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Internet of Things Data Collection Using Unmanned Aerial Vehicles in Infrastructure Free Environments

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ABSTRACT With the immensity of distributed Internet of Things (IoT) devices and the exponential increase in data generated from a variety of IoT-driven smart-world applications, how to effectively provide data driven service supported by IoT has become a critical issue. While the state-of-the-art technologies have been developed and network infrastructures with high capabilities have been designed to deal with the data collection problem, there are still application scenarios, in which network infrastructure is not available or appropriate in large target areas (e.g., farmlands deployed with IoT sensors in operation, providing precise agriculture; emergency responder with IoT sensors, providing public safety service). To address the issue of efficiently collecting data from IoT devices deployed in large areas without pre-deployed network infrastructure, we formalize the problem space in a three-dimensional model that considers task, resource, and methodology. Based on the designed problem space, we propose a novel solution that deploys an unmanned aerial vehicle (UAV), as a critical next generation mobile network, to achieve intermittent IoT device connections and enable data collection based on delay tolerant network (DTN) protocol. The UAV flight path is determined using a *Hilbert Curve*-based path planning algorithm. Through a series of quantitative experiments, we validate the effectiveness of our approach in a network emulation environment, and confirm its advantages in comparison with several baseline approaches. The results of our research shows the capability of quality and cost control in IoT applications such as smart agriculture, public safety disaster recovery and rescue.

INDEX TERMS Internet of Things, delay tolerant networks, next generation mobile networks, unmanned aerial vehicles, path planning, data collection.

I. INTRODUCTION

The Internet of Things (IoT) [1], [2] has received a significant amount of recent attention in both research and industry. The fundamental concept of IoT is the embedding of microchips and sensors into everyday objects, enabling computing and the interconnection of "things" across networks. With the increasing reliability and maturity of more advanced technologies, IoT has been widely adopted in a variety of smart-world systems, such as smart grids, smart transportation, smart agriculture, smart cities, smart healthcare, and smart public safety, among others [3]–[8], [8]–[15]. Moreover, the concept has been leveraged in smart manufacturing [16] to improve the capabilities of monitoring and controlling industrial systems, and instigating a vision for the next great industrial revolution [12].

Given near-certain expansion on a massive scale, the volume of IoT devices becomes unprecedented. By 2025, according to recent research [17], the number of IoT devices deployed across the globe is projected to reach 75.4 billion. Along with the exponentially increased scale of data generated from these devices in IoT-based systems, the requirements on effective data collection become more and more critical, with respect to latency, response time, and reliability. While it is true that the technologies that increase network capabilities have been developing rapidly, adoption of such

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technologies is not uniform. Indeed, in many IoT application scenarios, devices will need to be deployed in areas, in which network resources are constrained.

To support data collection in IoT, especially from constrained IoT devices that have limited capabilities in memory, storage, computation and connectivity, a number of research efforts have been conducted. For example, several protocols have been developed for efficient data transmission in networks with limited resources, including IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN) [18] and Constrained Application Protocol (CoAP) [19], [20]. According to the performance evaluation conducted by Gao *et al.* [20], these protocols are able to improve reliability in data transmission by optimizing retransmission schedules and reducing overhead. Nonetheless, these protocols still require the network to be available continuously when data is being transmitted, and in extreme scenarios, such as disaster recovery [15] or large agricultural lands [21], this may not be feasible. For example, IoT devices such as sensors for temperature, moisture, humidity, image, and others in a smart agriculture scenario may be deployed in a large farmland, in which network infrastructure (e.g., WiFi access points, base stations) may not be available, or do not exist from the start. In addition, in public safety disaster impacted areas, IoT devices such as image sensors will be deployed to monitor the disaster recovery scenes, where network infrastructure may not be available or overloaded [15]. In such out-of-coverage scenarios, how to reliably and effectively collect data from sensors becomes a challenging issue.

To address the issue of collecting data from IoT devices that are deployed in large areas without available network infrastructures, we propose a new data collection approach that leverages the Flying Ad-hoc Network (FANET) with the aid of an unmanned aerial vehicle (UAV) to enable a delay tolerant network (DTN). Moreover, we design a novel scheme based on the Hilbert Curve for the UAV flight path determination. By taking advantage of the mobility and flexibility of the UAV, the reliability in data transmission of the DTN, and the efficiency in path planning provided by the Hilbert Curve method, we are able to optimize the utilization of resources in IoT data collection in out-of-coverage scenarios. By conducting an emulation-based evaluation in a series of quantitative experiments, we confirm the benefits of our designed scheme in utilization and stability of data collection in comparison some baseline schemes.

In this study, we make the following four key contributions.

- We define a three-dimensional problem space for effective IoT data collection in large infrastructure-free areas, which considers the collectors, the scale of IoT devices, and the methodology of workload allocation. Then, focusing on one component of the problem space, we propose an effective data collection scheme that leverages a UAV using DTN technique to enable continuous data transmission in infrastructure-free, large-area IoT scenarios. We also propose an efficient path planning scheme based on the Hilbert Curve to optimize the utilization of the UAV regarding its limited capacity.
- We implement our proposed data collection scheme and conduct a series of quantitative evaluation experiments in an emulation-based platform using the Common Open Research Emulator (CORE). Our experimental results confirm the benefits of our proposed approach in comparison with baseline approaches. Our evaluation confirms the effectiveness of our proposed scheme in completing the task of data collection, and validates the advantages of DTN over Bare Transmission Control Protocol (TCP) in the scenarios studied herein. Utilizing our quantitative results, we can optimize the parameters used in our proposed path planning scheme. Moreover, our experimental results show that our proposed scheme outperforms the representative baselines in data collection in each scenario IoT device distribution and traversal speed.

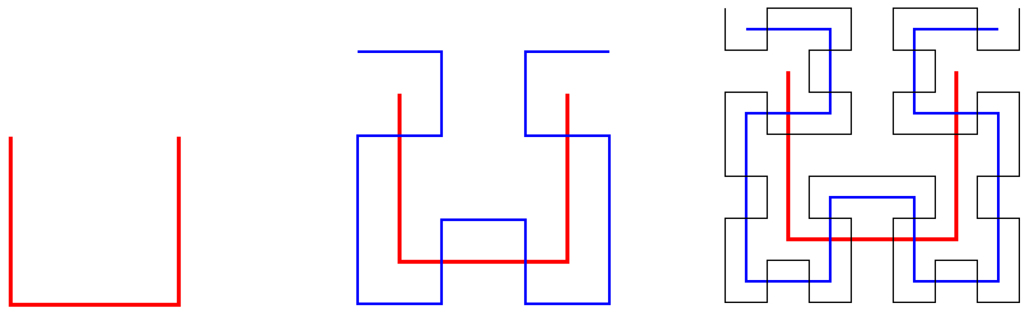
The remainder of this paper is organized as follows: In Section II, we introduce the key techniques and terms utilized in this research, providing brief definitions and specifications. In Section III, we formalize the problem and introduce the system model. Based on the defined problem, we introduce the approach and design rationale of our proposed data collection scheme in Section IV, and detail the algorithm design. An emulation-based experimental setup is introduced in Section V, including implementation of the proposed scheme and environment, metrics, and scenario groups. The results of the performance evaluation are provided and explained in Section VI. In Section VII, we conduct a brief literature review of existing research and applications relevant topics and techniques (smart agriculture, DTN, UAV-assisted networks, and the Hilbert Curve) in this paper. Finally, we conclude the paper and discuss the future research direction in Section VIII.

II. PRELIMINARIES

In the following, we provide some background concerning UAV-assisted networking, DTN, and the Hilbert Curve.

A. UNMANNED AERIAL VEHICLE (UAV)

Generally speaking, an unmanned aerial vehicle, otherwise known as a UAV, is an aircraft without a human pilot aboard, instead being controlled either remotely by a human operator or autonomously by an on-board computer. In recent years, UAVs have seen widespread use, having first been designed for military applications. Advances in technology and reductions in size and cost have made them ideal for many civilian applications, including across scientific, commercial, agricultural domains. With the advantages of mobility and flexibility, UAVs can be used in vast and remote areas with complicated terrain. Thus, research efforts have been conducted to apply UAVs in support of wireless sensor networks [22]–[24], including as relays to base stations, in energy optimization, and in re-establishing communications in emergency scenarios. Leveraging these



(a) First Order (b) Second Order (c) Third Order

FIGURE 1. Hilbert curve.

same advantages, we note that UAVs could be equipped with data collectors and be utilized for collecting data in infrastructure-free areas.

B. DELAY TOLERANT NETWORKS (DTN)

The delay tolerant network (DTN) [25]–[27] was developed to ensure reliable data transmission in networks, in which connections are not stable (typically wireless). Devices in the DTN are deployed with the Bundle Protocol [28], which, by design, implements a bundle layer between the application and transport layers. Traffic data generated from the application layer of a source device is packed into bundles and stored in the bundle layer before being sent. Through the transport layer, data bundles are forwarded to the next available intermediate node, and are stored in the bundle layer on that node as well. Relying on this store-and-forward mechanism, data can be delivered hop by hop through the network, all the way to the destination.

Based on this design, considering that data is not only forwarded to, but also stored locally at each next hop, we observe that the DTN is able to handle intermittent connectivity. Thus, it is not necessary to maintain connections continuously and simultaneously all the way from the source to the destination. As the initial target of this protocol was to support interplanetary communication with satellites obscured during planetary orbits, this feature enables reliable data transmission in unreliable networks, especially when the connection is wireless and the communication is discrete and affected by disruption or the mobility of devices.

With the capability to endure long and variable delays, the DTN shows its enormous potential in addressing the issues of data collection from IoT devices that are deployed in infrastructure-free areas. While the connection between target devices and data collectors is supposed to be discrete and periodic, applying DTN could guarantee the reliability of data delivery and ensure data integrity. Thus, the DTN becomes a viable technique in our research. There are several open-source implementations available for DTN-based applications. For example, ibr-drn [29] implements the bundle protocol [28] with a variety of features, including a Socket-based Application Programming Interface (API), implementation of the Bundle Security Protocol (RFC 6257) [30], bundle age tracking, and support for bundle-in-bundle and compressed bundle payloads.

C. HILBERT CURVE

The Hilbert Curve [31], first described in 1891 by the German mathematician David Hilbert, is a continuous fractal space-filling curve. As illustrated in Fig. 1(a), a square can be divided into four sub-squares and traversed in sequence by the first order 2-dimensional Hilbert Curve. Then, each sub-square can be further divided the same way. Figs. 1(b) and 1(c) show the second and third order Hilbert Curves. Thus, a square can be divided repeatedly and filled with the Hilbert Curve.

According to the description, the Hilbert Curve has three key advantages. First, it can map the multi-dimensional (2-dimensional in the most common case) space into 1-dimensional space. Thus, the multi-dimensional space can be traversed in sequence without any subspace being repeated. Second, any subspace can be further divided without breaking the continuous curve. Third, the largest number of continuous cells in a row in the Hilbert Curve is 3. Thus, skipping cells would reduce the total distance of the Hilbert Curve in almost all cases. Because of these features, Hilbert Curve has been widely used [32]–[34]. In our infrastructure-free IoT device data collection scenarios, we consider the Hilbert Curve as a candidate for path planning to achieve efficient traversal of all devices in a target area.

III. SYSTEM MODEL

In this section, we introduce the system model and present the problem space of our research.

A. INFRASTRUCTURE FREE IOT DATA COLLECTION

As introduced in Section I, we are interested in solving the problem of IoT data collection in a large area, in which the infrastructure (such as access points and base stations) is not available. The IoT devices can be considered to be dispersed within the target area and continuously generate data that must be collected. The following three key issues can be abstracted from this generic scenario.

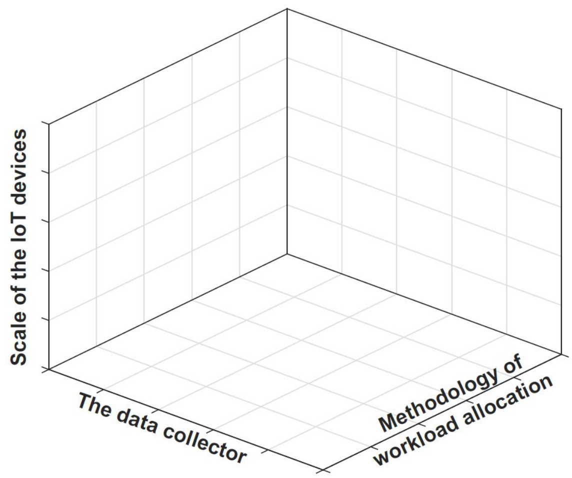


FIGURE 2. Problem space of the infrastructure-free IoT data collection.

- **Issue 1 - Scale of IoT Devices:** The issue of the scale determines the workload and the difficulty of the problem. It is related to the density and distribution of the IoT devices, as well as their data rates.
- **Issue 2 - Data Collector:** While infrastructure is not available, the data collection should be performed by data collectors. Thus, the consideration of the data collector determines the resources that are available to solve the problem of data collection. This includes enablers of the data collection (i.e., how the data is collected), and their available capabilities. For example, the former could be sending a person to visit all the IoT devices and use a flash-drive to copy the data, and the latter could be the number of people available to perform the task.
- **Issue 3 - Methodology of Workload Allocation:** This determines the efficiency of the data collection. Strategies are developed to allocate workload properly to optimize the utilization of available resources. Examples include path planning to traverse all the device locations with the shortest distance and assigning the workload subdivisions to multiple collectors to achieve the shortest collection time.

Thus, the problem space of the IoT data collection in a large infrastructure-free area can be generalized into a three-dimensional model, as represented in Fig. 2, in which each axis represents one of the three key issues generalized above.

B. PROBLEM FORMALIZATION

Based on the problem space that we have defined, we formalize the problem to design a data collection scheme for IoT devices in infrastructure-free areas. This scheme will include a mechanism that enables the collector to reach all IoT devices in the target area and a protocol that enables the data collection. In this research, we focus on the single data collector with limited resources (i.e., coverage and duration).

Meanwhile, the following two requirements should be satisfied in the provided scenario: (i) *Data Integrity.* In the infrastructure-free area, the data collection of any single IoT device occurs only when the collector is available. While the device periodically generates data to send, the transmission could be discrete. Thus, it is important to deliver intact data through discrete transmission. A desired data collection scheme should have a mechanism to ensure data integrity with the least overhead cost. (ii) *Collection Efficiency.* Considering that the data collector in the infrastructure-free area has limited resources, the collection efficiency is one of the most important metrics. Optimization is thus necessary in the solution such that collection occurs of as much data as possible within the limit of the resources available.

C. SCOPE

To focus this research on the major problem detailed above, we make the following assumptions: (i) The wireless connection applied in this research is relatively stable and disconnection only occurs when two nodes are out of the range to each other. Meanwhile, the signal is non-directional, and we consider only free space communication, so that the coverage is a circle. Any other propagation or clutter is out of the scope of this research. (ii) The deployment of the IoT devices are considered only in a 2-dimensional area, where the height and terrain are not considered in the result. (iii) We consider only one data collector in our basic scheme. The complexity and cooperation of multiple collectors are not introduced in this research. Note that our designed framework and algorithm can be extended to multiple collectors case, which is our ongoing research.

IV. OUR APPROACH

In this section, we introduce our approach to the design of our data collection scheme. In the following, we first introduce our design rationale to fulfill the concerns and requirements, followed by the detailed design of the proposed scheme. Finally, we discuss several key factors.

A. DESIGN RATIONALE

The design of an appropriate data collection scheme must solve the following three issues:

- **Infrastructure-free Area:** As we have mentioned, the target area is infrastructure-free, i.e., lacking access points and base stations for IoT devices to connect to. Thus, we consider that the construction of new base stations in such an area to be too costly both in time and money. Instead, alternative data collection solutions must be considered, such as the use of UAVs to carry data collectors as payload. Theoretically speaking, UAVs could easily get close to the IoT devices and establish temporary connections for the data collection. Other carriers, such as manned and unmanned land vehicles are viable, but not as fast or flexible, and do not have equivalent freedom of movement.
- **Transfer Data in Discrete Connections:** The TCP has widely used for the control of data transmission over different types of networks. In scenarios where data transmission occurs with discrete connections, however, it is less than ideal due to the inefficient retransmission

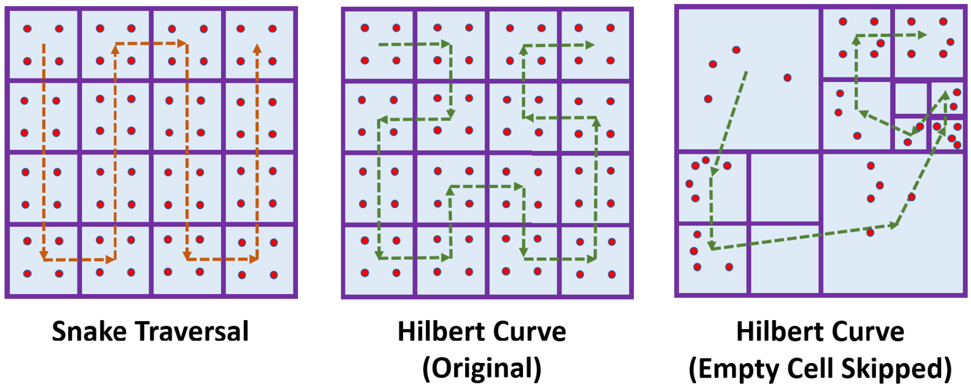


FIGURE 3. Snake traversal vs. Hilbert Curve.

process caused by disconnection during data transmission. The feature of tolerance to network disruption is required in this scenario, and implicates DTN as a desirable candidate for the data transfer protocol. In our prior research [35], we have confirmed that data transmission using DTN in disruptive networks performs better than TCP in both delivery time and overhead. In addition, it provides higher reliability in data delivery. Considering the discrete connections of data transmission in the target scenario, we choose DTN as a technique to control the data transmission so that data can be delivered reliably.

- **Efficient Path Planning:** We know that IoT devices are spread out across a large geographic area in the target scenario. To collect data from all IoT devices, the data collector should visit each during the data collection process. Thus, how to plan the path of the device traversal becomes a critical issue. The Snake Traversal is one of the strategies which follows a zig-zag pattern across every cell of an area (Fig. 3-left, where the dots represent the IoT devices and the arrowed lines represent the route). The route of the Snake Traversal guarantees coverage of all IoT devices. Nonetheless, when the devices are not evenly distributed, it becomes wasteful for the data collector to traverse large swaths of terrain with no IoT devices. While the Snake Traversal provides full coverage, it is designed to skip the empty cells. In contrast, the Hilbert Curve is a continuous fractal curve. It can be observed in Fig. 3-middle that it has a rare chance of having three continuous cells in a row. Thus, skipping empty cells almost always reduces the travel distance (Fig. 3-right). Meanwhile, the feature of a continuous fractal makes it easy to control the per-cell density of IoT devices, enabling stable data transfer for each individual IoT device.

B. PROPOSED SCHEME

Based on the design rationale, we propose our data collection scheme that is made of two components: the data collector and the route generator.

- **Data Collector:** In our proposed scheme, the data collector is the device with the DTN protocol implemented, which is equipped on an UAV. This design provides the data collector both mobility and the ability to communicate with DTN-implemented IoT devices.
- **Route Generator:** The Hilbert Curve-based route generator is the implementation of algorithm that takes the deployment of IoT devices as input, and generates the route map as the output for the data collector to travel. The parameters include the size and coordinates of the area, maximal number of nodes per cell, speed of the collector, and stop time. A detailed pseudo-code of the algorithm is provided in Algorithm 1. According to the algorithm, cells are split (subdivided) unless the following two conditions are satisfied: the width of the square-shaped cell is less than the width of the inscribed-square of the data collector's maximum coverage (which is the 1.414 times of the radius), and the IoT device density of the cell is lower than the threshold. By traversing (following depth-first-traversal) all the cells, the route path is generated by connecting all the centroid coordinates of the cells. Note that the algorithm takes a list of IoT devices as the input, and the route generated by the algorithm skips the cells that do not have deployed devices. This mechanism has flexibility in generating priority-based routes by simply including desired priority levels with devices as input to the list.

According to Algorithm 1, both creating and traversing the Hilbert Curve-based cells follows depth-first search mechanism. Thus, the complexity is $O(V+E)$, where V represents the vertex (Cells) and E represents the edges (parent-child relationships). While in the case of Hilbert Curve, a cell would have either 0 or 4 children, the number of edges is only related to the vertex. As a result, the complexity becomes $O(V)$. Recall that the number of cells is related to the density of IoT devices. In the worst-case scenario, each IoT device is deployed in an individual cell. As a result, the complexity of Algorithm 1 is $O(n)$ in the worst-case-scenario, where n is the total number of IoT devices.

Algorithm 1 Hilbert Curve-Based Path Planning

```
Set Parameters: AreaWidth, BasicCellWidth,
  MaxNodesPerCell, Speed, StopSecondsPerNode
Read the List of Coordinates of the IoT Devices as Input

Cell0 = new Cell(width = AreaWidth, x = y =
  AreaWidth/2, Nodes = List(DeviceCoordinates))
Stack.push(Cell0)
while !Stack.empty() do
    tmpcell = Stack.pop()
    if !tmpcell.hasChild() then
        if tmpcell.width > BasicCellWidth || tmpcell.Nodes.size > MaxNodesPerCell then
            tmpcell.Child() = tempcell.split()
    if tmpcell.hasChild() then
        for each cell in tmpcell.Child() do
            Stack.push(cell)

Queue = empty queue of cells
Stack2.push(Cell0)
while !Stack.empty() do
    tmp = Stack2.pop()
    if tmpcell.hasChild() then
        for each cell in tmpcell.Child() do
            Stack2.push(cell)
    else
        if tmp.Nodes.size > 0 then
            Queue.push(cell)
Output Queue as Hilbert Curve-based Route
```

C. PERFORMANCE FACTORS

The following factors will affect the performance of the data collection:

- *Density of the IoT devices.* This represents the total number of IoT devices in the target area and in each individual cell, which will affect the route as well as the volatility of data sent from individual devices.
- *Distribution of the IoT devices.* Based on different distributions of device deployment, the route will vary in total travel distance. In addition, this affects the route generation in the splitting of cells. Generally speaking, devices that are deployed with a normal distribution tend to require less travel distance.
- *Capacity of the UAV.* This includes the maximum speed and flight duration of the UAV. All factors affect the data collection through variation in the travel time of the UAV. Current civilian UAVs on the market have flight durations ranging from 20 to 25 minutes, and maximum speeds in a range of 80 to 110 km/h [36], [37].

V. IMPLEMENTATION AND EXPERIMENTAL DESIGN

In this section, we deploy our proposed scheme in an emulation-based environment using the Common Open Research Emulator (CORE) [38]. A series of experiments are designed for evaluating the performance of our proposed approach.

A. CONFIGURATION OF THE ENVIRONMENT

- **Emulation Platform:** As mentioned above, a series of experiments were carried out in an emulated network of IoT devices and the communication between them. To realize the emulation environment, we utilized the Common Open Research Emulator (CORE, v5.1) [38] as the emulation tool, running on a Linux system (Ubuntu Server v16.04 LTS). While the system model is based on wireless networks, we use OLSRv2 as the routing protocol for the communication on bare TCP, with the specific implementation being olsrd2 [39], acquired from the OLSR.org Network Framework (OONF). For the DTN communication, we choose ibr-dtn [29], which we have found to be stable and was used in our prior research [35].
- **Implementation of Route Generator:** We implemented the route generator based on the two path-planning strategies defined above (Hilbert Curve and Snake Traversal), implemented in Java. The parameters include size and coordinates of the area, maximal nodes per cell (for Hilbert Curve), speed of the collector, and stop time. The deployment of the IoT nodes can be input through a deployment generator (by inputting the number of nodes and the type of distribution), or from a list of coordinates of nodes. The output includes a route map and a mobility script for each path-planning strategy, which can then be applied by CORE.
- **Data Traffic and Tracking:** As indicated in the system model shown in Section III, the typical scenario of data collection can be represented as transferring files from IoT devices (source nodes) to the data collector-equipped UAV (destination node). In our experiments, we implemented and deployed a Python program for File Transfer Protocol (FTP) server and client in the emulated nodes for file transfer using bare TCP. The transfer of the same file using DTN was handled by the ibr-dtn implementation with its embedded commands *dtnoutbox* and *dtninbox*. To be specific, the sending queue of each IoT node is initialized to 500 MiB, with 10 MiB data added every 10 seconds, to mimic real-world IoT devices. The collector is set as the default in CORE, which uses a WiFi interface with a bandwidth of 54 Mb/s. These

values guarantee enough data for the collector to receive. We setup *tcpdump* running on the emulated nodes so that all the related traffic was recorded in *.pcap* files. Thus, the generated traffic data can be further analyzed and processed.

B. SCENARIOS

According to the performance indicators and objectives we defined in Section IV-C, we design the following scenarios for our experiment.

1) DTN VS. BARE TCP

In this scenario, we evaluate the effectiveness of DTN in data transfer with disruptive network connections. To be specific, we deploy a pair of nodes that represent the data sender and collector with the DTN protocol implemented. The same topology with Bare TCP is deployed as the baseline for comparison. A single file of 100 MiB is used as the data to send so that it will not be finished within 5 seconds at the collector's default bandwidth of 54 Mb/s. The two nodes disconnect 5 seconds after the data transfer begins, interrupting the transmission. The connection is then recovered after a time interval that we control as a variable. By comparing the data delivery status of the two groups, we can evaluate the tolerance of the schemes against interruptions.

2) CAPABILITY OF DTN-BASED DATA COLLECTOR

In this scenario, we evaluate the capability of a single DTN-based data collector in collection efficiency as the density of IoT devices varies. To be specific, we deploy a group of IoT devices within the data collector's coverage area and observe the data traffic in a fixed time period. These devices will keep sending data whenever a data collector is available (i.e., the device is in the coverage of the UAV equipped with the data collector). Considering the estimation that we have made in Section III-C for real-world IoT scenarios, we set the time periods that the UAV stays in a cell to be 10, 20, and 30 seconds. By fixing the parameters of the DTN (to the default values) and changing the density of IoT devices (i.e., the number of senders), we can observe the performance of the data collector as the density of the senders varies, and determine an optimal density or threshold of devices for generating the route by Hilbert Curve-based path planning.

3) EFFICIENCY OF PATH PLANNING STRATEGIES

In this scenario, we evaluate the performance of the DTN-based UAV data collector that follows the Hilbert Curve-based path introduced in our proposed approach. Meanwhile, we use the same DTN-based UAV data collector that follows the Snake traversal-based path as a baseline for comparison. Recalling the estimation that we have made in Section III-C for real-world IoT scenarios, we deploy 100 IoT nodes in a 2000x2000 m^2 area, where each node represents the data sender that aggregates its nearby IoT devices. To cover all the deployed IoT nodes, the UAV data collector travels from the upper-left of the area and exits at the upper-right, following the route generated from the applied path planning strategies. The radius of the maximum coverage of the data collector is set to 177 meters so that it covers the inscribed-square area with the width of 250 meters. As a result, the area can be divided into 64 (8x8) basic cells, 250x250 m^2 each. Additionally, considering 100 total deployed nodes, we have created three groups representing three distinct node distributions as follows:

- **Group 1 - Even Distribution:** In this group, the 100 nodes are deployed by following an even distribution. Thus, each of the 64 basic cells (250x250 m^2) has at least 1 node, and no cell will be skipped by the UAV.
- **Group 2 - Uniform Distribution:** In this group, the 100 nodes are deployed following a uniform distribution. Thus, each node is randomly deployed, but has the same chance to be deployed to either one of the basic cells. Although the density of nodes in each basic cell tends to be the same when the number of nodes is large enough, it can be different when the number of nodes is limited, as in our case. While the route of the Snake Traversal-based path planning would not change, the route generated from the Hilbert Curve-based path planning varies at each cell (the cell either stays the same, being skipped or further split). As a result, the total travel distance may differ between the two path planning strategies, and affect the overall data collection.
- **Group 3 - Normal Distribution:** In this group, the 100 nodes are deployed following a normal distribution. Thus, the density of the nodes in each basic cell will be different, where cells closer to the centroid of the area have larger node densities. The route of the Snake Traversal again does not change when the nodes are normally distributed. Nonetheless, the route generated by the Hilbert Curve tends to skip the cells at the edges and traverses the sub-cells near the center. As a result, the total travel distances of the two path planning strategies differ, resulting in differences in overall data collection efficiency.

Meanwhile, considering the technical specifications of the current civilian UAVs on the market with respect to speed and flight time, we design the following three groups of moving patterns to approximate and represent real-world data collection in practice.

- **Pattern (a) - Non-Stop at Full Speed:** In this pattern, the UAV follows the routes generated from the two path planning strategies that we compare. It travels at the full speed (set at 20 m/s) and does not stop. Thus, it will take the least time for the UAV to travel through the entire area, but the receiving time for transmission from each node will be the shortest as well. Of all the nodes, those that are closer to the center of the path have longer exposure to the data collector.
- **Pattern (b) - Non-Stop at Half Speed:** In this pattern, the UAV travels at half its maximum speed (set at 10 m/s) and does not stop. Thus, it will take twice the time for

the UAV to travel through the entire area compared to the non-stop at full speed pattern, which doubles the receiving time from each node. Considering the overhead in connection with multiple nodes, data collection following this pattern could be more efficient. As in the full-speed and non-stop pattern, the nodes that are closer to the center of the route have longer exposure to the data collector.

- **Pattern (c) - Full Speed with Stops.** In this pattern, the UAV travels at the full speed (set at 20 m/s), but it stops at the centroid of each cell to ensure stable receipt of the data. The stop time is based on the density of the nodes within the cell. Considering the UAV flight time, we assign 5 seconds for each node so that the total travel time will not exceed the flight limit. As a result, each node would have at least 5 seconds to transfer data, which guarantees data received from each individual node, resulting in better stability.

By testing the three moving patterns on each of the three node distributions, we create a set of nine total scenarios for our evaluation.

C. METRICS

Based on the outlined scope and experimental design, we evaluate the effectiveness of our proposed approach using the following performance metrics.

- **Data Integrity:** The data integrity is defined as the delivery status (Delivered or Failed) of the transmitted data. We note that the connection between the data sender and the collector is disruptive due to limited coverage of the signal, and that the data packets are not always continuous. This metric represents the effectiveness of the data collection, or the tolerance to disruption in the network connection.
- **Travel Distance:** The travel distance is defined as the total distance of the route generated by the selected path-planning strategy. The route starts from the upper-left and ends at the upper-right of the area map, and connects all centroids of the cells in sequence. The routes generated by more efficient path-planning strategies tend to be shorter in distance.
- **Utilization:** We define the average data collection speed as the total data collected divided by the total travel time. This metric represents the data collection efficiency of the selected path-planning strategy. While a higher average speed indicates a higher utilization of the UAV data collector, this metric can be further generalized as the utilization in the form of a percentage, by dividing the average data collection speed by the bandwidth of the UAV data collector.
- **Coefficient of Variation (CV) by Data Sources:** While the data received by the collector is from different nodes and may vary during the data collection period, we define the coefficient of variation of source data as the ratio of the standard deviation σ to the mean μ of the data sent from every source node. Lower CV indicates less difference in the amount of data collected from each node, resulting better stability.

TABLE 1. Data integrity over disruption.

Time Interval	TCP	DTN
150 s:	Delivered	Delivered
300 s:	Delivered	Delivered
600 s:	Delivered	Delivered
1,200 s:	Failed	Delivered
1,800 s:	Failed	Delivered

VI. EVALUATION RESULTS

We now detail the evaluation results of the experiments outlined in Section V. In the following, we first present the results of the comparison between DTN and Bare TCP for data transfer under disruptive connections (from Section V-B.1), explaining the reason for using DTN instead of TCP in the proposed data collection scheme. Then, we present the results of the evaluation regarding the capabilities of the DTN-based data collector (from Section V-B.2), from which a parameter is derived and used in the configuration of the next scenarios (Efficiency of Path Planning Strategies). Finally, we present the result of the nine scenario groups in Section V-B.3 to evaluate the advantages of using Hilbert Curve-based path planning.

A. DTN VS. BARE TCP

This scenario is used to evaluate the impacts of the mobility of the data collector. Table 1 presents the data integrity results of the two groups (DTN and Bare TCP) in collecting a 100 MiB data. The result indicates that the data transfer may only tolerate about 10 minutes of disconnection when using Bare TCP, as the retransmission has to wait and follows the TCP retransmission scheduling. In contrast, DTN-based data transfer ensures intact data delivery even when disconnection durations exceed 30 minutes and the recovery of the transfer is as soon as the link becomes available. In the data collection model that we mentioned in Section III-B, the connection between IoT devices (source node) and the UAV data collector (destination) is disruptive and the time between two collections for one particular IoT device tends be more than 10 minutes. Thus, it is better to use DTN instead of bare TCP for the data collection in the IoT scenarios that we have defined.

B. CAPABILITY OF THE DTN-BASED DATA COLLECTOR

This scenario evaluates the data collection efficiency of a single DTN-based data collector against the density of the IoT devices. Fig. 4 illustrates the bandwidth utilization of the data collector versus the density of the IoT devices with different collection times. The results indicate that the overall utilization increases with the increase in density of IoT devices up to 20, and drops rapidly when the density exceeds 20. This may be because of the configuration of the

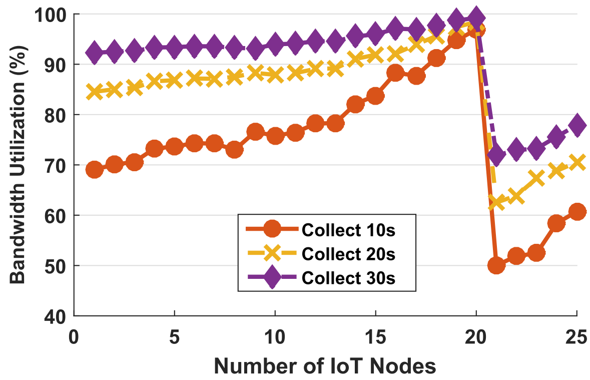


FIGURE 4. Collector bandwidth utilization over density of IoT nodes.

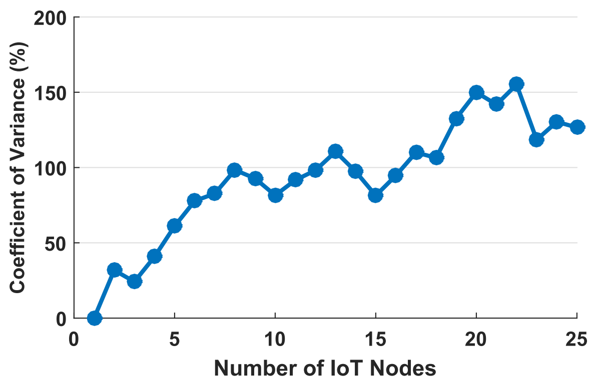


FIGURE 5. Coefficient of variance by data sources over density of IoT nodes.

DTN which defines the number of devices that can connect. As a result, the devices compete for the resources of the data collector, reducing the efficiency. It can also be observed that the overall utilization increases with the increase in duration of connection, which is logical, as the proportion of total time taken up by establishing the connection is smaller.

In addition, Fig. 5 represents the stability of the single devices in data collection. While in the ideal case where CV equals to 0, each device connections and transmissions when each sends the same amount of data to the collector. As can be observed, the data transfers tend to be more volatile when the node density increases. Thus, lower node density makes the data transmissions more stable.

To conclude, the density of the devices should be carefully selected to balance the utilization of collector bandwidth and the assurance of data collection from each device. Considering the results presented, we choose five as the maximum number of devices per cell for generating the Hilbert Curve-based route in our subsequent evaluation.

C. EFFICIENCY OF PATH PLANNING STRATEGIES

In this scenario, we compare the performance of the DTN-based data collector using different path planning schemes. Fig. 6 illustrates the UAV routes generated by Snake Traversal and Hilbert Curve-based path planning strategies under different deployment densities of IoT devices. The dots in each sub-figure represent the deployed IoT devices and the lines represent the routes, starting from the upper-left and exiting at the upper-right of the area. As can be observed, the Snake Traversal-based routes do not change over the type of distribution of the IoT devices, while the Hilbert Curve-based routes change corresponding to the density of the devices, affecting the travel distance of the UAV.

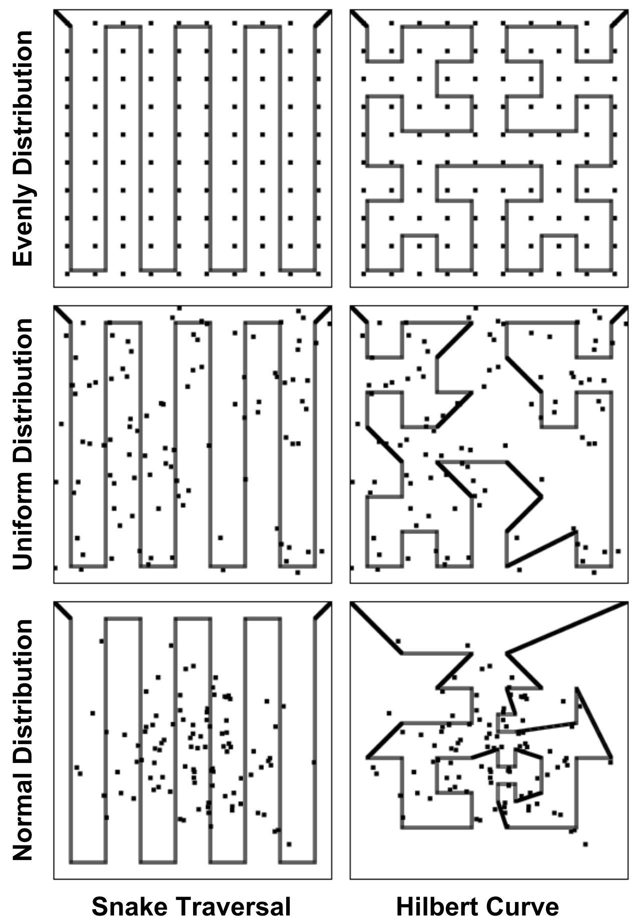


FIGURE 6. Snake traversal vs. hilbert curve for each distribution.

TABLE 2. Travel distances of path planning mechanisms over device distributions.

Distribution	Hilbert Curve	Snake Traversal
Even:	16557.829 m	16557.829 m
Uniform:	14857.947 m	16557.829 m
Normal:	13311.104 m	16557.829 m

Table 2 lists the travel distance of each strategy. As we can see from the table, the Snake traversal-based route maintains a fixed travel distance, the longest, for all distributions. The Hilbert Curve-based route has the same travel distance as the Snake Traversal on the even distribution, as the UAV must travel to every cell. However, the Hilbert Curve reduces the travel distance by about 10 % for the uniform distribution, and nearly 20 % over the normal distribution, as compared

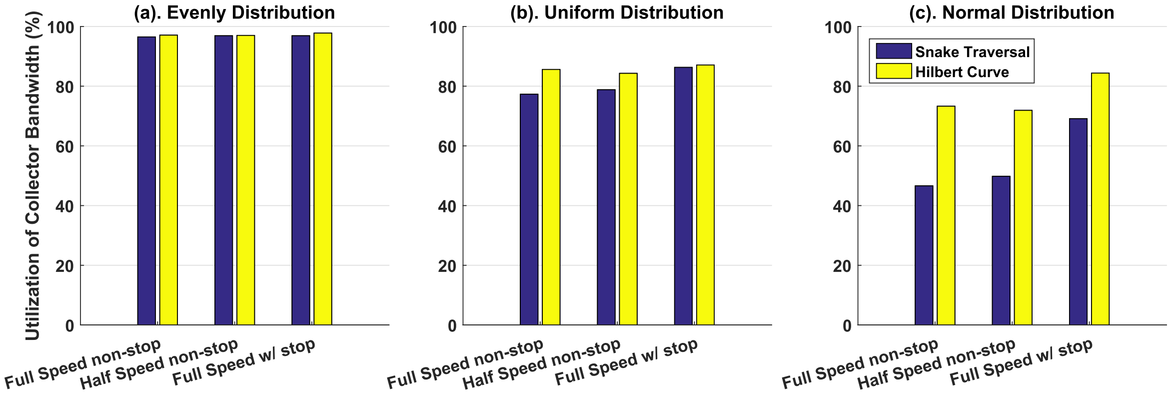


FIGURE 7. Collector utilization by path planning schemes under different IoT device distributions.

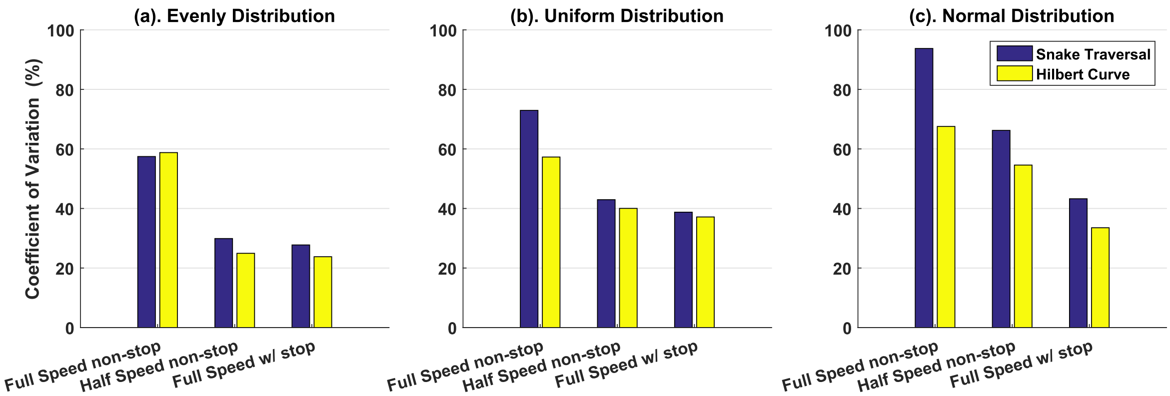


FIGURE 8. Coefficient of variance of path planning schemes under different IoT device distributions.

to the Snake Traversal. This is because the Hilbert Curve is able to skip empty cells caused by irregular spread of nodes, as presented in Fig. 6.

Being able to cover all the devices in a shorter travel distance, the strategy that uses the Hilbert Curve tends to utilize the data collector's bandwidth more efficiently, as it eliminates the time when no IoT device is actively covered. Recall from Section V-C, the utilization of bandwidth is computed by dividing the total data collected by the product of the data collector's bandwidth and the travel time. Fig. 7 compares the utilization of both strategies in the different deployment distributions of IoT devices, combined with the three flight patterns: (i) *full speed non-stop*, (ii) *half speed non-stop*, and (iii) *full speed with stops* (5 s per device in the cell). The result shows that both strategies achieve high utilization when the IoT devices are evenly deployed in the area, because the UAV travels through every cell, all of which have at least one device. In the other two scenarios, where IoT devices are deployed in uniform and normal distributions, the UAV could travel through cells where no IoT device is present, lowering utilization. The scheme that uses Snake Traversal suffers the most in this way, as it has to travel through all empty cells, especially in the scenario of the normal distribution, as the devices tend to be closer to the centroid of the area. In contrast, the scheme that uses Hilbert Curve tends to skip the empty cells, keeping the utilization high. Additionally, in comparison to only reducing the speed of the UAV, the utilization tends to be higher if the UAV stops to collect data at the centroid of each cell, as it guarantees data collection time for every device.

In addition to device coverage and bandwidth usage, the stability of data collection for each device is important. Fig. 8 presents the Coefficient of Variance (CV) calculated for all IoT devices. As we can observe from the figure, the CV becomes higher (more volatile) when devices are deployed irregularly. This is because the devices compete for the bandwidth in areas of high density. Both reducing the UAV speed and stopping will make the data collection from individual IoT devices more stable, especially in very high-density areas, such as near the centroid of the normal distribution. Moreover, as the scheme that uses the Hilbert Curve applies a density threshold to determine the splitting of cells, the number of devices that are connected simultaneously will not exceed the threshold (5 in our experiment). Thus, the Hilbert Curve-based scheme achieves better stability in data collection from individual IoT devices, compared to the Snake Traversal-based scheme, especially in the normal distribution scenarios.

To conclude, we can clearly see the advantage of using the Hilbert Curve-based path planning in terms of both utilization and stability in DTN-based data collection scenarios.

VII. RELATED WORKS

In this paper, our research is to address the issue of IoT data collection in large area with constrained network facilities. This is one of the crucial issues in a number of systems, including smart agriculture, smart cities, and public safety, among others. Using agriculture as an example, there have been a number of research efforts devoted on applying IoT techniques to the agriculture domain [11], [40]–[44]. For example, the concepts and models for smart farming using IoT have been introduced by existing research [11], [43], [44]. Yoon *et al.* [21] introduced several implementations. Padalalu *et al.* [45] investigated the smart water dripping system for smart farming. Likewise, JiHye *et al.* [46] tested the WiFi stability for the smart farm platform.

Existing research on UAV-based data collection have focused on applying UAVs in wireless sensor networks [22]–[24]. For example, Gong *et al.* [24] designed an algorithm to minimize the UAV's total flight time from a starting point to a destination. Pang *et al.* [23] proposed data collection using UAVs in wireless rechargeable sensor networks. Ho *et al.* [47] focused on energy efficient data collection for wireless sensor networks using UAVs as relays.

In our prior research [35], we conducted a thorough performance assessment of DTN in dynamic networks, using the same emulation-based platform, and compared performance in comparison with TCP. In addition, research efforts have been undertaken to evaluate the DTN from the perspectives of scalability, optimization, routing algorithms, application, security, and platforms [48]–[59].

Although the Hilbert Curve has been widely used in computer science research [32]–[34], only a few efforts have applied it to IoT scenarios. For example, Chowdhury *et al.* [32] applied the Hilbert Curve for scheduling wireless charging vehicles to charge wireless sensor networks. Ma *et al.* [33] used the Hilbert Curve in path recognition for mobile robots. Lawder and King *et al.* [60] employed the Hilbert Curve for node-based localization in wireless sensor networks. Other research areas includes multi-dimensional data indexing, image storage and retrieval [61], and location privacy protection [34].

VIII. FINAL REMARKS

In this paper, we have defined a three-dimensional problem space for IoT data collection in large, infrastructure-free areas, with respect to the collectors, the scale of the IoT devices, and the methodology of workload allocation. Based on the problem space, we have proposed a new data collection scheme that combines a single UAV with the DTN protocol to enable continuous data transmission in infrastructure-free, large-area IoT scenarios. In solving this problem, we leverage the Hilbert Curve as the path planning algorithm to optimize the utilization of the UAV within its limited capacity. Via implementing the proposed data collection scheme via emulation-based platform based on the Common Open Research Emulator (CORE), we have conducted a series of quantitative evaluation experiments and demonstrated the effectiveness of our proposed scheme in comparison with several baseline schemes. Our evaluation confirms the effectiveness of our proposed scheme in completing the task of data collection, and validates the advantages of DTN over Bare TCP in the scenarios studied herein. Utilizing our quantitative results, we were able to optimize the parameters used in our proposed path planning scheme. Moreover, our proposed scheme outperformed the representative baseline in data collection in each scenario IoT device distribution and traversal speed. Our research enables the capability of quality and cost control in the scenarios such as smart agriculture and public safety.

Based on the problem space that we have defined, our ongoing research efforts include several directions moving forward. With respect to the data collectors, we plan to extend our research from a single UAV data collector to the coordination and cooperation of multiple UAVs with and without differences in capabilities, integrating with the DTN protocol. Additionally, schemes for allocating the collection workload to multiple collectors should be considered. In the meantime, the Hilbert Curve-based path planning can be further extended into three-dimensional space and include terrain information. Further, based on collected data, leveraging machine learning techniques to extract insightful information in IoT systems and designing a cost-effective IoT search engine are our ongoing research as well.

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