1 + 1$. The rest will be further distributed to the α-rings one by one. The reason to fill up the β-ring before any α-ring is because comparatively, β-ring can yield a shorter data collection process duration for the same number of nodes. Furthermore, the maximum size of the β-ring is limited to $2\tau_1 + 1$ to ensure all its local N2N communications can be completed in the first τ_1 time-slots. For cases with $|N_\beta| = 2\tau_1 + 1$, the whole network will utilize u_{max} nodes in the first τ_1 time-slots, while data in the remaining nodes will take the BS τ_2 time-slots to collect. However, if $3k \leq |N_\beta| < 2\tau_1 + 1$, local N2N communications within the β-ring can be completed earlier than $t = \tau_1$. To ensure u_{max} nodes are being utilized in each of the first τ_1 time-slots, the following refinement procedures are required.

- Step–1: Initialize $t = \lceil \frac{|N_\beta|}{2} \rceil$
- Step–2: Initialize $\kappa = 1$.
- Step–3: At time-slot t of the κ^{th} data stream, identify nodes that a) were not involved in previous N2BS communications, b) were not senders in previous N2N communications, and c) are currently available. Put them into a set V.
- Step–4: Among nodes in V, further identify nodes that have been scheduled d) to be involved in future N2BS communications or e) to be senders in future N2N communications of the current stream. Put them into a subset $V' \subset V$.
- Step–5: Among nodes in $V \setminus V'$, assign one node n_x to be involved in a N2BS communication at time-slot t and another node n_y as the sender in a N2N communication at time-slot t.
- Step–6: Among nodes in V', assign one node n_z as the receiver in a N2N communication at time-slot t. This node will receive data from n_y and fuse that with its own.
- Step–7: Set $\kappa \leftarrow \kappa + 1$, while $\kappa \leq k$, repeat Steps-3 to 6.
- Step–8: Set $t \leftarrow t + 1$, while $t \leq \tau_1$, repeat Steps-2 to 7.

The above procedures ensure there will be u_{max} nodes being utilized in the first τ_1 time-slots. Similar to the aforementioned situations, data in the remaining nodes can be collected in τ_2 time-slots using DADCNS.

Example 2: Consider a network N with $|N| = 15$ nodes and $k = 3$ concurrent data streams. It can be considered as an α-ring with $|N_\alpha| = 6$ together with a β-ring with $|N_\alpha| = 9$. The u_{max} values of these two rings are 2 and 3, respectively, which can be added to yield $u_{\text{max}} = \lfloor 15/3 \rfloor = 5$. After time-slot $t = \tau_1 = 4$, the network will have 3 nodes waiting to transmit their data. Based on (6), $\tau_2 = 2$ time-slots are required for the BS to collect them. Therefore, its $T = 4 + 2 = 6$.

VI. Results and Discussions

The performance of the proposed network structure is further studied using computer simulations. In the simulations, the duration of a data collection process T with k concurrent streams is used as the performance indicator. T is expressed as the total number of time-slots required by the BS of different streams to collect data from all the nodes in the network. Simulations were conducted in Matlab. In each simulation, a network with $|N|$ IoT nodes is considered. In the tests, performance of the original DADCNS will be used as a reference. The DADCNS is configured to form a single cluster. In order to evaluate the effect of $|N|$ and k to the performance of networks with different network structures, $|N|$ is varied from 30 to 300 with a step-size of 15 while k is varied from 1 to 10. Results are shown in Figs. 3 and 4.

The results concur with the analyses in Section IV. Data collection durations of networks with the proposed

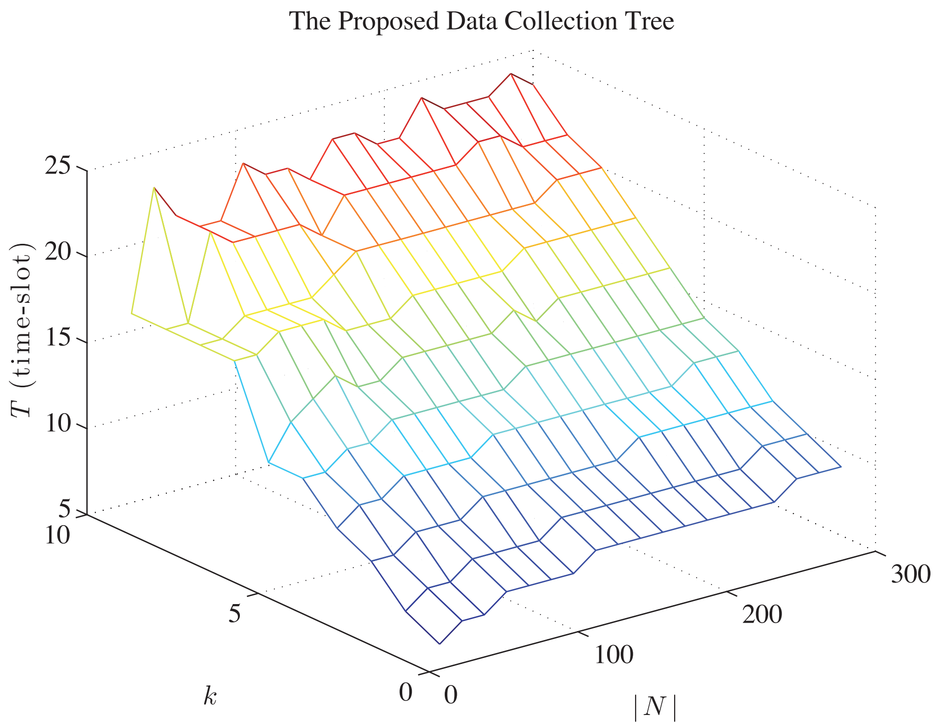

Fig. 3. Data collection durations of the proposed data collection tree in networks with $|N|$ nodes and k data concurrent data streams.

data collection trees are significantly lower than networks with the DADCNS. The performance gap between the two network structures under test becomes widened for larger values of $|N|$ and k. In networks with DADCNS, since concurrent data collection processes are required to be carried out sequentially, their T values increase linearly with k. An increase in $|N|$ will cause $u_{\max}$ of the proposed data collection tree to increase as well. As more nodes can be utilized to performance transmissions in parallel, the T values of the proposed tree structure increase slowly with $|N|$, comparatively.

It can be observed that the T values of networks with the proposed tree structure do not increase monotonically with k and $|N|$. It is because when, k or $|N|$ is incremented, $u_{\max}$ can be varied. The variations in $u_{\max}$ may change the numbers of α and β rings in the network and lead to such observation. Nevertheless, under all combinations of k and $|N|$, T values of networks with the proposed tree structure are lower than those obtained in networks with the DADCNS.

In the proposed network structure, the process for obtaining its transmission schedules can be modified easily to accommodate other optimization constraints or criteria. One common concern for mobile networks is the total communication distance of the data collection tree, which may seriously affect the lifetime of battery-powered mobile devices. Once the sizes and number of α and β rings are determined, N2N communication distance within each ring of the proposed structure can be reduced with the help of clustering algorithms with specified cluster sizes. Such parameter can be further reduced by adopting traveling salesman problem solvers to rearrange the nodes' order inside each loop, such that the total path length of the ring can be shorten. Other criteria, such as channel quality and bandwidth, can also be incorporate to transform the procedures into a multi-objective optimization process. Another concern is the interferences due to concurrent transmissions, which can be resolved or alleviated by imposing minimum separation constraints among conflicting nodes in the formation of feasible transmission schedules. Furthermore, interferences among IoT devices can be mitigated by using different communication channels, which is a feasible option for most modern transceiver modules.

VII. Conclusions

It can be foreseen that in the near future, public and private internet of things (IoT) systems will be jointed together to form an IoT federation. Under these interconnected systems, IoT devices will be shared among different parties. Multiple data collection processes initiated by different users can be carried out on the same set of IoT devices simultaneously. In this paper, a delay-aware network structure specifically designed for concurrent

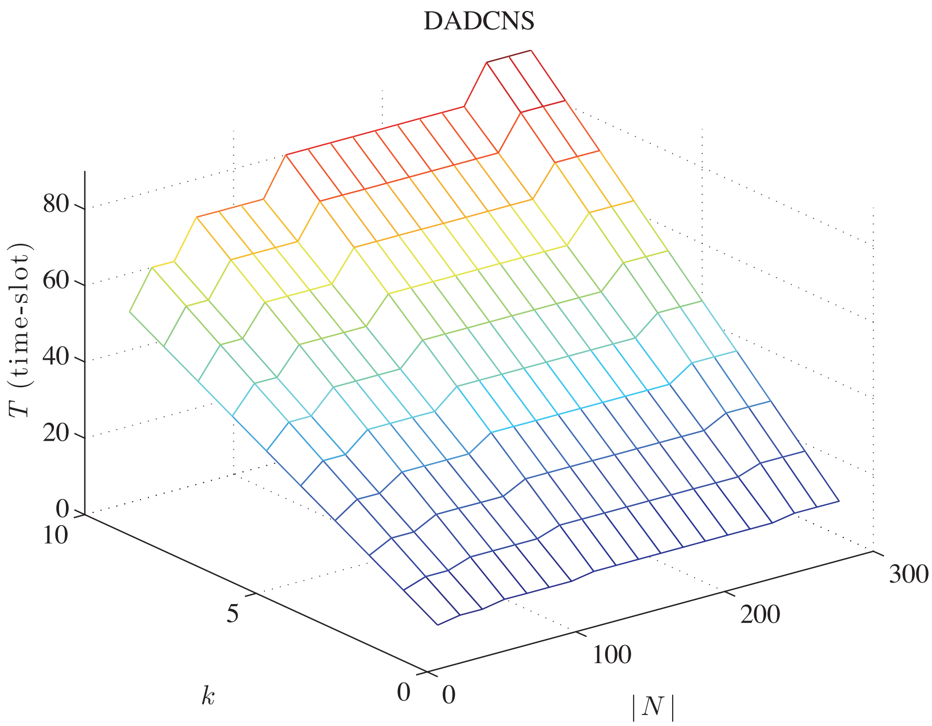

Fig. 4. Data collection durations of the DADCNS in networks with $|N|$ nodes and k data concurrent data streams.

data collection processes in IoT systems is proposed. The proposed network structure can shorten the delays of concurrent data collection processes. Results in this paper show that the proposed idea can yield shorter data collection durations than an existing data collection network structure designed for a single data collection process. Detailed procedures for obtaining feasible transmission schedules of the proposed network structure are also provided.

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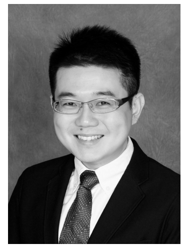

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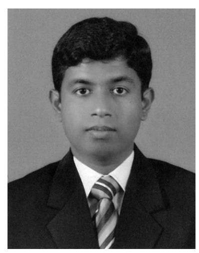

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