Enhancing Reliability of Community Internet of Things Deployments with Mobility

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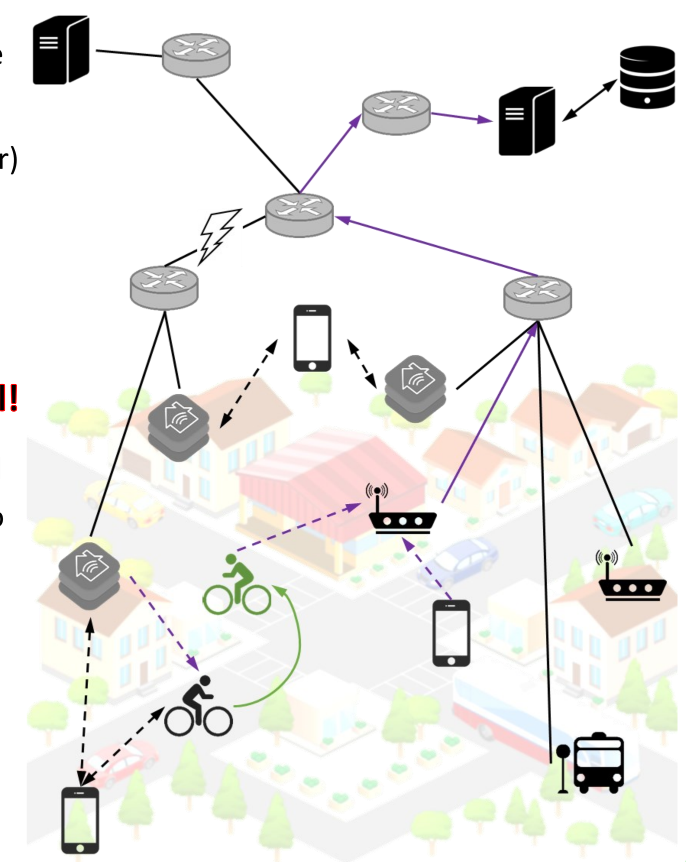
Goals and Overview

Internet of Things (IoT) systems are enabling the next generation of smart communities and cities. However, the current large-scale in-situ IoT systems have the following limitations:

- They depend heavily on public infrastructures (e.g. Wi-Fi, power)
- Maintenance of devices is expensive and labor intensive
- Physical limitations make it hard to deploy uniformly in certain areas

A flexible approach to address these issues is essential!



Nowadays, mobile devices are equipped with various sensors and network capabilities. We propose to leverage these capabilities to compensate and extend the in-situ smart community deployments.

Challenges

1. Heterogeneity of devices and networks
2. Dynamics in network availability and environmental changes
3. Scalability of system architecture

Scenarios and Testbeds

Victory Court Senior Apartments is a senior living facility in Montgomery County, MD and serves as a testbed for community IoT systems. We deployed the SCALE IoT platform to monitor indoor environments for public and personal safety; this is being currently extended for outdoor settings to monitor aspects of the environment (e.g. air quality).

- Wi-Fi is the primary communication modality
- Collecting data from outdoors devices is challenging

On the UC Irvine campus, SCALE deployments are used to enable smart campus applications. For example, we can create heat-maps with readings from multiple types of sensors on in-situ and mobile data collection platforms (e.g. bikes).

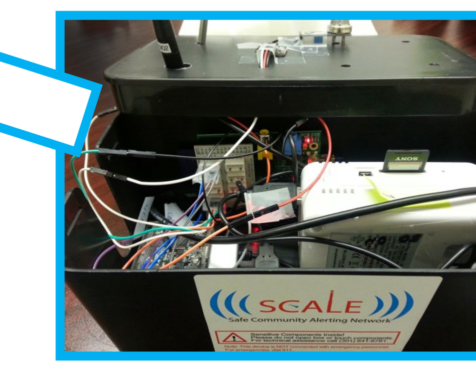
While campus Wi-Fi is available, coverage is non-uniform. Our approach uses available knowledge of connectivity conditions to drive collaborative sensing with heterogeneous sensing devices.

In emergencies (e.g. fires), we hope to collect relevant mission-critical data, but infrastructures are often damaged and networks are congested.

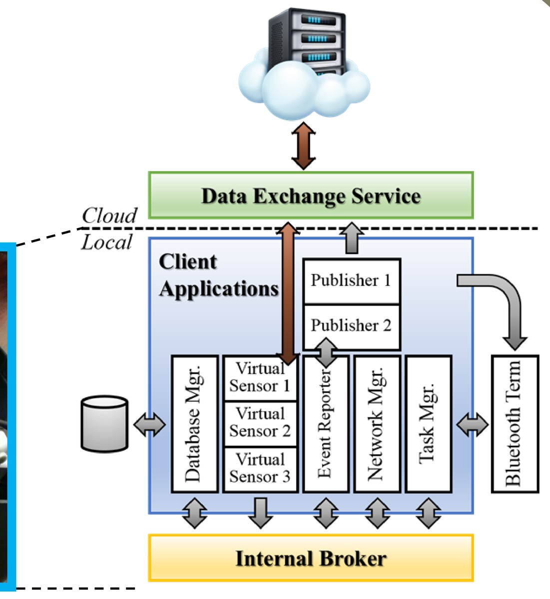
- Custom sensors (e.g. poisonous gas) on mobile data collectors are required in such events.
- Mobile agents can be used for help calibrate in-situ sensors to improve the overall accuracy of readings.

SCALECycle Platform

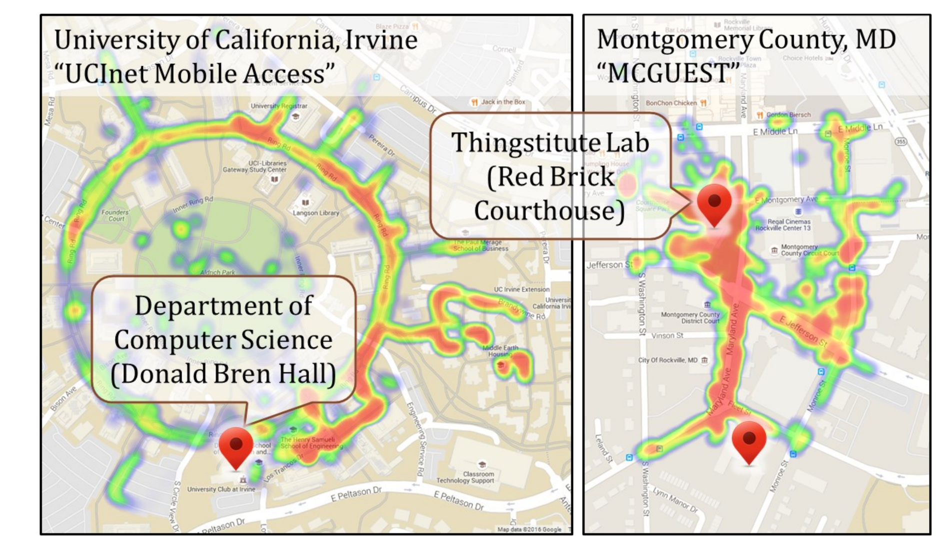
SCALECycle prototype on bike



An open SCALE sensor box



SCALECycle system architecture



Wi-Fi RSSI heat-maps created with SCALECycle measurements

Hardware prototype

- Raspberry Pi Model B or higher + Wi-Fi
- Sensors: Light, motion, gas (MQ-family), temperature, humidity, seismic, etc.
- GPS module and Bluetooth terminal

Software

- Abstracted virtual sensors generate sensed events, that are published via MQTT or stored in local database

Measurements on four testbeds: UCI, NTHU, Rockville (MD), Bangladesh.

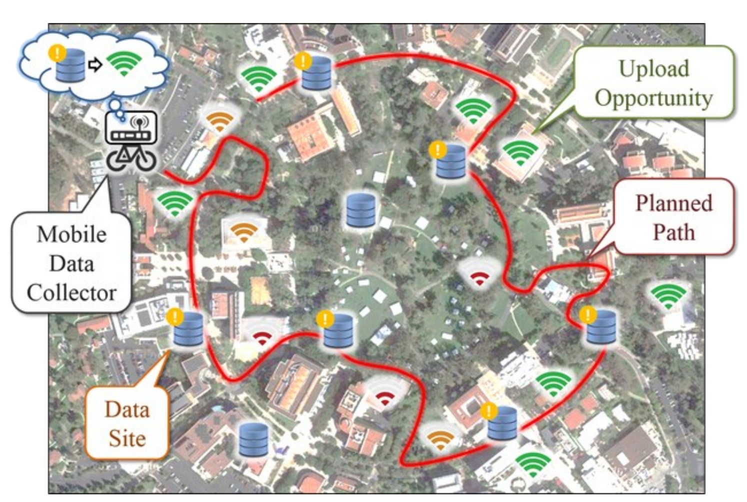
M. Y. S. Uddin, et al. *"The SCALE2 Multi-network Architecture for IoT-based Resilient Communities,"* SMARTCOMP '16

Upload Planning for Mobile Data Collection

A mobile data collector (MDC) is given a path, where there are several sites to fetch data, and several access points to upload data.

Plan for each *data chunk* fetched from data sites, which *upload opportunity* to use to upload it, in order to improve the overall timeliness.

Challenges: 1. Non-uniform network connectivity, 2. Data heterogeneity (e.g. size, importance, timing), 3. Environmental dynamics



Given an ordered list of data chunks $\{\boldsymbol{a}_i\}, i = 1, \dots, N$, with increasing $x(\boldsymbol{a}_i)$, and an ordered list of opportunities $\{\boldsymbol{u}_j\}, j = 1, \dots, M$, with increasing $x(\boldsymbol{u}_j)$.
Find global plan λ and its corresponding plan matrix $\boldsymbol{\Lambda}$, to maximize the WOU subject to the cause-and-effect constraint, i.e.

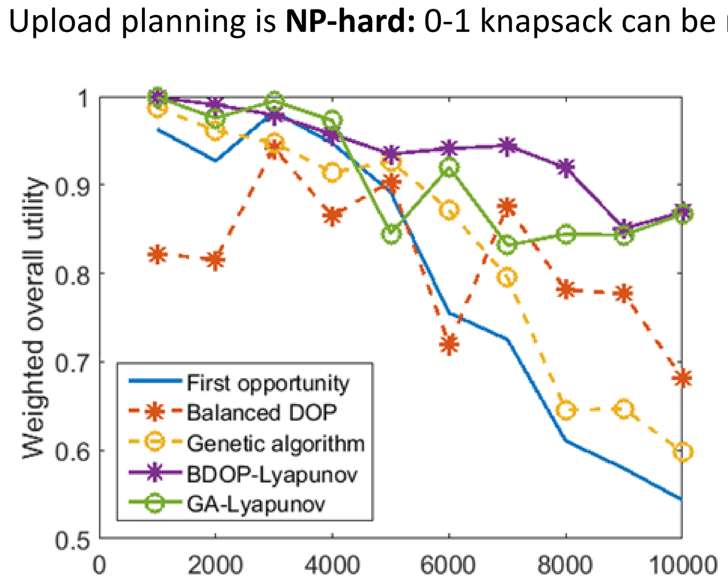
$$\text{maximize } U(\lambda, l) = \sum_{i=1}^{N} p(\boldsymbol{a}_i) \cdot f\big(\Delta(\boldsymbol{a}_i, \lambda, l)\big) \Big/ \sum_{i=1}^{N} p(\boldsymbol{a}_i),$$
$$\text{s.t. } \boldsymbol{\Lambda}_{i,j} \le \mathbf{C}_{i,j}, \forall i = 1, \dots, N, \forall j = 1, \dots, M.$$

Solution sketch:

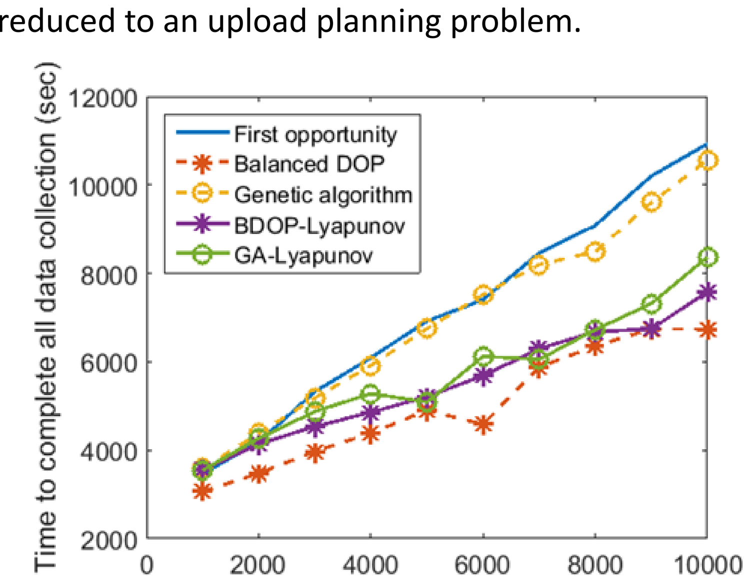
Two-phase approach with a static planning phase (on server) and a dynamic adaptation phase (on MDC).

Formulation of the upload planning problem as a constrained optimization problem (shown on the left).

Upload planning is **NP-hard:** 0-1 knapsack can be reduced to an upload planning problem.



The proposed two-phase approach performed more stable for large data chunks. For ~8 MB chunks, BDOP-Lyapunov resulted in 36-60% improvement in WOU.



Our approach also saves time for data collection! Compared with the naïve approach (first-opportunity), BDOP-Lyapunov saves up to 30% of time in completing all data collection tasks.

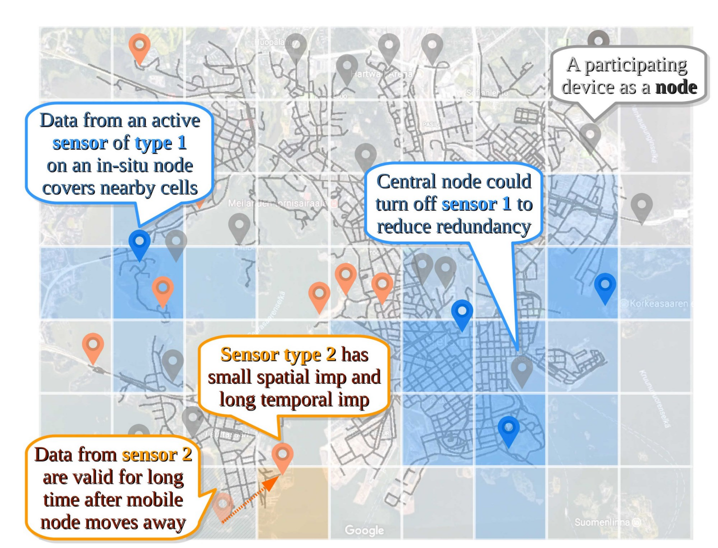
Q. Zhu, et al. *"Upload Planning for Mobile Data Collection in Smart Community Internet-of-Things Deployments,"* SMARTCOMP '16
Q. Zhu, et al. *"Data Collection and Upload under Dynamicity in Smart Community Internet-of-Things Deployments,"* PMC 2017

Spatiotemporal Scheduling for Crowd Sensing

Crowd-sensing allows large number of users/devices to help create situational awareness in urban regions. These include static IoT nodes in smart city/community deployments, mobile IoT nodes deployed on buses or other moving facilities, and mobile devices owned by residents. If not coordinated appropriately, the large number of devices generate redundant data that have little contribution to the overall coverage or accuracy resulting in inefficient use of resources.

We propose to use real-time online scheduling in smart city IoT systems that support crowd-augmented urban sensing applications; here, as subset of sensors/nodes can be switched off to improve the efficiency of the system while ensuring sufficient spatiotemporal coverage of sensing data.

We formulate the spatiotemporal scheduling problem as a multi-objective constrained optimization (on the right), which is NP-hard. We propose two heuristics (highest score first and Lyapunov control) that achieve near-to-best coverage under data constraints with lower costs (30% less active nodes).



Given inputs

- *Presence of sensors on nodes, i.e. matrix* $\mathbf{B}_{N\times K}$
- *Placement of nodes, i.e. matrix* $\mathbf{G}_{N\times M}[n], n \in \mathbf{N}$

Find: Plan matrix for each time frame $\mathbf{W}_{N\times K}[n], n \in \mathbf{N}$

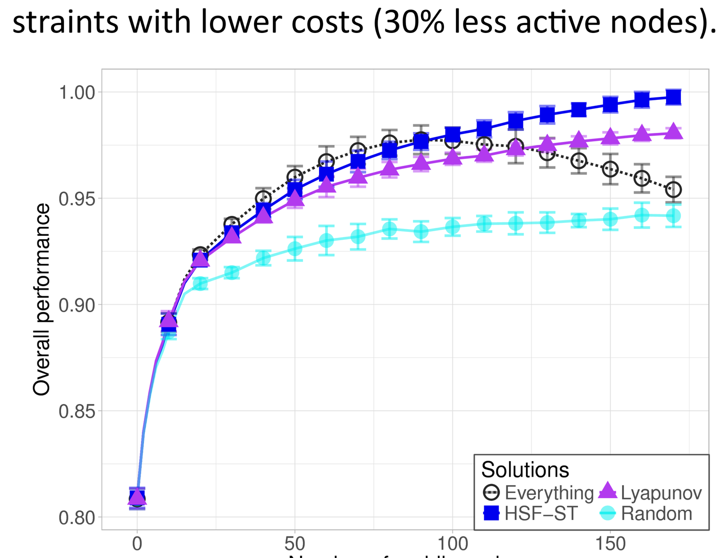
Optimize

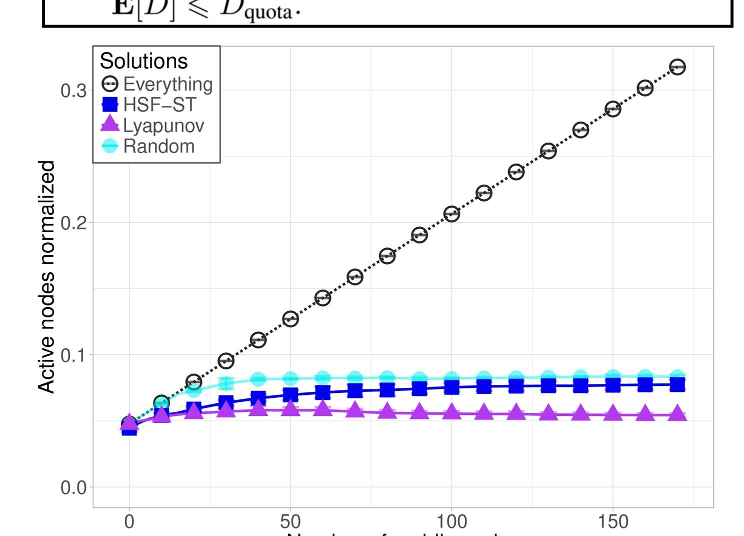
- *Overall coverage X and overall utility U (maximize)*
- *Average cost Y (minimize)*

Subject to

- *Presence constraint* $W_{j,k}[n] \le B_{j,k}, \forall j, k, n$
- *Data constraint* $D \le D_{\text{quota}}$

$$\max_{\mathbf{W}[n]} \mathbf{E}[\Gamma(X,U,Y)] = \gamma_1 \cdot \mathbf{E}[X] + \gamma_2 \cdot \mathbf{E}[U] - \gamma_3 \cdot \mathbf{E}[Y],$$
$$\text{s.t. } W_{j,k}[n] \leqslant B_{j,k}, \forall j = 1, \dots, N, \forall k = 1, \dots, K,$$
$$\mathbf{E}[D] \leqslant D_{\text{quota}}.$$





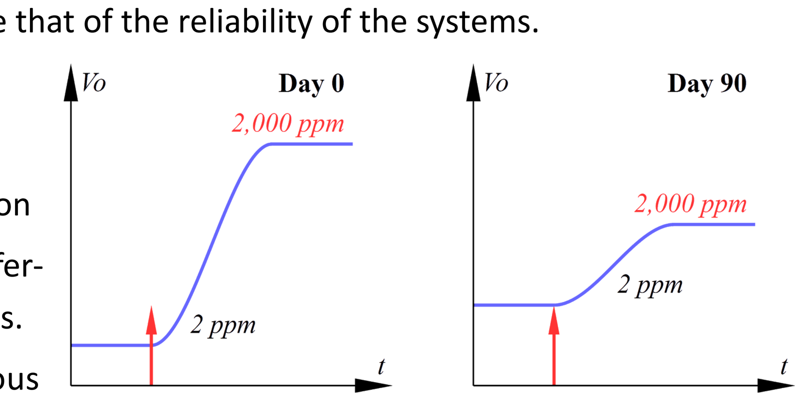
Q. Zhu, et al. *"Spatiotemporal Scheduling for Crowd Augmented Urban Sensing,"* INFOCOM '18

Planned Multi-Sensor Calibration

The low-cost commodity sensors used in IoT systems (e.g. smart buildings) are vulnerable to multiple issues that affect the accuracy of readings, hence that of the reliability of the systems.

- Different sensor manufacturers
- Sensor degradation and drift during operation
- Environmental changes affecting event detection

We propose to deploy mobile agents carrying reference sensors to calibrate sensors on in-situ nodes.



Challenges arise when we take the heterogeneous nature of the IoT devices into consideration. Different nodes may have different combination of sensors, and different types of sensors have different requirements on calibration period and accuracy. A tradeoff exists between the overall accuracy and the work needed to improve it.

We propose a two-level optimization scheme:

At the higher level, we determine which sensors need to be calibrated in each iteration (run), optimizing tradeoffs between calibration workload and overall accuracy.

At the lower level, in each iteration, we plan the paths for mobile agents so as to minimize the total time/distance travelled by all agents. (Work in progress)

Future Work

Future work will concentrate on:

- Context-aware partitioning and planning techniques in mobility augmented community IoT systems
- Edge computing and scheduling hierarchies to improve the scalability of real-time planning
- Security and privacy issues that emerge within smart communities/cities, mobile sensing, crowd-sensing, and complex network topologies
- Enhancement of backend services and the mobile agents to realize a complete feedback loop

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