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Modeling and Analysis of Data Aggregation from Convergecast in Mobile Sensor Networks for Industrial IoT

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***Abstract*—Estimating communication latency is a challenging task in the applications of industrial Internet of Things (IIoT). Mobile convergecast, as a many-to-one communication pattern, has been recently explored in mobile sensor networks (MSNs) for industrial IoT, where sensor nodes are usually in mobile status, and report the sensed data regularly or randomly to one or more stationary sinks through multi-hop routing path. As convergecast becomes increasingly relevant for industrial sensing and monitoring, a critical part of empowering information aggregation is to maintain consistent transmission. Path duration is one important component of end-to-end delay for communications along then path. In this paper, a probabilistic model for mobile convergecast has been proposed and evaluated to capture path duration times, by considering parameters including network models, sensor network scope, and mobility patterns of network elements. Through simulation, it has been verified that the proposed model can provide a feasible analysis of end-to-end delays in industrial networks implementing convergecast.**

***Index Terms*—Mobile convergecast, path duration modeling, data aggregation, data collection, industrial Internet of Things.**

I. Introduction

Many technologies, such as low-power circuit, wireless communication, and intelligent sensing help in the creation of industrial Internet of Things (IIoT) [1] deployments. The smart factory is a typical application of IIoT. In a smart factory, computing-enabled devices encompassing actuators, sensors, and radio frequency identification (RFID) interact cooperatively with each other carry out various tasks, including collecting sensed data and controlling message creation and delivery in enterprise production and management [2], [3]. Due to the pervasive features of IIoT in smart factories, industrial communication systems under mobile manufacturing scenario have become essential in many automation applications. Futhermore, they have been deployed in diverse areas, such as factory automation, motion control, process automation, networked control systems, and building automation [4], [5], [6].

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Smart factories generate vast amounts of data, including sensing information and control messages, during the working process. These data are transmitted between machines and the control room via wireless communication networks. To enable accurate data collection, transmission delays must be small. Thus, real-time performance and reliability are essential for industrial systems. Reliability of multi-hop connections and transmission delay minimization have been mentioned as the important networking metrics in the design of protocol stack for IoT [7], [8]. Mobile sensor networks (MSNs) [9], [10], serve as the mobile multi-hop infrastructure in monitoring and control of industry, production, and the environmental processes. These MSNs must be capable of supporting reliable, real-time communications in applicable IIoT applications.

A. Motivations

MSN deployments have been studied extensively. Additionally, they have been used to collect and transmit data by coordinating activities between sink nodes and sensing nodes. Within the architecture of MSNs, convergecast [11], [12] is a bedrock aggregation procedure, which are effected by data being collected at network sensor nodes and routed to a common sink node. This many-to-one communication pattern exhibits a feasible way for data collection in IoT applications, where end-to-end delay is an important performance metric. It is particularly important when the real time and time sensitive industrial applications are running above them [13], [14]. For mobile convergecast in IIoT, it is crucial to understand the wireless path duration time (*i.e.* time during which a path from mobile sensor to immobile sink is established). Path disruption in the convergecast paradigm marks the end of this period. Generally speaking, the end-to-end delay of a multi-hop routing protocol in a mobile network mainly consists of route discover time, data transmission time, route failure detection time, and route recovery time [15], which are all related to the duration time of a wireless path. Therefore, modeling and analysis of path duration could guarantee the delivery time of such data collection, especially in mission-critical applications with specific deadlines and periodic data delivery requirements [16], [17].

To better understand how delay occurs and scales together with the cardinality of the set of mobile or static nodes, a plenty of work have been done both from experimental observation and theoretical analysis for both multicast and unicast in ad hoc networks. In the pioneering work [18], Gupta and Kumar discovered that the capacity of a pure static ad

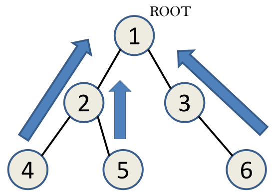


Fig. 1. Characteristics of convergecast communications: (1) packets sent from 4 and 5 may be collided; (2) addressing to root is much easier; (3) link 2–1 must be established earlier than link 5–2 to form path 5–2–1.

hoc network can be limited as the number of nodes increases. Based on it, the network can further reach a throughput of $\Theta(\sqrt{n})$, by conducting power control in [19]. In addition, adding a few of base stations [20] or mobile relay nodes [21] to a static ad hoc network also can achieve possible enhancement in capacity.

Compared to unicast and multicast in ad hoc network, there are several distinct characteristics for convergecast communication in MSNs, especially when mobility is considered in its context, which have motivated our work in this paper. As illustrated in Fig. 1, a static sink node (root) and other mobile sensor nodes (leaves and internal nodes) can form a tree structure in convergecast for data collection in MSNs. In this tree-based convergecast, since data packets that arrive at the root had been sent from leaves, child nodes should act in coordination to avoid collisions, when they are about to send data to their parent node.

In addition, the mobile sensor nodes always function as senders to sense and transmit data. The static sink node is the destination that is quite geographically stable and has a constant address. The corresponding data collection and aggregation from mobile sensors to sink is shown in Fig. 1. Furthermore, path availability is a key factor of the end-to-end delay in multi-hop MSNs. The wireless path in convergecast is always established from the root to the leaves, which is also different from the case in ad hoc networks. Therefore, new methodologies to model delay in convergecast network are needed for the provisioning of such information in networked mobile sensors.

B. Related Works

There have been several theoretical works on the scheduling at the link layer to reduce collisions and achieve optimal convergecast goals, such as minimum delay, minimum schedule length, and minimum energy consumption. More specifically, when upper time bounds can be found, some work using TDMA influenced scheduling algorithms to enable quick data delivery so as to minimize the time to complete the convergecast procedure. For example, minimizing the latency time. In [22], the authors have shown that minimum latency can not be guaranteed by minimum-length scheduling, and then they proposed a heuristic algorithm to minimize latency by scheduling the incoming links before the outgoing links. Link layer algorithms have also been proposed in ZigBee networks to allow speedy convergecast operations with minimum delay in [23]. However, TDMA-based scheduling algorithms are hard to be implemented in real world because an extra clock synchronization system is required, which is not practical in most sensor networks.

In mobile convergecast networks, path availability is critical to the performance of the convergecast protocol with respect to network delay. As a pioneering work, model of a link and path availability was originally derived in [24] for ad-hoc mobile networks with a mobile walk along a randomized trajectory. In [25], the authors presented a general ad hoc network model, and derived the statistical results of link and path availability properties in ad hoc network. The mobility and link dynamicity was added into the analytical evaluation process of a ad-hoc, multi-hop network in [26]. A grid shift scheme for channel access activation and multi-hop path establishment was proposed in [27] for scalable IoT. A more recent work [28] adopted the concepts of cooperative communication and opportunistic routing to select nodes, which will relay during the establishment of multi-hop path in wireless sensor based IoT.

Though path availability has been studied well in networks which are ad-hoc, none of these work incorporates convergecast characteristics to analyze path duration time in MSNs, which is an important networking structure in IoT. In another words, the existing proposals are not applicable in convergecast for mobile applications of IoT, as these work considered the path duration probability as the product of each hop's duration probability, which is not true in convergecast network. In addition, previous work did not exploit how network scales can affect the path duration. Our path duration model and delay analysis proposed in this paper will overcome these limitations to address convergecast in MSNs for IIoT.

C. Our Contributions

In this paper, we try to achieve modeling mobile convergecast and understand its delay from the availability of routing path. Specifically, we present a path duration time model in IIoT, given N *mobile sensors* and M *stationary sinks*. In the considered network, the stationary sinks could be the typical sink node in wireless sensor networks [29] that handles data aggregation as the network edge node, or normal wireless access points, *e.g.* static sensor nodes or mesh nodes, that are geographically deployed in stable position to gather data from mobile sensors. Instead of analyzing the transmission properties in link layer, we are trying to understand the nature of the interactions between node scale and the duration time in a wireless path at the network layer, which can serve as a guide to design and implementation of convergecast routing protocols. We will show that under specific mobility model and transmission model, the average duration time of the whole network is highly affected by the N and M.

In addition, characteristics of convergecast lead us to argue that the path availability, which was considered independent by hops in pure ad hoc network [25], is no longer a simple combination of each hop in convergecast. Actually, the availability of a hop is highly related to the next hop towards the stationary sinks. Therefore, a cumulative path availability model will

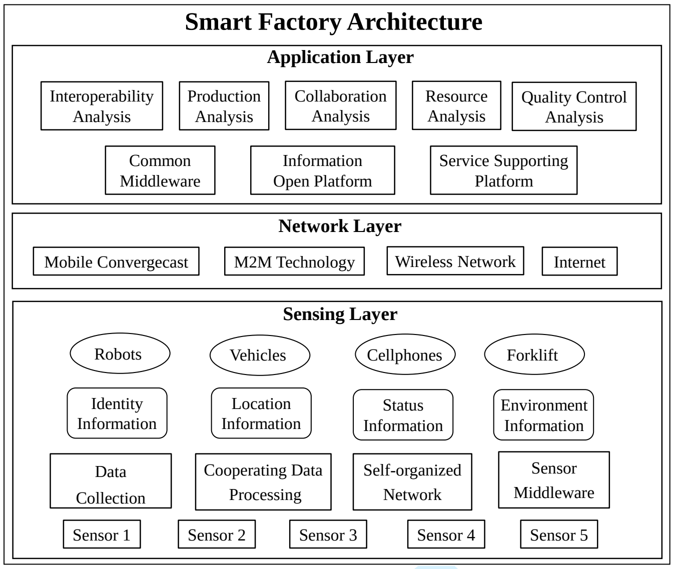


Fig. 2. Architecture of the IoT-based smart factory.

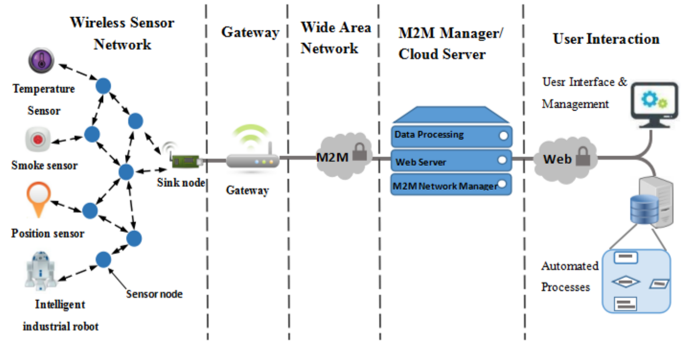


Fig. 3. Networking of the IoT-based smart factory.

be proposed to build wireless path from one-hop to k-hop [1]. Furthermore, our models have been verified through extensive experiments with comprehensive analysis on the results.

The rest of this paper is arranged in the following way: Section II focuses on the importance of convergecast in IIoT. Section III articulates the convergecast related network models and assumptions. Section IV presents the detailed analysis of our path duration model. Section V shows experimental validation, and Section VI concludes the paper with future research discussion.

II. Convergecast in Industrial Internet-of-Things

Convergecast is a fundamental component in IIoT to effectively collect data sensed by different wireless devices. In Fig. 2, we present an architecture of IoT-based smart factory system for data collection in industrial scenario. Smart factory delivers industrial services and information via real-time remote monitoring of machine operation and manufacturing process. Vital signs of machines, products and factory areas can be sensed by wearable or lightweight devices, and sent back to industrial practitioners through wireless communications and mobile computing.

As shown in Fig. 2, the IoT-based smart factory is basically composed of sensing layer, network layer, and application layer, with many groups involved, such as smart buildings, smart logistics, smart mobility, smart grids, smart machine, and smart product. Specifically, in sensing layer, different sensors collect the data for various information requirements, such as identity, feature, location, status, and environment. These information will be finally sent to the smart factory center for further analysis in the application layer. In the application layer, the data analysis can be applied for various purposes, such as interoperability, production collaboration, resource management, quality control, and process automation. Mobile convergecast in network layer functions as a connection component to aggregate data under mobile environment from the sensing layer, and then deliver them to the application layer. Therefore, it acts as an important part for mobile communications in IIoT scenarios.

In reality, the IoT-based smart factory network is organized in a form as illustrated in Fig. 3. The networking structure is similar to the convergecast of MSNs shown in Fig. 1. Many types of factory sensors installed on moving objects collect real-time machine and manufacturing data including but not limited to temperature, humidity, and spatial occupation of factory area; position, direction and speed of production process; fuel consumption, smoke emission and noise generation of running machine. Then those sensors send the collected data to communication infrastructure (sink node) in many-to-one (convergecast) communication pattern. Since these objects used for sensing are under mobile environments, data can be transmitted through both direct connection to sink node and multi-hop convergecast among mobile patients. Therefore, mobile convergecast is a typical communication method in IIoT for smart factory.

Note that it is important to ensure small delay of data collection and transmission in the monitoring process of smart factory and other IoT-based convergecast applications. As the path duration time is a key factor that affects end-to-end delay, we will focus on modeling and analysis of this fundamental problem of mobile convergecast in MSNs for IIoT in following sections.

III. Models and Assumptions

The network model, mobility model and other related assumptions are given in this section for our convergecast analysis in MSNs for IIoT.

A. Network model

The MSN consists of N mobile sensors and M stationary sinks deployed in a 2-dimensional unit square area with side length 1. The stationary sinks include all static wireless access points that can gather and aggregate data from mobile sensors. These stationary sinks have fixed locations,

[1]From the view of stationary sinks. For example, one-hop means one mobile node and one sink, and the distance between them is one hop. Two-hop means two mobile nodes and one sink, where one mobile node is connected with the sink through the other mobile node.

which are deployed in the unit square area with a uniform pattern. The mobile sensors periodically send data to a unique central node (usually the data server) via stationary sinks, as shown by the smart factory example in Fig. 3. Since the links between the central node and stationary sinks are usually wired connection and well maintained by infrastructure providers, we could easily get the path duration from these stable links. In comparison, due to the existence of mobile scenarios and multi-hop wireless links, the accurate estimation of path duration between mobile sensors and stationary sink is a challenge, and will be addressed in the paper. We model this many-to-one communication as a convergecast problem in MSNs functioning in a tree structure for data collection and aggregation, as illustrated in Fig. 1. The mobile sensor nodes are distributed uniformly at random in the unit square area at time t=0. Later, their positions and velocities are given by the mobility model described as follows.

Note that there are mainly two places we used uniform distribution. One is the way we place the nodes in the space and the other is the mobility model. For the first one, we just want to make the placement be generic enough; also it would be difficult to come up with a normal distribution without a more comprehensive application scenario. For the second one, we used random walk model which has been proved to maintain a uniform property in the related literature [25].

B. Mobility model

Random work model is widely used in wireless ad hoc network and simulation tools hence we think it is more convincing to build the mobility analysis model based on random work model. Based on the model, each node's movement consists of a sequence of random-length intervals called mobility epochs. A node moves at a random velocity during these mobility epochs. The velocity is a vector composed of two elements: speed and direction. The speed is a random variable v distributed uniformly between V_{min} and V_{max}. The direction is a random variable θ distributed uniformly between 0 and 2π. We define the probability density function (PDF) of each velocity as:

$$f_v(v,\theta) = f_v(v) \times f_v(\theta) = \begin{cases} \frac{1}{2\pi \times (V_{max}-V_{min})} & \text{if } v \in [V_{min}, V_{max}] \text{ and } \theta \in [0, 2\pi] \\ 0 & \text{Otherwise.} \end{cases} \quad (1)$$

We believe in a common MSN scenario, there should be mixed of movable and immovable nodes. However, the essentially realistic problem we are trying to solve in this paper is how to leverage the opportunistic networking connectivity for mobile convergecast in MSNs. The opportunistic connectivity comes from the uncertainty of the node mobility in terms of the velocity and direction. In our MSN scenario with a number of stationary sinks and mobile nodes, the opportunistic connectivity specifically means the mobile node that is within the range of the stationary sink can act as relay for the mobile node that is out of the range of the stationary sink. We are trying to model this kind of moving behavior and understand this opportunistic connectivity, therefore in our mobility model the speed is a random variable v distributed uniformly between V_{min} and V_{max}.

C. Link duration time

All nodes have same communication range R in our models. If two nodes are within a range R of each other, there exists a bidirectional link between them. For each mobile sensor node MN in our convergecast network, the link between nodes MN_1 and MN_2 is up when the distance between them is shorter than R. Otherwise, it is regarded as downlink. The link duration is defined as the interval between two successive up and down.

D. Other assumptions

We focus on small amount of data, such as network state information, in the data collections system. Therefore the generated data packet size and its transmission time are small as well. Consider the speed of mobile sensor in most application scenarios is low and it does not change a lot once initiated, we conclude that transmission time scale should be much smaller than moving time scale. So in this paper we try to analyze the link availability time inside only one epoch of our mobility model, denoted as T_E. In addition, because of small volume of data, we also can ignore the queueing delay in the routing node. Therefore, the end-to-end delay in our models mainly consists of route discovery delay, route failure and recovery delay. Through this way we can obtain a direct correlation between end-to-end delay and path availability.

IV. Theoretical analysis

Based on above models and assumptions, we analyze path duration time in this section for convergecast scenario in MSNs for IIoT. We first present detailed analysis of one-hop path availability towards the stationary sink, and then use its theoretical results as the basis for further analysis in multi-hop cases.

A. One-hop path duration time

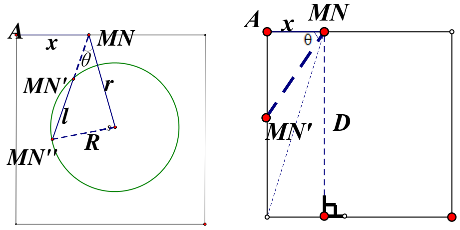
As mentioned above, there are M stationary sinks uniformly distributed in the unit square area. Each stationary sink dominates a sub square, with side length $\Theta(\frac{1}{\sqrt{M}})$. We choose one such sub square to analyze the one-hop path duration time.

In this sub square, all mobile sensors send data to a stationary sink. When a mobile sensor node MN is about to enter a dominated area of the stationary sink (on the border of the sub square), the distance between MN and the stationary sink S is denoted by r. Based on distance r, communication range R and the velocity information, we can analyze the one-hop link duration time of this mobile sensor by following steps.

Assume the distance that MN has traveled during the link duration period is l, as shown in Fig. 4(a). We have:

$$l(r,\theta) = 2\sqrt{R^2 - r^2 \sin^2 \theta} \quad (2)$$

$$r = \sqrt{(D/2)^2 + (D/2 - x)^2} \quad (3)$$



(a) One-hop duration time (b) Square area duration time

Fig. 4. One-hop mobile scenario in industrial IoT.

where D is the side length of the sub square. x is the initial position of MN on the dominated area's border. θ is the clockwise moving direction based on its initial position to the sink. According to our assumption, x is uniformly distributed in $[0, D]$.

According to Fig. 4(a), when MN moves to MN', the link between the mobile sensor and the stationary sink is up. And the link turns down while MN moves to MN''. Therefore, we can write the CDF (Cumulative Distribution Function) of the link duration time T, *i.e.* $P(T \leq t)$, as:

$$F_t^{[1]}(t) = \int_0^D \int_{-\arcsin(R/r)}^{\arcsin(R/r)} \int_{V'_{min}}^{V_{max}} \frac{f_v(v,\theta)}{D} \, dv \, d\theta \, dx \quad (4)$$

where $f_v(v,\theta)$ has been defined in our mobility model in Section III-B. V'_{min} is the minimum required velocity from MN' to MN'' within time t:

$$V'_{min} = \frac{l(r,\theta)}{t} \quad (5)$$

The corresponding PDF (Probability Density Function) of T can be obtained by:

$$f_t^{[1]}(t) = \frac{\partial F_t^{[1]}(t)}{\partial t} \quad (6)$$

Then, the expected duration time of the one-hop link in one dominated area is:

$$E_t^{[1]}(t) = \int f_t^{[1]}(t) t dt \quad (7)$$

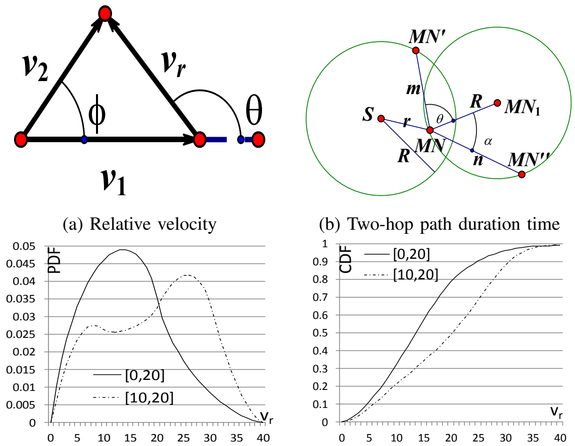
In addition, given different numbers of stationary sinks (different dominated area size) and the need to evaluate the one-hop link duration time under these stationary sinks, we could analyze the average time that a mobile sensor takes to move across a dominated area with the side length D. As show in Fig. 4(b), θ is the counterclockwise moving direction based on one of the square boundaries. When $0 < \theta < \arctan(D/x)$ the distance between point MN and MN' is:

$$k_1(x,\theta) = \frac{x}{\cos\theta} \quad (8)$$

while $\arctan(D/x) < \theta < \frac{\pi}{2}$, it becomes:

$$k_2(x,\theta) = \frac{D}{\sin(\theta)} \quad (9)$$

Assume Ts is the time that a mobile sensor spends to cross a square area, the CDF (Cumulative Distribution Function) of



(a) Relative velocity (b) Two-hop path duration time

(c) Probability density (d) Cumulative distribution

Fig. 5. Two-hop mobile scenario in industrial IoT.

Ts, *i.e.* $P(Ts \leq t)$ can be expressed as:

$$F_{ts}(t) = \begin{cases} \int_0^D \int_0^{arcsin(D/x)} \int_{\frac{k_1}{t}}^{V_{max}} \frac{f_v(v,\theta)}{D} \, dv \, d\theta \, dx \\ \int_0^D \int_{arcsin(D/x)}^{\frac{\pi}{2}} \int_{\frac{k_2}{t}}^{V_{max}} \frac{f_v(v,\theta)}{D} \, dv \, d\theta \, dx \end{cases} \quad (10)$$

For case $\frac{\pi}{2} < \theta < \pi$, it is the same as we described above. So its $f_{ts}(t)$ and $E_{ts}(t)$ can be obtained accordingly.

Note that the side length D of a dominated area is determined by the number of the stationary sinks, denoted by M. The bigger M is, the more frequently a mobile sensor moves across the dominated area and the more likely the mobile sensor can have a one-hop link. Therefore, given the length of the whole epoch T_E, the average one-hop duration time can be derived by $\frac{E_t^{[1]}(t) * T_E}{E_{ts}(t)}$.

B. Two-hop path duration time

Two-hop path for convergecast in MSNs contains an one-hop link from the mobile sensor (mobile sensor that senses and collects the data) to the the relay node (mobile sensor that relays the data), and an one-hop link from the relay node to the stationary sink, as illustrated in Fig. 1. We first present the relative velocity of mobile sensors, and then analyze two-hop path duration time between two mobile sensors.

1) relative velocity of mobile sensors: Similar to the concept introduced [30], mobile sensor's movement is also centrosysmmetric, as shown in Fig. 5(a). Assume mobile sensor MN_1 has a velocity$(v_1, 0)$, MN_2 has a velocity (v_2, ϕ) and their relative velocity is defined as (v_r, θ). Without loss of generality, we also assume v_1 is parallel to X-axis here.

Note that the angle ϕ between v_1 and v_2 is uniformly distributed in $[0, \pi]$. v_r also has a angle θ, which is uniformly distributed in $[0, 2\pi]$. Following the cosine rule, we have:

$$v_r^2 = v_1^2 + v_2^2 - 2v_1v_2\cos\phi \quad (11)$$

Since θ, v_1 and v_2 are independent, the PDF of the joint function is:

$$\begin{aligned} f_{v_1,v_2,\phi}(v_1,v_2,\phi) &= f_v(v_1)f_v(v_2)f_\phi(\phi) \\ &= \frac{1}{\pi(v_{max} - v_{min})^2} \end{aligned} \quad (12)$$

Follow Jacobian transform, we can have the PDF of the relative velocity, as:

$$f_{v_1,v_2,v_r}(v_1,v_2,v_r) = \frac{\partial \phi}{\partial v_r} f_{v_1,v_2,\phi}(v_1,v_2,\phi) \tag{13}$$

where

$$\frac{\partial \phi}{\partial v_r} = \frac{2v_r}{\sqrt{2v_1^2v_r^2 + 2v_2^2v_r^2 + 2v_1^2v_2^2 - v_r^4 - v_1^4 - v_2^4}} \tag{14}$$

Hence, we can derive the CDF of the magnitude of the relative velocity, as:

$$f_{v_r}(v_r) = \int_{v_{min}}^{v_{max}} \int_{v_{min}}^{v_{max}} f_{v_1,v_2,v_r}(v_1,v_2,v_r)\, dv_1\, dv_2 \tag{15}$$

To illustrate the visual results of the relative velocity between mobile sensor MN_1 and MN_2, Fig. 5(c) and Fig. 5(d) show the PDF and CDF of the relative velocity $f_{v_r}(v_r,\theta)$ where the speeds of MN_1 and MN_2 are in the range of $[10,20]$ and $[0,20]$, respectively.

2) Analysis of two-hop path duration time: Contrasted to pure ad hoc wireless network, the path for convergecast in MSNs is established from the stationary sink to the mobile sensors, following a tree structure as shown in Fig. 1. During data collection phase, a mobile sensor always reports its data to its parent in the tree. Thus, when a two-hop path is about to be established, the distance between the relay node and the mobile sensor is exactly the same as the communication range R, while the distance between the stationary sink and the relay node may be shorter than R, which means this one-hop link is already up for some time to aggregate the data from the mobile sensor.

We denote the stationary sink, relay node and mobile sensor by S, MN and MN_1 respectively, as shown in Fig. 5(b). For the established path S-MN-MN_1, the distance between MN and MN_1 has to be R. The distance between S and MN is denoted by r, and $r < R$. The mobile sensors are assumed to be uniformly distributed in the experimental area, then we have $f_r(r) = \frac{2r}{R^2}$. To analyze the two-hop path duration time, we further use T,T_1,T_2 respectively to denote the duration time of S-MN-MN_1, S-MN, and MN-MN_1. T is bigger than t only if T_1 and T_2 are bigger than t. According to these, we have:

$$P\{T \le t\} = 1 - P\{T_1 > t\} \times P\{T_2 > t\} \tag{16}$$

$$P\{T \le t\} = 1 - (1 - P\{T_1 \le t\}) \times (1 - P\{T_2 \le t\}) \tag{17}$$

We use $F^{[2]}(t)$, $F_1(t)$ and $F_2(t)$ as the Cumulative Distribution Functions of T, T_1 and T_2. When MN moves to MN' by a distance m with a velocity of (v,θ) in the network, where θ is the counterclockwise moving direction based on MN-MN_1, the distance between S and MN is also changed accordingly. Therefore, we can obtain the CDF of T_1, as:

$$F_1(t) = \int_0^R \int_0^{2\pi} \int_{\frac{m}{t}}^{V_{max}} f_v(v,\theta) f_r(r)\, dv\, d\theta\, dr \tag{18}$$

where

$$m(r,\theta) = \sqrt{R^2 - r^2\sin^2\theta} - r\cos\theta \tag{19}$$

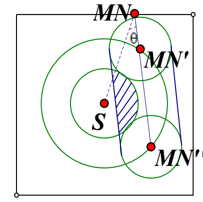


Fig. 6. Two-hop path in square.

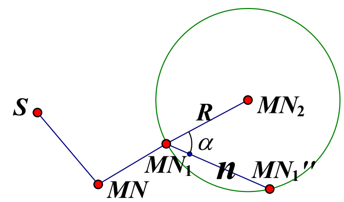


Fig. 7. Three-hop mobile scenario in industrial IoT.

So the PDF of T_1 can be expressed as:

$$f_1(t) = \frac{\partial F_1(t)}{\partial t} \tag{20}$$

The CDF of T_2 is similar to T_1. However, we use relative velocity here considering MN and MN_1 are mobile nodes. The starting distance between MN and MN_1 for path establishment is exactly R. Accordingly, we can have:

$$F_2(t) = \int_0^{2\pi} \int_{\frac{n}{t}}^{V_{max}} f_{rv}(v) \frac{1}{2\pi}\, dv\, d\alpha \tag{21}$$

where

$$n(\alpha) = 2R\cos\alpha \tag{22}$$

The PDF of T_2 is:

$$f_2(t) = \frac{\partial F_2(t)}{\partial t} \tag{23}$$

Then, the CDF of the two-hop path duration time T can be derived, as:

$$F_t^{[2]}(t) = 1 - (1 - F_1(t)) \times (1 - F_2(t)) \tag{24}$$

And its PDF is:

$$f_t^{[2]}(t) = f_1(t)(1 - F_2(t)) + f_2(t)(1 - F_1(t)) \tag{25}$$

Thus, we can have the expectation of the two-hop path duration time, as:

$$\bar{E}_t^{[2]}(t) = \int f_t^{[2]}(t) t dt \tag{26}$$

Note that $E_t^{[1]}(t)$ and $\bar{E}_t^{[2]}(t)$ are very different. When we calculate $E_t^{[1]}(t)$, the starting position of the mobile sensor is on the the dominated area' border. But the starting position for $\bar{E}_t^{[2]}(t)$ is where a mobile sensor establishes a path towards stationary sink. Therefore, for the case of one-hop path establishment, the link is always up right after the mobile sensors entering the communication zone of the stationary sink. But it is not true for the case of two-hop path establishment.

Assume all mobile sensors have the same communication range R, there are two main prerequisites that a mobile sensor can have a two-hop path towards to the stationary sink, as shown in Fig. 6: 1) This mobile sensor needs to move across the ring area, $[R, 2R]$. 2) At least one other mobile sensor in the shadow area should serve as a relay node. As for the first prerequisite, we only consider the ring area rather because it is reasonable that when a mobile sensor moves into the communication range of a stationary sink, it will change its two-hop path towards the stationary sink to be one-hop path immediately. We can simply get the probability of a mobile sensor moving across the ring area, say P_a, using the similar idea of previous one-hop case. As for the second prerequisite, because we assume the whole area as a unit square area and all sensors are deployed in the area, let S be the size of the shadow area, then $P\{$at least one sensor existing in $S\}=1-(\frac{1-S}{1})^{N-1}$, where N is the total number of mobile sensors.

S is a function of θ, as depicted in Fig. 6:

$$\begin{aligned} S(\theta) &= \frac{2\arccos(\frac{2R\sin\theta - R}{R})}{2\pi}\pi R^2 \\ &= R^2\arccos(\frac{2R\sin\theta - R}{R}) \end{aligned} \tag{27}$$

So given a variable s, $P\{S \leq s\} = p\{Theta > g(s)\}$, where $g(s)$ is the inverse function of $S(\theta)$, we have the CDF:

$$F_s(s) = 1 - F_\theta(g(s)) = 1 - \int_{\frac{\pi}{6}}^{g(s)} \frac{1}{\pi}\, d\theta \tag{28}$$

And its corresponding PDF, as:

$$f_s(s) = \frac{\partial F_s(s)}{\partial s} \tag{29}$$

Then, the expectation that at least one relay node, which functions as mobile sensor too, in the shadow region is:

$$E' = \int_0^{\frac{\pi * R^2}{2}} [1 - (\frac{1-S}{1})^{N-1}] f(s)\, ds \tag{30}$$

Therefore, the expectation of the two-hop path duration time is

$$E^{[2]} = P_a E' \bar{E}_t^{[2]}(t) \tag{31}$$

C. Multi-hop path duration time

Based on above two-hop path case, we can derive the expectation of k-hop path duration time iteratively from it. According to the structure of the convergecast tree, when a mobile sensor is about to join the convergecast tree, its parent should already has a path towards to the root node. Therefore, along the available path, each relay node (internal node in the tree) has a distance $r(\leq R)$ away from its parent, while the mobile sensor (leaf node in the tree) has a distance R from its parent (R is the communication range). As shown in Fig. 7 for a convergecast case with a three-hops path in MSNs, we will use it to briefly describe how to calculate the three-hop path duration time so that it can be extended to other k-hop cases.

We use $T^{[2]}$ and $T^{[3]}$ here respectively to denote the duration time of path $S-MN-MN_1$ and path $S-MN-MN_1-MN_2$. Also we use T_3 to depict the duration time of link $MN_1 - MN_2$. $F^{[3]}(t)$ and $F_3(t)$ are used to present the Cumulative Distribution Functions of $T^{[3]}$ and T_3. Assume MN_1 moves to MN_1'' by a total distance n, with a velocity of (v, α), in the network. Similar to Eq. (21), we can describe the CDF of T_3, as:

$$F_3(t) = \int_0^{2\pi} \int_{\frac{n}{t}}^{V_{max}} f_{rv}(v) \frac{1}{2\pi}\, dv\, d\theta\, dr \tag{32}$$

where

$$n(r, \alpha) = 2R\cos\alpha \tag{33}$$

And the PDF of T_3 is:

$$f_3(t) = \frac{\partial F_3(t)}{\partial t} \tag{34}$$

Therefore the CDF of the three-hop path duration time $T^{[3]}$ can be formulated as:

$$F_t^{[3]}(t) = 1 - (1 - F_t^{[2]}(t)) \times (1 - F_3(t)) \tag{35}$$

And its corresponding PDF is:

$$f_t^{[3]}(t) = f_3(t)(1 - F_t^{[2]}(t)) + f_t^{[2]}(t)(1 - F_3(t)) \tag{36}$$

Finally, we can have the expectation of three-hop path duration time, as:

$$\bar{E}_t^{[3]}(t) = \int f_t^{[3]}(t) t dt \tag{37}$$

Based on the characteristics of convergecast in MSNs, above analysis steps also can be extended to support the calculation of path duration time in other k-hop cases.

V. Performance Evaluation

We have verified the correctness of our models by comparing the results of our theoretical models with the actual simulation results, using Qualnet simulator. The simulated smart factory scenario is a two-dimensional space that represents a square area of 3000m $\times$ 3000m. Note that the reason that we define the length of square side as 3000m is to be able to place more nodes in the simulator. The node speed and communication range in this simulated area are chosen accordingly to make sure we can get enough data point within a reasonably short time.

In the simulation, one static central node is set with Ethernet connections to M randomly deployed stationary sinks. N mobile sensors move around in the factory area using random way point mobility model. Both mobile sensors and stationary sinks are equipped with wireless radio interfaces. Mobile sensor can periodically send data to the central node through close-by stationary sinks directly, or through possible relay nodes to stationary sinks by multi-hop path. We have modified the AODV routing protocol built in Qualnet so that the path duration time and its average performance can be derived by calculating the life time of routing entries in mobile sensors. We set the magnitude of velocity in mobile scenario is uniformly distributed in two different ranges: [10m/s, 20m/s] and [1m/s, 11m/s], and its direction is uniformly distributed in [0,2π]. The communication range of all nodes is set as 400m.

The CBR (Costant Bit Rate) application is used in the data collection process. Each packet is set as 500 bytes long and the traffic rate is one packet per second. We set the simulation period (T_E)as 250 seconds, and collect simulation result by averaging 25 explicit runs.

A. One-hop path duration time

In one-hop path scenario we have $N = 1$, and only one-hop path duration time is considered. Fig. 8 shows the simulation results are quite similar with the expected time from our model. In the set of simulation, the number of stationary sinks M is scaled up to 12, and they are uniformly distributed. There is little overlap of their communication ranges. Their total coverage area is almost same as the experiment area. In other words, if there are more stationary sinks, the whole experiment area might be fully covered by them, hence the mobile sensor can always be connected with one of these stationary sinks no matter where the mobile sensor is, which will be meaningless in this experiment.

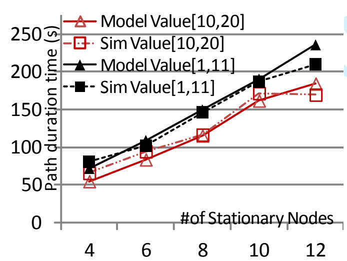


Fig. 8. One-hop path duration time.

In Fig. 8, the number of the stationary sinks M is labeled on the X-axis, and the path duration time is presented on the Y-axis. The number of mobile sensor $N = 1$. Two different velocity distribution ranges, which are [10,20] and [1,11] respectively, are used in the simulation. The mean error rate between the model value and the experiment value for the range [10,20] is 9%, and for the range [1,11] is 7%. The reason for the results is that the transmission range in Qualnet is not exactly depicted as a circle, instead it adopts a physical model to simulate wireless communication. In this physical model, a node can send radio frame successfully as long as the its signal strength sensed by the destination exceeds a specific threshold. The results also demonstrate that mobile sensors with higher velocity will have shorter path duration time. In other words, dynamicity will incur poor connectivity.

B. Two-hop path duration time

We next add one more mobile sensor and explore a two-hop path connection, which implies $N = 2$. A speed range [10,20] is used in the two-hop case and following three-hop case. We only consider M up to 6, and the dominated area is set to encompass the two-hop coverage area (*i.e.* the two-hop coverage area will be overlapped if M=7). Note that as the number of stationary sinks M decreases, the size of dominated area will be enlarged; this indicates that a larger number of hops may be existed within one dominated area. So we only choose $M = 4, 5, 6$, to guarantee that only one and two-hop paths are considered. To verify our models, we also study the two-hop scenario with another approach that is often used in mobile ad hoc networks [25], [30]. We call it Independent Path Duration (IPD) model and compare with it using our model. Each hop durations in our simulation are modeled as independent random variables.

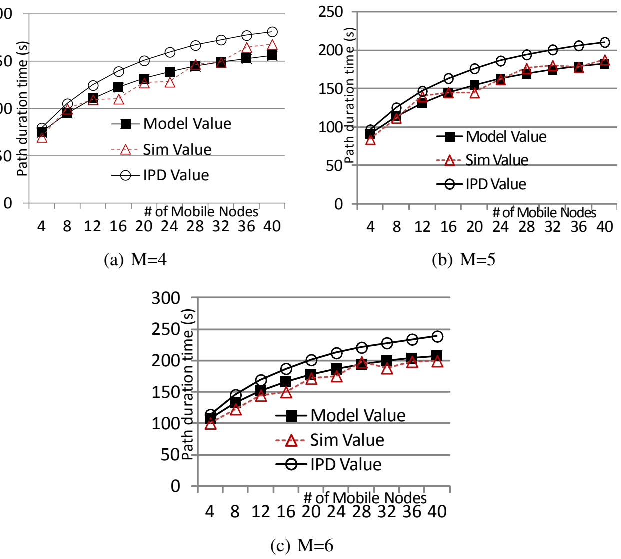


Fig. 9. Two-hop path duration time.

Results in Fig. 9(a), 9(b) and 9(c) show that the simulation results are quite consistent with the model results, and the average error rate is around 5%. It is also worth noting that our model outperformed the IPD model in terms of accuracy, where the error rate is about to 20%. An interesting observation from the results is that when $M = 4$ and $M = 5$, if the number of the mobile sensors exceed a threshold, say $N = 30$, the duration time from the simulation become higher than the one from our model. This is mainly because when N becomes larger, the opportunity that a sensor has a multiple-hop (more than two) path increases, especially when it is out the two-hop coverage area (the circle with radius of $2R$). Because we do not take the multiple (more than two) hops path into consideration when $M > 4$, the duration time calculated by our model is less than the simulated one. The multi-hop path scenario indeed exists, but its probability is very low as we argued above. When $M = 6$, the mobile sensors are almost covered by the two-hop coverage area. In this case there is less chance that a sensor finds a multiple (more than two) hop path. However, according to these simulation results, more stationary sinks will incur more handover, resulting in less path duration time. This explains the results obtained from our model are slightly bigger than the simulated results in Fig.9(c).

C. Three-hop path duration time

To consider three-hop path scenario, we further decreased the number of stationary sinks M to 2 in the simulation. Possible three-hop paths can be accommodated under this setting because the dominated area is slightly larger than the circle with radius of $3R$. As described in Section IV-C, the duration time of three-hop path depends on its first two-hop links. A mobile sensor also may be connected with the stationary sink by one-hop path or two-hop path, according to its position in the simulation scenario. However, we argue that although there may be four-hop or five-hop path existing in the circle with radius of $3R$, the probability of these paths is extremely low and hence can be negligible in our simulation. Fig. 10 shows the results of the path duration time by counting the maximum number of hops in a path from mobile sensor to stationary sink as three. Correspondingly, we can obtain its average error rate which is below 10%. The result is due to our three-hop analysis in our model, where only three-hop path can be established, according to our assumption, when the third mobile sensor falls in the ring area whose radius is between $[2R, 3R]$. In fact, if a mobile sensor falls into the ring of $[R, 2R]$, it can also have the opportunity of establishing a three-hop path, which however is hard to model. The IPD based approach needs more complicated and accurate computation in three-hop case. We can reasonably infer its inferiority from the results of two-hop case. Hence its quantitative value is omitted here.

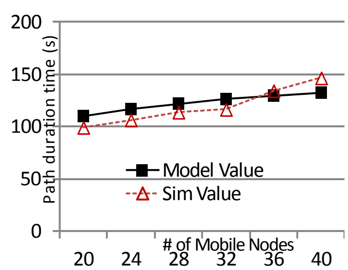


Fig. 10. Three-hop path duration time.

D. End to end delay and the duration time

Two aspects are considered when establishing a relation between end-to-end delay and the path duration: 1) In the ideal case, whenever the application on a mobile sensor sends data, there is always an available path already established by the routing layer towards the stationary sink. However, the mobile sensor usually needs to wait to send application data before the path is established, which will incur delays. 2) Since handover will cause extra time, more stable links are preferred for data transmission. For example, if there are two different paths with duration time $5s$, it is possible that each will incur bigger delay than a single path with duration time $10s$, due to the handover processing. So the less dynamic the paths are, the smaller delay will be achieved.

Fig. 11 shows our results revealing the correlation between delay and the path duration time in convergecast network. The number of mobile sensors has been scaled from 4 to 40. Given different number of stationary sinks ($M = 4, 5, 6$), we have tested three scenarios correspondingly. As discussed above, more stationary sinks will increase the size of coverage area and provide more network access opportunities. The results show that the path duration time obtained when the number of stationary sinks $M = 6$ is lasted longer than $M = 5$ and $M = 4$, therefore the path has smallest delay when $M = 6$. When the number of mobile sensors is increased, the path duration time also increases. However, the distribution of end to end delay is bimodal. As for the end to end delay, along with the increase of mobile sensor number N, it first increases from $N = 4$ to $N = 12$ and then decreases. The second local maximum point of end to end delay is reached around $N = 32$. We obtain the reason accounted for the results is that when the network scale is small the path duration time becomes quite short. With more mobile sensors added, there will be more time spent on handover and the newly obtained path availability can not compensate the handover time consumption. So it will cause the end to end delay to increase. If mobile sensors continues being added, there are more network access opportunities that the handover time can be compensated. Thus the delay decreased accordingly. When the network scales to some extent, traffic congestion occurs, and this in turn increases data transmission time. As we can observe, the delay increases again around $N = 32$. After that the enhanced path availability again dominates the end to end delay. As shown in Fig. 11, the delay decreases when $N > 32$.

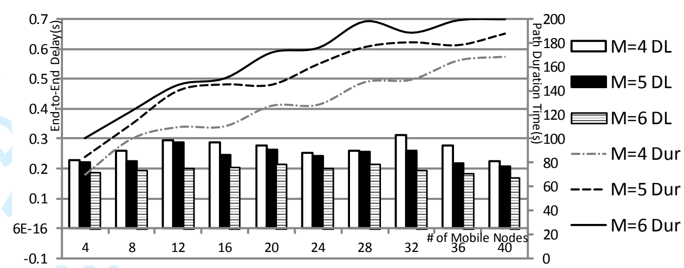


Fig. 11. Delay and duration time.

From the experiments, one inference is that adding more nodes either stationary or mobile can improve the link availability in the network, while only adding stationary sinks can continuously decrease the delay. This makes sense since the stationary sinks provide the first hop connections which are more stable. In reality, the network administrators usually deploy more stationary routers and access points to improve delay. On the other hand, carefully planning the scale of mobile sensors can also improve the end to end delay, which requires a more comprehensive understanding of delay, congestion and link availability. We will study it in the future.

E. Mobile node to stationary sink upload throughput

To further verify the efficacy of our model on the estimation of path duration for multi-hop convergecast, we adopted a real factory scenario and evaluate the upload throughput from a mobile node to a stationary sink, as shown in Fig. 12. The stationary sink is connected to the Internet service and there are five sensor nodes fixed in the factory as the data relay nodes. The mobile node moves in the factory and uses the closest relay node to upload its data to the sink via multi-hop path. The communication range of the sink and relay nodes is marked by the circular line in Fig. 12.

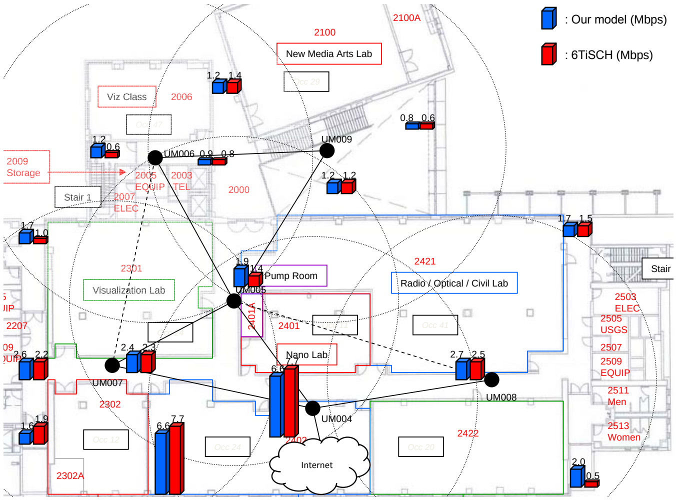


Fig. 12. Comparison of mobile node to stationary sink upload throughput.

IEEE/IETF recently proposed 6TiSCH [8] protocol for IIoT scenarios which uses time slotted channel hopping (TSCH) MAC with IPv6 addressing. This protocol dynamically assigns bandwidth resources to the nodes in the network according to the application requirements. In our experiments, we have extended the 6TiSCH by our path duration model. Specifically, once the mobile node established a multi-hop path to the sink, we used the model to estimation the path duration time and the extended 6TiSCH could stopping uploading in advance while approaching the ending time slot of the deterministic duration time. For all the cases that the mobile node connects to all the relay nodes or the sink, we have compared the performance of the extended 6TiSCH assisted by our model with the vanilla version of 6TiSCH on the upload throughput. From the results marked in Fig. 12, we observe that the throughput is higher when the model node uses less number of hops to connect the sink. In addition, it is obvious our model could increase the upload throughput when the number of hops to connect sink increases, due to the fact that the extended 6TiSCH could efficiently estimate the live time of a multi-hop path, and stop the uploading at the right time to avoid invalid or dropped data transmission. After that, new bandwidth resources could be assigned to the mobile node immediately to continue the effective multi-hop transmission for data uploading to the sink.

VI. Conclusion

In this paper, we proposed a novel path duration time model for data collection using convergecast in mobile sensor networks, and it can be used in the applications of industrial Internet of things (IIoT). We claim that the probability of multi-hop path duration time from mobile sensors to stationary sinks is not simply a product of each link along the path. According to our modeling and analysis, the path duration time of the n hop path is constrained by its previous $n-1$ hop path. In addition, we have shown how the path duration time can be affected network density in MSNs for IIoT. The theoretic and experimental results demonstrate that our mobile convergecast model presented in the paper can accurately reflect the path duration time in simulations. We also give the analysis on the correlations between the path duration time and end-to-end delay; it can help us to obtain and understand the relationship between path duration time, node's density and network delay in mobile convergecast network.

Sensor networks of the future for IIoT are likely to incorporate multiple access technologies with varying network properties and transmission characteristics. Our modeling and analysis of path duration time can assist in the acquisition of end-to-end network properties and the improvement of resource utilization in such industrial multinetworks. This work can be further extended to employ multiple access technologies of industrial multinetworks in future pervasive and sensing networks for IIoT applications.

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