Evaluating Time Varying Connectivities and System Throughput in Opportunistic Networks for Smart Grid Applications

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***Abstract*—With increasing proliferation of smart phones, there is an opportunity to employ mobile ad hoc networks to connect to distributed energy assets located in remote areas. With embedded intelligence and edge computing capabilities, autonomous 'edge control nodes' can enable a decentralized energy nexus, without the need for on-demand communications. Authors have developed an opportunistic networking framework using Bluetooth Low Energy and a specialized mobile phone application that enables delay tolerant networking for the above framework. This paper presents the analysis of time varying graph connectivity for such an opportunistic mobile ad hoc network. Dependence of connectivity on different network parameters such as radio characteristics, the mobility of data mules and parameters governing how connections are established are explored. Simulation results showing the variation of above trends have been presented.**

Keywords - Bluetooth, delay tolerant networking, edge-control devices, internet of things, mobile ad hoc network

I. Introduction

As the electric grid evolves, distributed resources (like DERs, rooftop solar/PV, EV charging stations etc.) are proliferating in it. There is a need for developing decentralized control architectures that can address scalability, cybersecurity and interoperability issues, while keeping the overall costs of implementation to a minimum. Numerous internet-of-things (IoT) solutions have been proposed by researchers [1], [2], but have struggled to justify returns on investment, and as such have not seen widespread deployment by electric utilities.

Some of the challenges that cellular and other long range radio systems face are deployment costs in remote areas, dependence on back-haul technology migration, country-specific certification issues, a high degree of customization and cyber-vulnerability. Besides, Wi-Fi-access points or cellular network coverage may not be available in areas of deployment, which is often the case for electric utility assets.

In contrast to 'on-demand' connectivity models, a decentralized framework has been proposed in [3], called the GAMMA platform. Here, intelligence has been embedded in the edge devices called GAMMA Kernels (referred to as nodes), which report only actionable information to the cloud. These nodes are equipped with long range Bluetooth Low Energy (BLE) radios [4] and have local computation power, data storage, power management and can exert control action if needed. The device to cloud connectivity is enabled by "data mules" allowing for delay-tolerant networking [5]. These are devices from trusted partners (like smart-phones, utility trucks etc.) that relay data from the end nodes to the cloud in an opportunistic fashion. The data exchanged between the end node and the server are encrypted end-to-end with a unique AES-128 key, and as such, the data mule only acts as a store and forward system from the end node to the cloud. It does not have access to; and cannot interpret the data being exchanged between the server and the end node. The overview, operating principles and various components involved in the system design for GAMMA platform have been presented in [3].

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A. Opportunistic Network with Edge Intelligence

The GAMMA Platform framework allows utilities to operate assets autonomously, without the need for constant, bandwidth-intensive, real-time data reporting to the cloud. The edge devices can exert control actions based on some 'rules' set by the system operators. These are often times slow changing 'set-points' and need to be reported to the end nodes infrequently (once a week or few times a month). Doing so opportunistically; by leveraging the mobility of the data mules can result in an ecosystem of decentralized, distributed, autonomous devices at very low capital and operating costs. GAMMA platform has been operational at Center for Distributed Energy, Georgia Tech since April 2018 and has demonstrated numerous applications as noted in [3], [6]. The platform also enables asset monitoring applications, where data packets are small (few kB in size) and generated intermittently. Intelligence built into the end nodes extracts only the actionable information and reports to the cloud, so that the cloud is not overloaded with data.

As data mules move around, they discover and connect to the end nodes located near them with specific inputs from the cloud. End nodes advertise their presence using long range

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BLE, over the Bluetooth advertisement channels (channels 37, 38 and 39). Whenever a data mule passing near an end node picks up the advertisement, it initiates a connection request and exchanges data between the node and the cloud server. Although it is assumed that the data mule has access to the GAMMA cloud server at all times, it can also work in an offline environment, as a simple 'store-and-forward' system i.e. caching data locally until internet access has been restored.

B. Contributions

The contributions of this paper are to develop an understanding of a random time varying nature of the connectivity graph along with models to study data transfer from the end nodes to the cloud. Since the system can be large (hundreds to thousands of end nodes) and geographically dispersed (assets can be located in remote areas), it becomes important to model and understand the expected behavior of the system prior to deployment. It is also necessary to capture the stochastic nature of the connection process- a process largely dependent on various aspects of the motion of the data mules (speed and distance from nodes), and the process of pairing over Bluetooth. Besides, it is necessary to understand the overall coverage that can be achieved with a completely randomized motion of the data mules, and its relation with parameters like radio coverage range.

In this paper, in continuation from [3], a dependency on various parameters such as number of data mules, RF line of sight (LOS) range, connection parameters etc is studied and results presented. A simulation model has been developed, which uses the motion of data mules, and probabilistic nature of connection to study how the throughput of the system varies with above mentioned parameters.

II. Time Varying Connectivity Graphs

This type of networking falls under the traditional opportunistic networks and mobile ad-hoc networks (MANETs), which have been extensively studied [7], [8], [10]. Consider $\mathcal{N}$ end nodes distributed in a given region, with $\mathcal{M}$ data mules traveling in it. The data mules get specific inputs from the GAMMA server in order to discover and pair with specific end nodes- typically those which have not been synchronized in a long time, or if the cloud wants to downlink information (like commands or rule updates) to particular nodes. This process is shown in Fig. 1. The resulting time varying connectivity graph is shown in Fig. 2. The time intervals on each link indicate the period for which the individual links are active. The graph $\mathbb{G} = (\mathbb{V}, \mathbb{E})$ has vertices $\mathbb{V}$ = set of all end nodes, and edges $\mathbb{E}$ = set of all links existing temporally.

The following entities have been defined in the context of time varying graphs [7]:

$\rho : \mathbb{E} \times \mathcal{T} \rightarrow \{0, 1\}$ the 'presence function', indicating if the given link is valid or not. In this opportunistic network, ρ depends on :

(1) whether a data mule is in the vicinity (RF LOS range) of the end node.

(2) whether the end node advertises its presence to the data mule (through BLE advertisement process).

(3) whether a data mule is 'scanning' for nearby end nodes.

Establishment of the link and consequently the presence function ρ heavily depend on the probability of end node being in advertisement mode (indicated by $\mathbf{P}$[advertisement]) and the probability of the data mule being in scanning mode ($\mathbf{P}$[scanning]). These are explained in section III. We assume that the data mules are always connected to the cloud (cellular or other means). Besides, if the connection is disrupted, the data mules can locally store and cache data till the connection is securely established again [3].

$\xi : \mathbb{E} \times \mathcal{T} \rightarrow \mathcal{T}$ the 'latency function' indicating the time it takes for a packet to cross the particular link. With BLE data rates ($>$ 100 kbps), this term can be neglected.

III. Connectivity Model

We use a vertex centric evolution of the connectivity graph as shown in Fig. 3. The parameters governing the connectivity

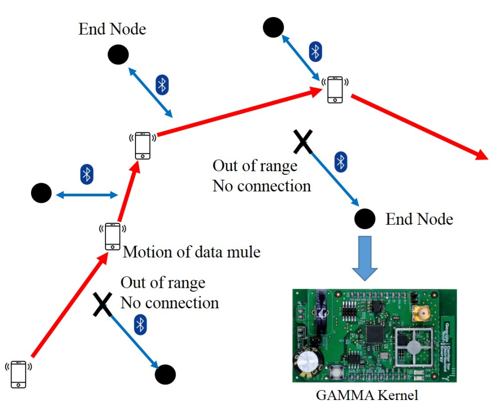

Fig. 1. Spatio-temporal representation of opportunistic connectivity. The end nodes are the autonomous edge control devices of GAMMA platform, called GAMMA Kernels, as discussed in [3].

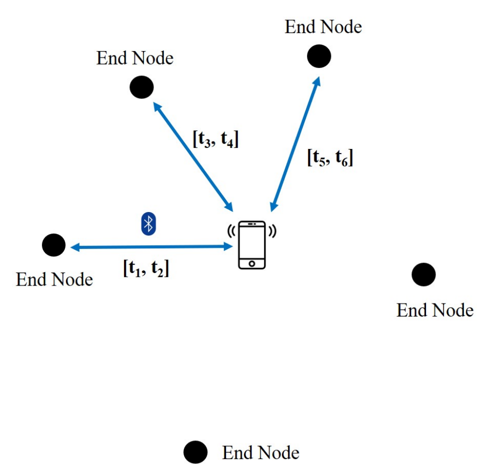

Fig. 2. Time varying graphs when connectivity exists between end nodes and data mule only during specific time windows.

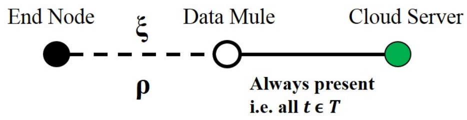

Fig. 3. 'Vertex centric' evolution of the time varying graphs with presence and latency functions. It is assumed that the data mules always have a stable cloud connection (through cellular or Wi-Fi access). However, if internet access is unavailable, data can be locally cached and transmitted later.

(mainly ρ) are as follows:

A. Process of Pairing

The presence function ρ depends on the process of pairing between the end node and the data mule. These are governed by scanning and advertisement processes in BLE specifications [4], [11]. The process of pairing is visualized in Fig. 4. Pairing can occur when the end node is 'advertising' over the BLE channels and the data mule passing-by, picks up these advertisements during its scanning phase.

Consider the data mule being in scanning phase for t_s duration and in the idle phase for T_s duration. Since it is a $2-$state Markov chain, the probability of the data mule being in scanning phase at the n^{th} step when $n \to \infty$ is $\frac{t_s}{T_s}$.

Similarly, it can be shown that, for the end node, $P[advertising] = \frac{t_a}{T_a}$ where t_a is the duration the end node advertises, in a total cyclic period of T_a.

Several studies [12] - [14] have shown the dependence of device discovery on BLE scanning, advertisement intervals and duty cycles. The optimal choice of scanning and advertisement intervals depend on parameters like energy consumption, intended advertisement miss rate, discovery latency among others. Relating network throughput with scanning and advertisement parameters is out of the scope for this work and will be addressed in the future. In the simulation setup, the overall process has a timeout implemented, with connections being considered valid only if they last longer than 5 sec (as an upper limit on the device discovery + connection phase), i.e. $\rho(t) = 1 \Leftrightarrow (t_1 - t) > 5 \; \forall \; t_1 =$ first connection instant. The process of evolution of ρ is visualized in Fig. 5.

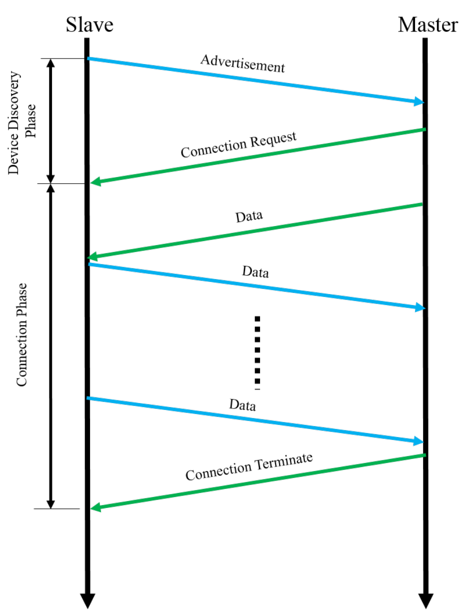

Fig. 4. Pairing process timeline. End nodes are BLE peripherals or 'slaves' while data mule applications on smart-phones act as BLE 'masters'

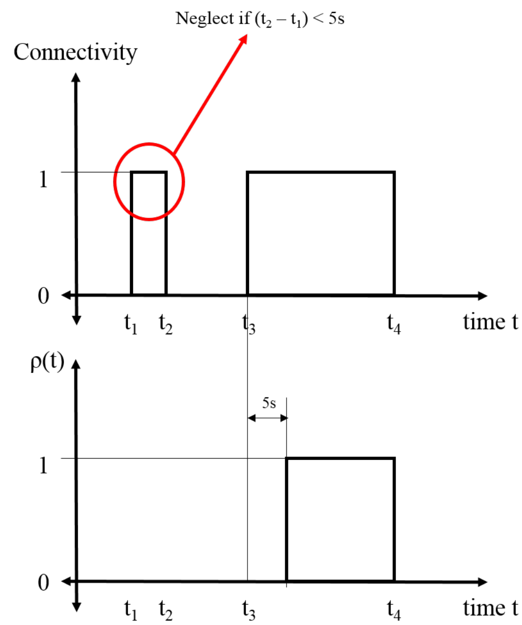

Fig. 5. Evolution of ρ for a given pair of data mule and end node. Connectivity indicates whether a data mule is in the vicinity of an end node.

B. RF and Radio Characteristics

The presence function ρ depends on the BLE EIRP (effective isotropic radiated power) and RF sensitivity of the end nodes and the mobile phones. Since the system should be compatible with numerous phones from different manufacturers, the dependence is heavier on the RF parameters of end nodes. As seen in [3], the BLE EIRP of the nodes is $+20$ dBm, sensitivity is -101 dBm and the LOS distance over which a connection between a smart phone and an end node can be sustained, is > 250 m. These parameters effectively govern how long a connection can be maintained, once the pairing process is successful.

C. Data Mule Mobility Models

The presence function ρ also depends on the mobility of data mules. These aspects and mobility models have been studied for VANETs and MANETs. In general, a stochastic motion was of interest and hence the Gauss-Markov mobility model was chosen [8], [9]. The motion of data mules was simulated in $x - y$ planar space as follows: Speed (s_n) and direction (d_n) are the two parameters of interest at the n^{th} instant. They are varied as:

$$s_n = \alpha s_{n-1} + (1-\alpha) s_{mean} + s_{rand}\sqrt{1-\alpha^2} \quad (1)$$

$$d_n = \alpha d_{n-1} + (1-\alpha) d_{mean} + d_{rand}\sqrt{1-\alpha^2} \quad (2)$$

The speed statistics are adopted from [15], [16] and plugged into the mean speed parameter above. Here, s_{rand} and d_{rand} are normally distributed speed and direction variables, with $s_{rand} \in [1,5]m/s$ and $d_{rand} \in [0,360]^\circ$. In the $x-y$ grid, the motion is governed by:

$$x_n = x_{n-1} + s_{n-1} \sin d_{n-1} \quad (3)$$

$$y_n = y_{n-1} + s_{n-1} \cos d_{n-1} \quad (4)$$

Compared to other models like random direction mobility and random waypoint, Gauss-Markov model has some advantages:
(1) It tunes the randomness of the motion through a single parameter α, with $0 \leq \alpha \leq 1$. By setting $\alpha = 1$, linear motion can be obtained, while $\alpha = 0$ yields totally randomized motion. For the mobility models of data mules, a value of $\alpha = 0.8$ is chosen to model real world motion.
(2) It allows for past velocities and directions to influence the present values, an important factor affecting the trajectories of data mules. Since data mules are objects like smart phones, drones, utility trucks, the velocity cannot vary randomly. The velocity at the n^{th} instant governs the velocity at the $n+1^{th}$ instant in time.
(3) The trajectories obtained are close to the ones one might expect in real-world scenarios [8].

An interesting aspect to note is that the actual connectivity and throughput of the network is *insensitive* to the speed of the data mule [14], but only depends on the time the data mule spends in the coverage of a particular end node.

IV. Simulation Results and Discussion

In order to study the interaction with mobile data mules, a simulation study was conducted using MATLAB. The link layer over BLE was emulated by constructing the connectivity graphs (as shown in Fig. 1 - 5) based on the trajectories of the data mules to study variation of overall network parameters. A grid of 10 km by 10 km was constructed, with all data mules beginning their transit at random points within the grid. End nodes ($\mathcal{N} = 100$ in number) were scattered randomly across the grid. Data mule transit for 10 hrs was simulated, with a 1s granularity.

Time step for the Gauss-Markov mobility model was 1s, however, a new speed value chosen from speed distribution statistics [15], [16] every 600s. This ensures that enough granularity is obtained in the trajectories of data mules, while updating the velocities as per (1) and (2). The trajectory of data mules is governed by (3) and (4) noted above. A snapshot of the data mules' mobility with respect to the locations of the end nodes is shown in Fig. 6.

To study the overall performance of the opportunistic network, we look at total data exchanged between data mules and end nodes. Several parameters affect this throughput, namely: number of mules ($\mathcal{M}$), connectivity range of end nodes, scanning duty cycles on data mules, advertising duty cycles on end nodes, and pairing time duration. Once the trajectory of data mules is obtained, the connection process is modeled as close to real life scenario as possible. Once an end node is in the vicinity of the data mule (governed by the RF LOS range), the connection process begins, and is modeled as a period of 5 sec when no data transfer takes place. This is captured by the fact that $\rho(t) = 0$ for that period of initial connectivity (seen in Fig. 5). This process is carried out for all the $\mathcal{M}$ data mules with respect to the $\mathcal{N}$ end nodes.

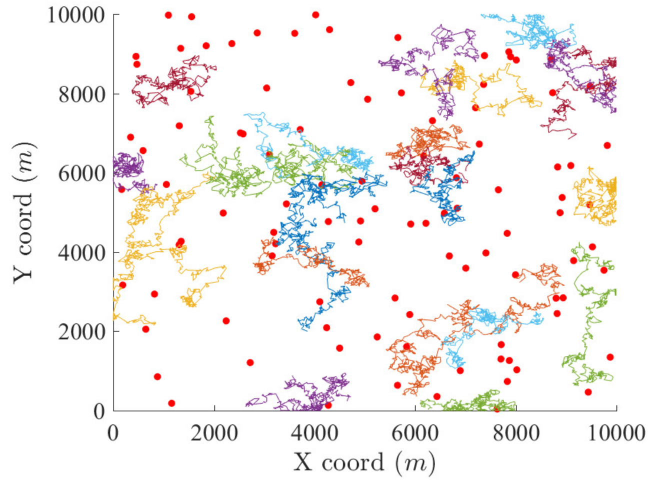

Fig. 6. Sample trajectories of data mules around the $x-y$ grid. The red dots show locations of end nodes ($\mathcal{N} = 100$) while the colored traces are the trajectories of data mules ($\mathcal{M} = 25$).

Once a connection has been established, the data are exchanged as per over the air rates for BLE protocol. Even though BLE supports raw data rates upto 1 Mbps, the GAMMA protocol has some overhead in it, and this has been accounted in the study. An effective data rate of 1 kbps has been modeled.

A. Variation of number of data mules

It is clear that the overall throughput of such an opportunistic system would increase with the number of data mules $\mathcal{M}$. In fact several studies have shown the dependence of overall throughput on data mules [17]. However, it is interesting to see that the overall throughput has a *linear* dependence on $\mathcal{M}$. As seen in Fig. 7, the overall network throughput increases linearly with $\mathcal{M}$, in 100 different stochastic simulation scenarios.

Fig. 8 shows the number of end nodes (out of a total of 100) that were covered (i.e. a connection was established over BLE $\Rightarrow \rho = 1$, and data exchanged successfully) during the simulation as a function of $\mathcal{M}$.

However, in a practical scenario, with targeted inputs from the cloud, data mules can be directed to cover areas that have been poorly serviced. Thus the utility fleet managers can direct certain data mules to cover parts of the system that have not

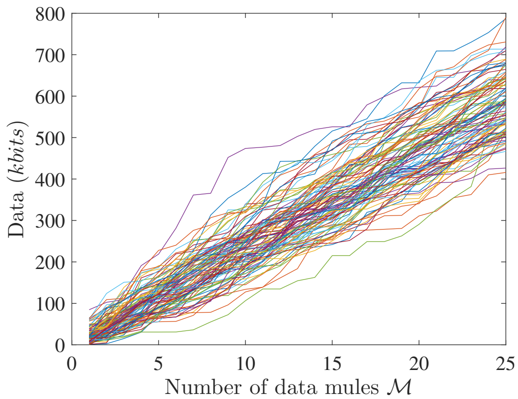

Fig. 7. Stochastic simulation, showing 100 instances of variation of the throughput of the system (data in kbits) with respect to number of mules $\mathcal{M}$ for a period of 10 hrs, when LOS range is 400 m, t_s = 30s, $T_s = 180$s, $t_a = 10$ ms, $T_a = 1$ s, and overall data rate = 1 kbps.

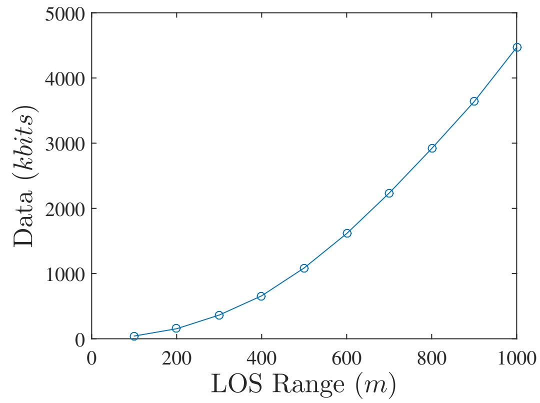

Fig. 9. Variation of the throughput of the system (data in kbits) with respect to LOS range for a period of 10 hrs, when no. of data mules, $\mathcal{M} = 25$, t_s = 30s, $T_s = 180$s, $t_a = 10$ ms, $T_a = 1$ s, and overall data rate = 1 kbps.

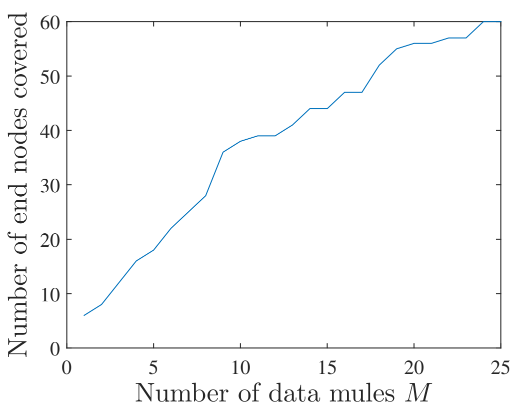

Fig. 8. Number of end nodes covered (out of a total 100) as a function of $\mathcal{M}$ when t_s = 30s, $T_s = 180$s, $t_a = 10$ ms, $T_a = 1$ s, LOS range = $400m$ and overall data rate = 1 kbps.

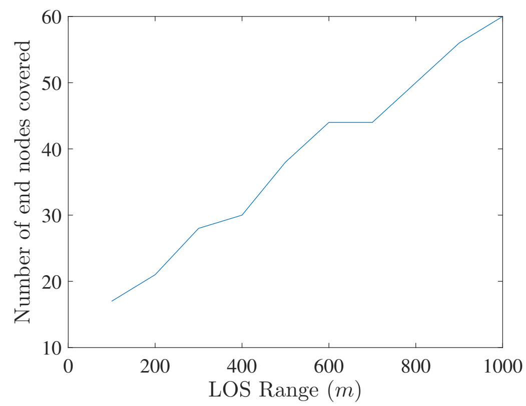

Fig. 10. Number of end nodes covered (out of a total 100) as a function of LOS range when $\mathcal{M} = 25$, t_s = 30s, $T_s = 180$s, $t_a = 10$ ms, $T_a = 1$ s, and overall data rate = 1 kbps.

been covered in a given time period. This ensures that all the end nodes in the network get connected to the cloud in a specified time frame.

B. Variation of LOS range of end nodes

When the overall RF (LOS) range increases, effective ‘coverage’ in the area increases. This phenomenon has been studied in coverage problems in ad-hoc networks [15]. With appropriate BLE repeaters and range extension devices, the effective communication range can be extended beyond 1 km. This is analogous to a greater portion of the area being under the coverage of end nodes (or data mules), hence increasing the overall throughput of the network. This trend can be seen in Fig. 9.

It is obvious that the overall network throughput would increase with an increase in the range over which data mules and end nodes can communicate [18]. Fig. 10 shows the number of end nodes covered as a function of LOS range. For GAMMA platform, it has been shown [3] that BLE connections between end nodes and smart phones can be established at distances between 200 and 400m, in scenarios where the data mules (smart phones in cars) are moving at various speeds near stationary nodes. However, there are techniques to increase the RF radio range between a data mule (smart phone) and the end node- by using BLE repeaters. The repeater is just another end node (GAMMA Kernel) that acts as an interface between another end node in the field and the data mule, and due to enhanced BLE-RF specifications (EIRP +20dBm and sensitivity −101dBm) can improve the LOS range significantly.

V. Conclusion and Future Work

This paper presents a vertex centric dependent graph for a data mule-based opportunistic networks for distributed energy assets. Simulation results show that a small population of data mules can cover a large area, opportunistically connect to and synchronize the end nodes with the cloud server. With enough number of data mules, and specific inputs from the fleet managers, data mules can synchronize with large number of end nodes, providing enough visibility to the network operators.

Overall throughputs of > 500 kbits have been achieved in a short duration of 10 hrs. This shows the viability of the concept in the context of decentralized, distributed smart grid applications, especially like asset monitoring/management.

In the future, studies to find optimal choice of BLE scanning and advertisement intervals and duty cycles will be performed, considering the trade-off with energy consumption and throughput. A test bed has been setup to emulate the effect of data mules' motion, in order to get the same time-varying connectivity graphs. This enables an evaluation of expected throughput when parameters like BLE scanning and advertisement intervals are varied.

Future work also includes overlaying an actual sensor deployment scenario (i.e. GPS coordinates) on a map, and including representative traffic flow information and comparing it with actual experimental data from the field.

Although the normal speed statistics [15] have been chosen for this work, the effect of choosing different speed distributions, specific routes and other controllable aspects of the data mule's mobility have not been considered. However, these can be evaluated in the actual deployment to verify the end to end performance of the system.

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