

IoT-enabled Knowledge Extraction and Edge Device Sustainability in Smart Cities

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Abstract—Internet of Things (IoT) deployments are becoming the backbone of all future Smart City (SC) environments. They can, therefore, act as massive crowd-sourced data aggregators, driven by device-to-device interactions with SC users' mobile devices and their wireless interfaces. Provided that, our research focuses on developing probabilistic and machine learning models to (a) enable knowledge discovery from passive user interactions with the wireless IoT infrastructure and (b) apply the collected intelligence to increase the energy-efficiency and resiliency of the Smart City's IoT network. In this extended abstract we elaborate on the motivation behind our work, and the related challenges, while pointing to the solutions developed so far.

I. INTRODUCTION AND MOTIVATION

Until now the realization of the "Smart City" concept by urban planners and city governments has been relying on plain digitalization and automated implementations that often overlook the whole equation's human aspect. The inclusion of those who work and reside in the Smart City (SC) environment into the design process is becoming highly significant especially since the current urban population represents 55% of the world's population, a number that is expected to reach 68% by 2050. In addition, more and more municipalities and governments actively participate to discuss and address challenges with EU's Smart City Initiative and UN's United Smart City Initiative being two cases in point.

Without a doubt, the backbone of any SC undertaking is an Internet of Things (IoT) infrastructure that supports city-wide communications and consists of a vast group of computationally powerful participants including sensors, smart furniture, EVs, drones, 4G/5G eNBs, and WiFi hotspots [1], [2]. The increasing edge IoT network introduces significant challenges that pertain to various infrastructure aspects:

- 1) IoT devices should continuously function with minimal operational and maintenance costs. Thus, extending the edge's battery life is important for large-scale adoption.
- 2) The existence of multiple network protocols and wireless interfaces (WiFi, 5G, Bluetooth, NFC, etc.) should be addressed and utilized to collectively aid the availability and connectivity of the massively deployed devices.
- 3) The edge network's resiliency should be enhanced in the face of public-safety critical events [3].

Apart from the static IoT infrastructure, modern smart cities are developed around their citizens that carry mobile devices

or other User Equipment (UE) with capabilities that far exceed those of the equipment found around cities nowadays (smart wearables, etc.). In this setting, the IoT infrastructure is the ideal instrument to conduct mobile crowdsensing [4]. The main characteristics of mobile crowdsourcing in a SC include (i) dynamic mobility of the citizens' UEs that mirror their own, (ii) collaboration, namely the ability of crowds to create social structures and work together to achieve their goals, and (iii) the dual nature of each SC occupant that is at the same time data producer, and consumer as the sensing, communication, and processing of his data enhance the performance of the SC services. Evidently, there are many challenges associated with the above reality related to the efficient design of non-intrusive crowdsensing mechanisms, protection of the SC user's data privacy, and the application of distributed algorithms able to fully exploit the generated data streams in a cooperative and complementary manner for Smart City services.

Given that (a) the IoT infrastructure will be a critical component of almost all provided services of a future Smart City, (b) within the Smart City this vast edge network of IoT devices coexists and interconnects with mobile devices owned by citizens, and (c) current crowdsourcing mechanisms put user data privacy at significant risk while demanding exhaustive incentive mechanisms, our research aims to answer the following research questions:

- How can future Smart City systems utilize wireless interactions of citizens' mobile devices with the existing IoT infrastructure to extract actionable intelligence without involving other types of data?
- How can we optimize the operation, and increase the sustainability and resiliency of the Smart City's IoT infrastructure?

Our focus is on designing and analyzing cognitive mechanisms across different layers of the SC's communication infrastructure to address the aforementioned questions and challenges.

II. REAL-WORLD PASSIVE IoT INTERACTION DATA: THE BLEBEACON DATASET

As passive user-IoT device interactions, we consider non-intrusive advertising of a user's mobile device facilitated by any of their communication interfaces with the most common being WiFi probe request frames and Bluetooth Low Energy (BLE) advertisement packets. To the best of our knowledge,

there are not many available datasets that collect such interactions with IoT deployments over long periods. A recently published work in [5] captures multiple smartphone-based interactions between users (proximity, records, social media) without the involvement of a static IoT deployment.

In order to bridge this gap, we utilize our BLEBeacon dataset [6] that was the outcome of an IRB-approved one-month trial with real participants. The trial's design enabled us to track spatio-temporal interactions of university students with a network of IoT devices (32 Raspberry Pis) installed on three floors of a campus facility in a way that emulates a future edge device topology in a smart environment. To generate interactions with this infrastructure, forty-six students carried BLE beacons with them during their daily routines for over one month. Among others, we collected over 17 million data points of physical proximity indicators, and we have made the BLEBeacon dataset available as part of the CRAWDAD Community Resource repository [6].

III. RESEARCH OUTPUT AND DISCUSSION

Next, we discuss developed tools, and research outcomes that harvest passive interaction data for various applications.

A. Spatio-Temporal Smart Facility Management

In [7] we explore how spatio-temporal data from smart environment users can be utilized to perform real-time facility management towards optimizing energy consumption and maintenance operations. In [8] the use of an IoT deployment within smart spaces is extended to facilitate accurate occupant tracking using Received Signal Strength Indicator (RSSI) modeling and Geofencing for edge IoT nodes.

B. Unsupervised Radio Map Update and Localization

In [9], we showcase how IoT deployments in smart spaces can act as massive crowdsensing mechanisms towards simplifying and optimizing underlying services (e.g., micro-location in this case). We utilize RSSI readings from IoT edge devices as crowdsourced fingerprints to enable unsupervised learning of radio maps in a smart space. We construct a finite naive Bayes Gaussian mixture model (GMM) for occupant localization and use Expectation Maximization with unlabeled RSSI fingerprints to train it. This approach eliminates the need for exhaustive site surveys to construct and renew radio maps, while the positioning accuracy is maintained regardless of changes in the underlying hardware or physical space, and is even improved over time as more crowdsensed data are becoming available. We present a detailed performance analysis for static and mobile user localization accuracy while evaluating the impact of important system design parameters including training dataset size, feature number, real-time decision periods, and deployment density of edge IoT devices.

C. Energy-Efficient Communications for Edge Nodes

As seen in [10] the analysis of spatio-temporal correlations of passive RSSI packets can lead to the extraction of reliable social behavior of the mobile users, and thus social

relationships between their communication nodes. In our work in [11], [12], and [13] we present frameworks that exploit social graphs expressing communication interest among nodes to construct optimal clusters and increase energy-efficiency during wireless data aggregation. In [11] this mechanism is accompanied by a reinforcement learning process that utilizes socio-spatial information to further optimize the data aggregation according to the needs of the underlying application. In addition, wireless powered communications are introduced to prolong the overall IoT infrastructure's lifetime. Finally, the other two works focus on wireless networks that take over during public safety threatening situations in Smart Cities and increase their resiliency. In [12] the socio-physical clustering is again accompanied by learning-mechanism that chooses the optimal wireless communication interface for each node's data aggregation, while in [13] the optimal path of a mobile data aggregator is constructed in an attempt to maximize the IoT infrastructure's energy availability.

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