

NB-IoT Coverage and Sensor Node Connectivity in Dense Urban Environments: An Empirical Study

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Wireless sensor networks have enabled smart infrastructures and novel applications. With the recent roll-out of Narrowband IoT (NB-IoT) cellular radio technology, wireless sensors can be widely deployed for data collection in cities around the world. However, empirical evidence regarding the coverage and connectivity of NB-IoT in dense urban areas is limited. This article presents an empirical study that focuses on evaluating the coverage and connectivity of NB-IoT in a dense urban environment. We have designed a NB-IoT sensor node and deployed over one hundred of them in high-rise apartment buildings in Hong Kong. These sensor nodes utilize a commercial NB-IoT network to collect high-resolution water flow data for machine learning model training and provide timely feedback to users. We collect and analyze the empirical NB-IoT signal measurements from the sensor nodes deployed in various challenging outdoor and indoor environments for over three months. These empirical measurements reveal correlations between NB-IoT connectivity and sensor installation environments. We also observe that inter-cell interference, as a result of coverage by multiple neighboring NB-IoT cells in a dense urban environment, is a source of connectivity degradation. We discuss potential issues which IoT application designers and system integrators might encounter in practical NB-IoT devices deployment, and propose a transmission decision algorithm based on signal measurements for mitigating energy wasted due to transmission failures. Finally, we demonstrate the results and the benefits of using high-resolution water flow data collected by our purpose-built NB-IoT sensor nodes for studying the patterns of domestic water consumption in Hong Kong.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; **Sensor networks**; • **Networks** → **Network performance evaluation**; **Sensor networks**; • **Computing methodologies** → *Machine learning*.

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1 INTRODUCTION

More than half of the world population are living in urban areas currently and the rate of urbanization is growing, particularly in Asia. Rapid urbanization has put an increased strain on resources, such as water. According to the World Health Organization, half of the world's population will be living in water-stressed areas by 2025 [46]. To meet the resources requirements of the present and future generations, fast-growing metropolises are looking for ways to achieve a myriad of sustainable development goals. Internet of Things (IoT) technologies play an important role in transforming communication and operational paradigms in various application domains [12, 21, 43, 49]. In the era of IoT, wireless sensor network and artificial intelligence (AI) can be used for continuous monitoring of the environment, efficient management of natural resources and provision of utilities like water.

Many major cities around the world have registered a steady and gradual decline in per capita domestic water consumption level in the past 20 years. However, Hong Kong has wandered into the opposite direction. To help the Water Supplies Department, the water agency of Hong Kong, to achieve the policy target of reducing per capita freshwater consumption, we have designed a *Smart Water Auditing* system that can collect and analyze water consumption data to facilitate the evaluation of water conservation interventions [18]. Fine-grained flow rate data collected by a smart meter will be, through machine learning algorithms, analyzed and classified into specific types of end-uses, such as cooking, laundering, and showering. Consumers can then receive timely feedback on how much water is being used for what purposes inside their home. Visualizations of classified data that are made available to consumers through a web application shown in Fig. 1, constitute a powerful feedback mechanism that can empower an average person to experiment with and embrace habit-changing water conservation practices.

To develop a machine learning model for domestic water end-use classification, we have to collect ground truth water consumption data from multiple domestic households. In 2020, we conducted a pilot study to evaluate the feasibility of using in-line, tap-based turbine flow sensors to collect ground truth data in a few households [22]: Tap-based water flow rate data of high temporal resolution (i.e., short sampling interval) are key to developing accurate classification models. Our previous prototype IoT sensors system used Wi-Fi for transmitting the high-resolution ground truth data to the cloud. While Wi-Fi offers high bandwidth for data transfer, we concluded that it is not a suitable wireless technology for scaling up data collection from more households. In our application, tap-based sensors are placed inside cabinets of bathrooms and kitchens, which are usually deep, obstructed locations inside apartment units in high-rise residential buildings. 2.4 GHz Wi-Fi connectivity is limited in such challenged and unusual environment due to signal attenuation through indoor obstacles. On top of that, the high power consumption of Wi-Fi transmission is unfit for battery operations for extended periods. Moreover, a Wi-Fi-based sensors system needs additional network equipment set up in the participating households, which could discourage participation in the study because of added inconveniences and privacy concerns.

As scalability of the tap-based ground truth data collection system has been given a high priority, we thus have upgraded our system to adopt low-power wide-area network (LPWAN)



Fig. 1. Web application for visualizing a household's daily water consumption by end-use categories

technology. Among the LPWAN technologies that can be used in Hong Kong, we decided to make use of Narrowband IoT (NB-IoT) for collecting the large volume of high-resolution water-use data generated by each tap-based sensor. NB-IoT is a fast-growing cellular radio technology recently launched by mobile network operators (MNOs) as an integral part of 5G. With the city-wide coverage offered by MNOs, NB-IoT sensor nodes can be deployed in most locations in Hong Kong without the need of establishing custom wireless network infrastructure. Fig. 2 presents a high-level overview of the system architecture. Since May 2021, we have deployed 130 NB-IoT sensor nodes in 21 households to collect their water-use data for training machine learning models for end-use classification.

This article focuses on evaluating the performance of NB-IoT in dense urban environments. In particular, we investigate the effects of signal strength and quality on reliability and stability of using NB-IoT for transmitting sensor data to a cloud server. We argue that high reliability and stability are vital to battery life of the sensor nodes, as well as timely retrieval of the ground truth data collected in the field. This is evidenced by empirical NB-IoT signal measurements collected by the sensor nodes deployed in various challenging outdoor and indoor environments for over three months. Furthermore, we have identified potential issues which IoT application designers and system integrators might experience in practical NB-IoT devices deployment. Possible mitigation approaches are also discussed. The contributions of this article are threefold:

- We have designed and deployed a fleet of over 100 NB-IoT sensor nodes in the dense urban environment of Hong Kong. This fleet leveraged a commercial NB-IoT network to collect high-resolution water flow data for machine learning model training and for providing timely feedback to users.

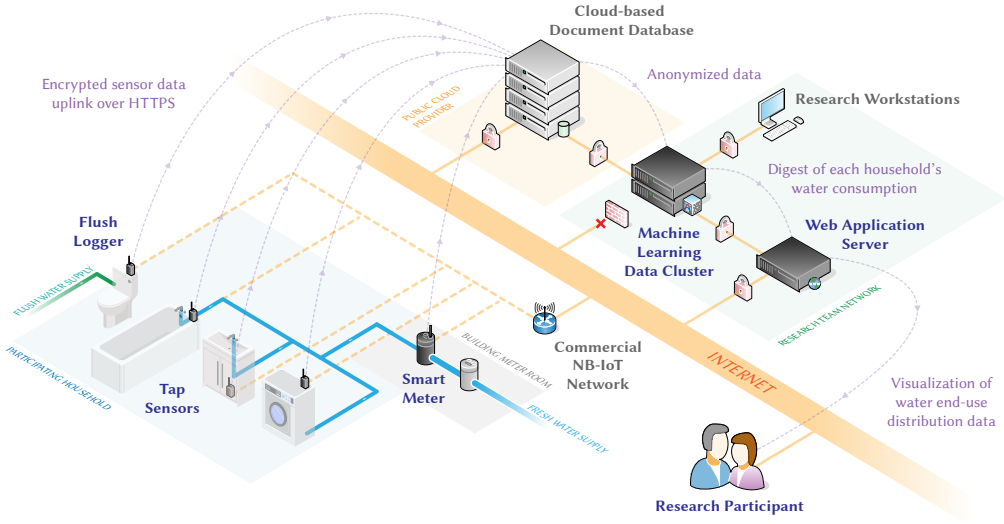


Fig. 2. Architecture of the ground truth data collection system for Smart Water Auditing

- We measured NB-IoT signal strength and quality from the fleet of sensor nodes for a period of over three months empirically. These empirical measurements revealed correlations between NB-IoT connectivity and sensor installation environment.
- We identified that inter-cell interference is a possible source of NB-IoT connectivity degradation in a dense urban environment. As the degraded signal quality leads to higher chance of transmission failure, we proposed a transmission decision algorithm to predict such failures and mitigate the energy wasted.

The rest of the paper is organized as follows: Section 2 reviews the relevant literature on LPWAN technologies and NB-IoT in urban environments. Section 3 outlines the requirements and design of the NB-IoT-based data collection system. Section 4 describes the deployment of our system in 21 households in the unique urban landscape of Hong Kong. Section 5 presents the empirical NB-IoT signal measurements and their analysis. Section 6 discusses the implications of the signal measurements, as well as the applicability of NB-IoT in our sensing application and beyond. We conclude this article in Section 7.

2 RELATED WORK

This section provides the background of predominant LPWAN technologies. After the brief discussion of the salient features of NB-IoT technology, various aspects concerning its deployment in urban environments are scrutinized.

2.1 LPWAN Technologies

Recent years have witnessed LPWAN technologies as a promising enabler for the realization of large-scale IoT ecosystems. As opposed to established wireless communication technologies (e.g., Bluetooth, Wi-Fi, ZigBee, and conventional cellular networks), LPWAN technologies aim to provide IoT devices with an energy-efficient radio connectivity over ultra-long distance. Many IoT devices like remotely operated sensors and actuators, seldom need a high data rate or low latency connection; instead, they require a low cost and reliable wireless communication protocol that supports exchange of small volume of data (e.g., sensor readings and commands) at scale.

The emergence of the LPWAN technology family has, thus far, gained great attentions from both industrial and consumer electronics sectors, and has realized a plethora of automated, delay-tolerant IoT applications in various domains, such as agriculture, utility metering, building automation, healthcare, etc. Sigfox, LoRa, NB-IoT, and Long Term Evolution for Machines (LTE-M) are four predominant LPWAN technologies that are taking the lead in the IoT races.

As a commercialized LPWAN technology, Sigfox networks are laid out in a cellular-like topology where Sigfox-enabled devices talk to a back-end server via proprietary base stations sitting one hop away [29]. Despite operating in the license-free industrial, scientific, and medical (ISM) bands (e.g., 920 MHz in Hong Kong), Sigfox is provisioned as a paid service by a sole commercial operator. Sigfox leverages a Binary Phase Shift Keying (BPSK) modulation scheme to support asymmetrical bi-directional communications, with the maximum uplink and downlink data rates of 100 bit/s and 600 bit/s, respectively. Randomly accessing channels of 100 Hz bandwidth, each device can transmit up to 140 uplink (UL) messages of a 12 B payload each, and receive up to 4 downlink (DL) messages containing an 8 B payload each per day. Due to the constrained DL capacity, Sigfox's link reliability is offered via repetitive transmissions of up to three times by default.

Patented by Semtech, LoRa [38] (abbreviated from Long Range) is a radio interface building on chirp spread spectrum (CSS) modulation technique, whereby the frequency of signal (a *chirp*) increases or decreases linearly with time [8, 20]. LoRa also utilizes the ISM bands, operating at 923 to 925 MHz in Hong Kong. Various parameters, such as uplink and downlink frequencies, spreading factor, bandwidth, coding rate, and transmission power, can be adjusted in actual deployment [4]. These adjustments can furnish IoT devices with ultra-long-range connectivity and interference immunity in the potentially crowded ISM bands, at the expense of degraded energy efficiency and data rate. Coupled with its well-known medium access control (MAC) protocol called LoRa Wide Area Network (LoRaWAN), IoT devices can conserve their limited battery resources by spending most of their lifetimes in a sleep mode without the need of periodic synchronization to a gateway when operating as a Class A device [7]. Unlike Sigfox, LoRaWAN offers the unlimited bi-directional transmissions of a larger payload size of up to 242 B [6]. Depending on spreading factors, bandwidths, and regulatory requirements (e.g., restrictions on airtime and duty cycle), different payload lengths can be supported. As an open standard, LoRaWAN networks can be freely deployed in the ISM band, subject to regulatory requirements. There is also a commercial LoRaWAN network operating in selected areas of Hong Kong.

NB-IoT, also known as Long Term Evolution (LTE) Cat-NB1, is a cellular LPWAN technology standardized by the 3rd Generation Partnership Project (3GPP) in Release 13 in 2016. It is designed to co-exist with LTE and 5G New Radio (NR) in the licensed spectrum for cellular communications (e.g., 900 MHz and 1800 MHz). Contrary to 5G NR which emphasizes on very low latency and high data rate mobile applications, NB-IoT serves the delay-tolerant massive Machine-Type Communication (mMTC) applications in the IoT ecosystem [28]. Compared to Sigfox and LoRa, NB-IoT provides better link reliability, lower downlink latency, and fairly guaranteed quality of service [29]. NB-IoT can be deployed using the existing LTE infrastructure, thus reducing the costs and speeding up adoption by both mobile network operators and customers [23].

LTE-M, also known as LTE Cat-M1, is another cellular LPWAN standard first introduced in 3GPP Release 13 [17]. Similar to NB-IoT, LTE-M employs Orthogonal Frequency Division Multiple Access (OFDMA) in its downlink communications [32], and is compatible with LTE and 5G NR. Unlike NB-IoT, LTE-M can only be deployed using the in-band mode [44] as it occupies a wider bandwidth of 1.4 MHz [36]. With the increased bandwidth, LTE-M supports higher data rate and lower latency than NB-IoT. Voice service and mobility support via cell handover are unique to LTE-M. However, it is reported that LTE-M connectivity is more limited than NB-IoT in deep indoor and basement environments [17]. Although the high data rate feature appears to be favorable to

Table 1. Key characteristics of NB-IoT, LoRaWAN, and Sigfox [6, 28, 29]

	NB-IoT	LoRaWAN	Sigfox
Spectrum	Licensed	ISM	ISM
Frequency Plan in Hong Kong	900 and 1800 MHz	923 to 925 MHz	920 MHz
Theoretical Range (Urban)	1 km	5 km	10 km
Maximum Data Rate	UL: 62.5 kbit/s DL: 27.2 kbit/s	11 kbit/s (DR7 configuration)	UL: 100 bit/s DL: 600 bit/s
Maximum Message Size	1600 B (MTU)	242 B (DR7 configuration)	UL: 12 B DL: 8 B
Daily Messages Limit	No	Depends on airtime regulations	UL: 140 DL: 4
Network Deployment	Commercial	Commercial or self-built	Commercial

our application, LTE-M services are, unfortunately, not present in Hong Kong for our experimental evaluation.

Table 1 summarizes the distinctive technical features of three major LPWAN contenders available in Hong Kong from an IoT application designer's perspective. In comparison with Sigfox and LoRa, NB-IoT offers the highest data rate and the largest payload size at the expense of shorter theoretical communication range.

Since our application involves deploying sensors to high-rise apartment units in different districts of Hong Kong, we desire a solution that provides city-wide coverage at the lowest possible cost. Sigfox provider in Hong Kong claims a high coverage ratio, but its message size and daily limits cannot fulfill our requirements for collecting high-resolution water flow data. For LoRaWAN, it is likely that a custom network deployment is necessary to provide coverage in our deployment locations, which involves prohibitive costs. NB-IoT thus appears as the most promising LPWAN technology for our application scenario, as mobile network operators can provide coverage in all parts of the city, including residential areas.

2.2 NB-IoT in Urban Environments

NB-IoT is a brand new radio interface with some heritage in LTE [28, 37]. This radio access technology enables IoT devices (also known as User Equipment or UE) to communicate with a base station (also known as an eNodeB) using a narrow bandwidth of 180 kHz. Using only a subset of LTE functionalities, NB-IoT is a more compact standard that allows cost reduction in the manufacturing of UE [14]. For instance, only half-duplex is supported to simplify RF design. New features enhancing energy efficiency are also introduced to the new standard, allowing extended battery life of IoT devices [47]. NB-IoT can be deployed by MNOs with three modes [3]:

- (1) Stand-alone mode where a 200 kHz Global System for Mobile Communications (GSM) channel is occupied.
- (2) In-band mode where a single 180 kHz wide Physical Resource Block (PRB) within LTE band is leveraged.
- (3) Guard-band mode where a PRB within LTE guard band is allocated.

In either mode, NB-IoT deployment can co-exist with a network operator's existing LTE services [29]. Network operators can opt to enable NB-IoT deployment through software upgrade of their LTE infrastructure [5, 16]. Particularly, the LTE resource grid could be reused. It is worth emphasizing that the following discussion will be LTE-oriented as our cellular network provider offer NB-IoT services in LTE Band 8.

On the physical layer design, NB-IoT employs OFDMA in a downlink transmission, where a PRB of seven OFDM-symbol duration is divided into 12 sub-carriers of 15 kHz bandwidth each [28]. This division results in 84 resource elements (REs) whereby each RE can carry an OFDM symbol modulated using Quadrature Phase-Shift Keying (QPSK) scheme [5, 28]. Relying on Single Carrier Frequency-Division Multiple Access (SC-FDMA), the carrier spacing of an uplink transmission is conversely either 15 kHz or 3.75 kHz whereby the distinguish number of sub-carriers (also known as tones) can be assigned to different UEs.

As a newly emerged radio interface, NB-IoT signals possess different propagation characteristics. Particularly, [5] revealed that traditional (cellular-based) path loss models may not be sufficiently accurate when it comes to the evaluation of NB-IoT's radio propagation characteristics. To come up with more realistic path loss models, the well-known Alpha-Beta-Gamma and Close-In models were characterized. These two models leveraged on the large-scale empirical measurements performed in Oslo, Norway. While indoor path loss can be estimated via $\overline{PL}_{indoor} = 0.5d$, where d denotes the distance between the UE and the outer wall in meters, path loss in outdoor (urban) scenarios can be derived through $PL = \overline{PL} - X$ dB where $\overline{PL}$ and X represent average path loss and shadowing distribution components, respectively. Investigating the deep indoor signal attenuation, [23] performed small-scaled empirical RSSI measurements and concluded that the $0.5d$ equation fitted relatively well in ground-floor cases. On the other hand, to evaluate the coverage of NB-IoT in outdoor, indoor and underground scenarios, [26] conducted moderate-scale measurements in an area where multi-storey buildings exist. Based on RSSI measurements, it was revealed that NB-IoT could perform well in outdoor and indoor scenarios where the maximum -60.5 dBm and -72 dBm could be achieved, respectively. However, it was also reported that packet losses occurred significantly in indoor and underground scenarios, and that severe interference from LTE traffic was observed.

To reinforce service reliability of delay-insensitive IoT applications, re-transmissions of up to 128 (for uplink) and 2048 (for downlink) times are allowed [16], depending on the estimated channel conditions or the Coverage Enhancement Level (CEL) employed by UEs. Particularly, the determination of a proper CEL, which is ranging from good, average, to bad channel conditions [48], can be derived from the latest Reference Signal Received Power (RSRP) estimated during the cell (re-)selection process, and the configurations contained in the control messages sent by an eNodeB). Different CELs also imply different transmission power. Consequently, NB-IoT devices could communicate with the eNodeB even when being deployed in difficult environments such as deep indoor and dense urban areas [16], though at an elevated power consumption level [47].

As illustrated in Figure 3, a NB-IoT-enabled eNodeB broadcasts Narrowband Reference Signal (NRS) periodically in every sub-frame of 1 ms duration. 8 or 16 NRS symbols would be transmitted by an eNodeB configured with one or two antenna ports, respectively [14]. Given the considered frequency bandwidth of 180 kHz, RSRP is a signal measurement indicating the averaged power of resource elements (REs) that carry NRS symbols, represented in dBm. To figure out the positions of REs the NRS occupies, Narrowband physical Cell ID (NCellID) carried by Narrowband Secondary Synchronization Signal (NSSS) will be used [37]. As opposed to RSRP where noise and interference are excluded, given a single PRB, Reference Signal Received Quality (RSRQ) is essentially the ratio of RSRP to Received Signal Strength Indicator (RSSI). By taking the averaged power of all twelve

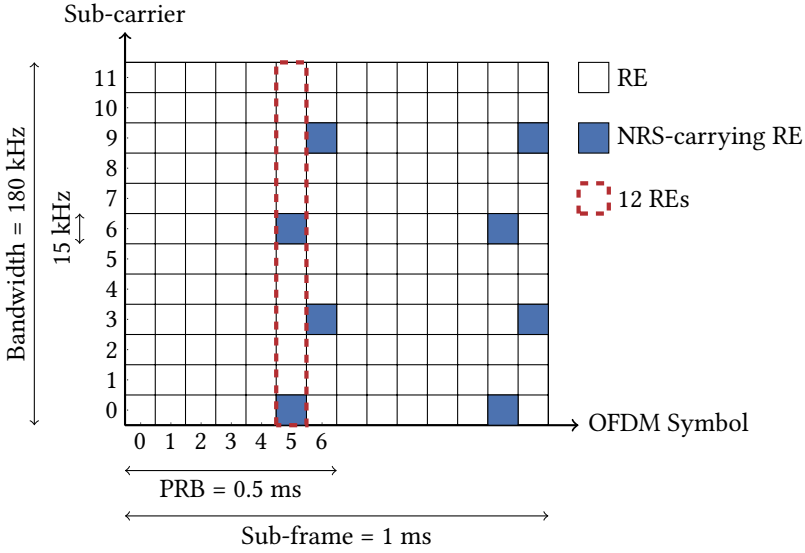


Fig. 3. Illustration of a NB-IoT sub-frame carrying eight NRS symbols from a one-antenna-port eNodeB

REs within the whole considered bandwidth (i.e., RSSI) into account, RSRQ is able to provide more fine-grained channel condition than that of RSRP.

Compatibility with pre-existing LTE infrastructure makes NB-IoT an appealing LPWAN technology for reliable connection of a massive number of IoT devices in urban scenarios [29]. Nevertheless, urban environments often cause severe signal attenuation, which fuels rapid battery depletion of UEs [7, 9] and drastic range degradation [8]. In-band NB-IoT deployment could also introduce negative impacts on both LTE and NB-IoT services: [16] contested the benefits and drawbacks of a partial NB-IoT deployment at only selected eNodeBs, as opposed to a full deployment throughout all eNodeBs. A partial deployment sacrifices fewer LTE radio resources, which are of high demand. On the other hand, the hybrid nature of partial deployment (i.e., mixing LTE-only and NB-IoT-plus-LTE eNodeBs) might result in non-negligible interference.

A good understanding of network performance and limitations of NB-IoT is vital to creating reliable and robust massive IoT applications. This work fills the research gap by presenting findings of a large-scale longitudinal investigation of issues of real-world NB-IoT sensor node applications. With empirical data on and insights into how cellular LPWAN performs in dense urban environments, we aspire to pave the way for future research and development of resilient NB-IoT applications for various kinds of critical infrastructure, such as localization [42], smart grid [19], smart urban drainage systems [25], smart hospital [50], etc.

3 SENSOR NETWORK ARCHITECTURE

This section outlines the high-level requirements of designing an IoT sensors system for collecting domestic water-use data in Hong Kong, and examines the hardware and software design of some of the system components. Since this work focuses on the NB-IoT sensor network of the system, we limit our discussion to the relevant components, namely the NB-IoT sensor node and the data transfer mechanism. Details of other implemented sub-systems, such as the data processing pipeline in cloud and on-premise servers, are beyond the scope of this article.

3.1 Requirements and Operational Constraints

Hong Kong adopts a dual-supply system where fresh (potable) water and flush water are separately fed into a household¹. To accurately meter a household's water usage, our system has to exploit different sensing mechanisms for measuring these two main classes of water-use. Fine-grained fresh water usage data are required for training of a machine learning model for domestic water end-use classification. Our previous work [22] detailed the concepts of collecting tap-based ground truth data, and explained the practical considerations of using turbine flow sensors. We demonstrated that collecting flow events²

Our prior experience of deploying the Wi-Fi-based prototype sensor network in [22] also provided insights on operational constraints in a domestic setting: To minimize disturbances to research participants, the sensor node hardware should be compact, and does not require any external power supply. The devices also have to be robust, resilient, and be able to last for months on battery power, in order to avoid frequent maintenance visits.

Taking into account our specific data collection requirements and corresponding operational constraints, we need a distributed wireless sensor network to achieve reliable, energy-efficient collection of large volume of high-resolution water-use data from battery-powered sensors located in participant households scattered over Hong Kong, at low cost and low complexity. NB-IoT was selected as the backbone of our data collection system, as it satisfies our city-wide network coverage and high-volume data transfer requirements.

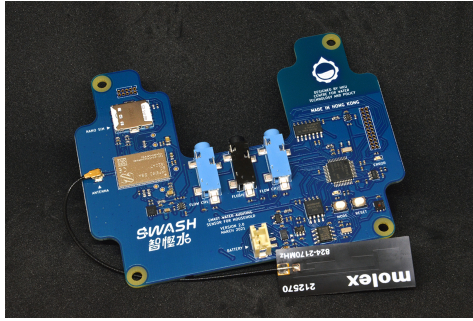
3.2 Multi-purpose Sensor Node

Since there is no off-the-shelf NB-IoT tap-based sensing solution that can satisfy our specific data collection requirements discussed above, we have designed and built a versatile NB-IoT sensor node for fresh water and flush water usage measurement. The sensor node's printed circuit board (PCB) assembly is shown in Fig. 4(a). The sensing application firmware runs on a Microchip ATSAMD21G18 [30] microcontroller (host MCU). Turbine flow sensor(s) and float switch are interfaced with the host MCU's input pins via the color-coded 3.5 mm audio jacks located on the top concave part of the PCB. The combination of plugged-in sensor(s) sets the sensor node to one of its three operating configurations: Tap Sensor, Smart Meter, or Flush Logger.

Both the Tap Sensor and Smart Meter configurations are used for recording high-resolution water flow profile at $T_s = 1$ s using SIKA VTY series Hall-effect turbine flow sensors [41]. As water flows through the turbine flow sensor, pulse signals of pulse width inversely proportional to flow rate are generated. All types of flow sensors in the series share this working principle, but have different calibration parameters used to calculate the perceived flow rate. When water flow is being sensed, the host MCU is interrupted every second to calculate the flow rate in mL/s from past second's pulse widths. A flow event is formed by the start timestamp and an array of (compressed) flow rate values. The Tap Sensor configuration is used with one or two VTY10MA turbine flow sensor(s) for tap-based flow data collection. By supporting two flow sensor channels, water-use outlets with two

¹For each domestic water user, fresh water is first delivered to a stand-alone billing meter at the head of the water service pipe that enters into the user's apartment. On the other hand, flush water is not billed and is often supplied directly from a building's tank to toilet cisterns via pipes constructed on exterior walls.

²Each flow event is a time series data representing a spontaneous, discrete water-use incident at a water tap. It describes the amount of water flowing out of the tap at every sampling interval. of high temporal resolution (i.e., short sampling interval T_s) is a pre-requisite for producing an accurate classification model. To maximize the level of classification accuracy, we decided to collect flow events at $T_s = 1$ s sampling interval at the expense of increased data transfer volume. On the other hand, as the flush water supply is independent from the fresh water supply, we do not need to construct an accurate flow profile for machine learning purposes; however, the flush water consumption data are still valuable for providing feedback to users. Therefore, instead of using a turbine flow sensor, we utilized a float switch mechanism to detect the onset of a toilet flush event and approximate the water usage.



(a) Printed circuit board assembly with a flexible antenna attached



(b) Waterproof box containing the printed circuit board and battery pack

Fig. 4. NB-IoT sensor node hardware for measuring fresh water and flush water usage

inlet pipes (e.g., hot-and-cold water at a faucet, or bathtub-and-showerhead combination) can be wired to the same sensor node to save device costs and space. The Smart Meter configuration is for installation in series with the billing meter at a household-level inlet pipe, using a larger diameter VTY20 turbine flow sensor.

The Flush Logger configuration operates with a mechanical float switch installed inside a toilet cistern. As the toilet flushes, the water level in the cistern changes because of draining and refilling water. This causes the float switch to close the circuit when it is submerged by water, and to open the circuit otherwise. The host MCU keeps track of the duration of such changes. Combined with the cistern volume measurement obtained at installation, the amount of water-use during each toilet flush event can be approximated.

After the occurrence of each flow or flush event, the recorded event is encrypted using the AES-256-CBC standard onboard and encapsulated into a 256 B formatted data structure. This data structure, or a data page³, includes metadata like sequence number and checksum to facilitate reliable data upload over NB-IoT. The data page is then pushed to a first-in-first-out (FIFO) queue stored on a 16 MiB NOR flash memory chip. The procedures for uploading the stored data pages, and how resilience is achieved, are discussed in the next subsection.

Each sensor node is equipped with a Nordic Semiconductor nRF9160 [33] NB-IoT modem, attached with a Molex 2125700100 [31] flexible antenna. Communicated via AT commands [34] over a UART interface, the host MCU can make use of modem's built-in HTTPS client and TCP/IP stack for bi-directional data transfer over NB-IoT network. To minimize its quiescent current, the modem is power-gated using a MOSFET load switch. In this way, the modem is powered off completely when there is no need for NB-IoT communication. Hence, the NB-IoT power-saving features of PSM and eDRX are not used in our implementation.

Moreover, firmware over-the-air update via NB-IoT is implemented on the sensor node. This allows us to patch bugs and introduce additional features, without requiring to replace or service the devices on-site. Periodically, the host MCU checks for new version of firmware binary image (designated for its unique device ID) from a RESTful API endpoint. If a new image is available, it would be downloaded to the sensor node. Upon verifying the signature and integrity of the downloaded image, the host MCU updates itself. In the event of a failing update, the host MCU would revert to the previously known working version. This ensures that a failing firmware update would not cause extended downtime of data collection, or permanently disable the device.

³It is named a "page" as it fits to a 256 B page in the NOR flash memory.

A sensor node is designed to operate for three months with a 4000 mAh nickel metal hydride (NiMH) rechargeable battery pack. An industrial-grade NiMH battery pack is used to withstand the potentially hot and humid deployment environment of household bathrooms and kitchens. The PCB and its battery pack are enclosed in a waterproof box for deployment as shown in Fig. 4(b), since the installation may be subjected to weather and occasional water splash (e.g., Smart Meter installed outdoor and Tap Sensor installed inside the shower room).

3.3 Resilient Data Transfer

Each sensor node schedules to perform data upload once an hour, with the exact minute randomized to minimize the chance of interference due to simultaneous NB-IoT traffic from nearby sensor nodes. As the sensor node wakes up to this hourly data transfer window, it first generates a device health report to provide diagnostic information, including battery voltage, NB-IoT signal strength and quality, etc. Such information enables the research team to understand the operational status of each deployed device, and arrange (predictive) maintenance visits to the households when necessary. The health report is also pushed to the aforementioned FIFO queue. In other words, three types of data pages are queued for upload: Flow events, flush events, and device health reports.

After generating the health report, the host MCU powers up the NB-IoT modem. The modem automatically searches and attaches to the network. Once network attachment is successful and a Packet Data Network (PDN) connection is established, the host MCU synchronizes its onboard real-time clock with the network time, to ensure an accurate clock for logging flow and flush events. On the other hand, if it fails to attach after 60 s, the data upload is aborted to avoid draining battery power. In this case, the host MCU would power the modem off and wait until the next data upload opportunity (i.e., the next hour).

Next, up to four untransmitted data pages would be loaded from the front of the FIFO queue. They form a HTTP POST request “chunk” with a maximum body size of 1024 B (due to size limitation implemented on nRF9160). A RESTful API endpoint is set up to forward the raw, encrypted data pages received from sensor nodes to storage in a cloud-based document database. It is hosted on a serverless service of a public cloud provider, so that scalability can be maximized while minimizing the need for infrastructure maintenance.

The modem on the sensor node then attempts to transmit this chunk of binary data to this RESTful API endpoint via HTTPS. If a HTTP 200 “OK” response is received, the chunk is considered successfully transmitted. These data pages on the FIFO queue would be marked as transmitted. This process repeats until all pages in the FIFO queue are marked as transmitted, unless a failure occurs, indicated by a HTTP error response or a timeout. In the event of a failure, the data upload operation would be aborted. Untransmitted data pages stay on the FIFO queue for a later re-transmission, until they have been marked as transmitted.

Reliability and resilience in data transfer are assured by this mechanism. By requiring a HTTP 200 response as acknowledgment, each data page is guaranteed to be delivered at least once to the cloud database. This is particularly important for our ground truth data collection exercise, as losing flow events would be undesirable. Having the data pages queued also ascertains the order of data transfer, such that any missing data page can easily be tracked down. As illustrated in Fig. 2, the research team’s on-premise server periodically pulls the raw data pages from the cloud database, then decrypts and decodes them for analysis. An automated data processing pipeline generates a de-identified dataset for machine learning researchers to develop end-use classification models.

4 FIELD DEPLOYMENT

The NB-IoT sensor network has been deployed in actual households. In this section, we first introduce the data collection exercise, then we describe the sensor installation environment in the unique urban landscape of Hong Kong.

4.1 Data Collection Exercise

We have recruited 21 volunteer households to participate in a six-month study between May and November 2021. In each household, we would install the following data collection devices introduced in Section 3.2:

- One Smart Meter, accompanied with a SIKA VTY20 turbine flow sensor, in series with the billing meter to record high-resolution water flow data at household-level.
- Typically four Tap Sensors at the bathroom basin tap, shower, kitchen sink tap, and washing machine⁴, where each Tap Sensor is equipped with one to two SIKA VTY10MA turbine flow sensor(s) in series with the tap's inlet pipe(s) for recording high-resolution tap-based flow data.
- One Flush Logger at each toilet cistern to approximate the amount of water-use of every toilet flush event.

Installing the in-line turbine flow sensors involves modification to the households' existing plumbing pipes. These in-line installations conform to drinking water standards, and we had to hire a licensed plumber to carry out the works. We have encountered some cases of complex plumbing design installation of in-line flow sensor is impractical (e.g., inlet pipes are hidden behind a wall). These cases explain why we have also installed the Smart Meter in the households, which is not strictly necessary for collecting tap-based ground truth data. The Smart Meter, recording aggregated water-use of all taps, offers an $N + 1$ redundancy. In case of a missing tap (or a faulty Tap Sensor), all flow profiles from the missing tap could still be obtained by subtracting the rest of the Tap Sensors' readings from the Smart Meter readings. On the other hand, installation of the Flush Logger is simple. It needs only adhering a 3D-printed float switch mounting to the interior of a toilet cistern with waterproof tapes. A total of 130 sensor nodes were deployed to all 21 households.

4.2 Sensor Installation Environment

Fig. 5 shows the 21 participating households are scattered across different districts in Hong Kong. The majority of them are single-family apartment units situated in 30-story or taller high-rise residential buildings. 20 households are located in urban areas and are surrounded by other residential or commercial towers; only one household is located in the rural part of Hong Kong.

As this work concentrates on investigating how different urban environments affect NB-IoT performance, we focus only on the 20 households in urban areas, and the NB-IoT performance of sensor nodes placed in the rural household is outside the scope of discussion of this paper. To facilitate investigation, we have classified the environments of sensor installation into three *building density* levels and three *penetration depth* levels. While building density level indicates different amount of outdoor signal blockages, the penetration depth category models the different levels of material and obstacle penetration in indoor scenarios.

4.2.1 Building Density. The surrounding environment of a household is categorized into three *building density* levels, based on the approximate density of the built environments: *Medium* refers

⁴Dishwashers and other appliances requiring fresh water supply are uncommon in Hong Kong's homes, and none of our participating households have them. Households with two bathrooms or additional water taps would be outfitted with extra Tap Sensors.



Fig. 5. Geographical distribution of the 21 participating households in Hong Kong



(a) Medium density



(b) High density



(c) Very high density

Fig. 6. Examples of the three building density levels

to an environment surrounded by 50 or fewer 4-storey-or-taller buildings within a 500 m radius of the building our participants live in; *high* and *very high* mean there are 51 to 100 and over 100 buildings within the 500 m radius, respectively. Medium density environments are areas with fewer high-rise developments, usually surrounded by natural terrains (e.g., on a hilltop or in a valley), and they are usually further away from the town centers. High density environments are primarily residential zones in new towns, filled with high-rise apartment buildings of similar heights. On the other hand, very high density environments refer to the inner city area that is characterized by mixed, high-density commercial and residential developments. Fig. 6 visualizes the landscapes of the three building density levels through aerial views. According to the literature reviewed in Section 2.2, we hypothesize that NB-IoT signals would generally degrade in the denser built environment, due to more severe shadowing and multipath interference.

4.2.2 Penetration Depth. In each household, sensor nodes are placed in different locations adjacent to the billing meter, water taps, and toilet cistern(s). We classify an installation location as either *outdoor*, *shallow indoor*, or *deep indoor* to reflect the likelihood of suffering from signal attenuation



(a) Sensor node with waterproof box



(b) Confined environment of a typical meter room

Fig. 7. Smart Meter installation in a high-rise apartment building

Table 2. Summary of building density and penetration depth of deployed sensor nodes

		Building Density		
		Medium	High	Very High
		(4 Households)	(13 Households)	(3 Households)
Penetration Depth	Outdoor	–	–	2
	Shallow Indoor	11	34	9
	Deep Indoor	14	49	4

due to outdoor-to-indoor material penetration and indoor obstacles. Shallow indoor refers to sensor node installations inside a room with window(s). They might or might not have line-of-sight to a NB-IoT base station, but they are not obstructed by any furniture or large objects in the room. On the other hand, deep indoor means the sensor node installation is in a confined environment with no window, including inside a cabinet. We hypothesize that NB-IoT signal strength decays as the sensor placement moves from outdoor to deep indoor, as a consequence of increased path loss reviewed in Section 2.2.

Fig. 7(a) shows an example on-site installation of a Smart Meter. In Hong Kong's residential buildings, the billing meters on the same floor are typically clustered in a centralized, concretized meter room, as shown in Fig. 7(b). Hence, Smart Meters are considered to be placed in a deep indoor environment, meaning that perfect line-of-sight communication with any NB-IoT base station is impossible, and drastic signal attenuation is expected. However, in older buildings, billing meters are commonly installed outdoor, on rooftops or in back alleys. The signal attenuation is thus expected to be more subtle in such case.

All Tap Sensors and Flush Loggers are deployed indoor in the households' bathrooms and kitchens. Nevertheless, many of them have to be placed in locations with obstructed signal, such as cabinets underneath basin taps and kitchen sinks, to minimize disturbances to the research participants. The bathroom installations in Fig. 8(a) (Tap Sensor on the left; Flush Logger on the right) are examples of shallow indoor. The two Tap Sensors in kitchen cabinet shown in Fig. 8(b) are examples of deep indoor, as they are surrounded by more obstacles.

Table 2 summarizes the building density and penetration depth levels of the 123 sensor nodes deployed in the 20 urban area households.



Fig. 8. Example Tap Sensor and Flush Logger installations inside an apartment

5 NB-IOT SIGNAL MEASUREMENTS

In the following, we describe the methods of measuring NB-IoT signal strength and link quality, then present the empirical measurements obtained by our sensor nodes deployed across the 20 households.

5.1 Measurement Methods

Prior to presenting the data, we introduce some key concepts pertaining to the interpretation of the measurements, and describe how these measurements were obtained empirically in the field.

5.1.1 Narrowband Reference Signal. The radio interface of NB-IoT inherits many existing features and architecture from LTE, despite their differences reviewed in Section 2.2. This part further elaborates how the signal measurement indicators are derived. Essentially, a UE (i.e., the sensor node in this work) is meant to communicate with a *cell* of an eNodeB established by a licensed MNO. An eNodeB, which interfaces with the core network (also known as Evolved Packet Core or EPC in LTE), can host one or more cells co-located at the same location. Usually, multiple cells of an eNodeB are set up with directional antennae to serve UEs in different directions. In Hong Kong, multi-sectoral cells are commonly seen mounted on rooftops of high-rise buildings. In other words, most multi-sectoral cells are placed over 100 m above ground level, facing multiple azimuth and elevation angles. Each cell, distinguished by a Narrowband Cell ID (NCellID)⁵, regularly transmits Narrowband Reference Signal (NRS)⁶ in the downlink channel at specific OFDM symbols of every PRB (i.e., symbol positions 5 and 6 as depicted in Fig. 3). The sub-carriers the NRS symbols occupy are, conversely, determined by NCellID [14]. As illustrated in Fig. 3, each PRB has four⁷ Resource Elements (REs) carrying the NRS. It is worth noting that, NRS-carrying REs are transmitted at a higher power than the rest.

NB-IoT UEs measure Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ) as indicators for signal strength and link quality, respectively. RSRP refers to the average signal power of a particular cell's two NRS-carrying REs during one symbol measured

⁵Unlike LTE where Physical Cell ID (PCI) is obtained from the Primary and Secondary Synchronization Signals (PSS and SSS for short), the NCellID of NB-IoT, on the other hand, is embedded in Narrow SSS (NSSS) alone. Ranging from 0 to 503, NCellID is used for cell search and (re-)selection. Because the limited range of numbers, the same NCellID may be reused by other eNodeB located in different geographical areas.

⁶The N-prefix, which stands for "Narrowband," is added to the NB-IoT terminologies to distinguish themselves from their LTE counterparts.

⁷Depending on the number of antenna ports, either four (one antenna port) or eight (two antenna ports) REs will be used.

Table 3. Network deployment of NB-IoT operators in Hong Kong

		Operator A	Operator B	Operator C
Spectrum	Frequency Band(s)	B3 and B8	B3 and B8	B3 only
	Deployment Mode	B3: Guard-band B8: In-band	B3: Guard-band B8: Uncertain	In-band
Cell Selection	RSRP Threshold	-140 dBm	-134 dBm	-128 dBm
	RSRQ Threshold	-23 dB	-26 dB	-23 dB

by the UE, which neglects noise and interference in the NRS or adjacent sub-carriers. RSRQ is computed by Equation (1) [1] where N is the number of PRB(s) in use ($N = 1$ for NB-IoT), and RSSI is the average power that the UE measures across the entire 180 kHz bandwidth, during the symbol with NRS-carrying REs present. In other words, RSSI would increase as a result of strong noise or interference in the non-NRS sub-carriers. Thus, RSRQ serves as a signal-to-noise indicator and implies link quality. The nRF9160 modem is capable of reporting RSRP and RSRQ values of the currently connected cell⁸ in the ranges of -140 to -44 dBm (at 1 dB resolution) and -19.5 to -2.5 dB (at 0.5 dB resolution) respectively [34].

$$RSRQ = \frac{RSRP}{RSSI \div N} = \frac{N \times RSRP}{RSSI} \quad (1)$$

5.1.2 System Information Block. Various System Information Block (SIB) messages containing additional information and UE configuration parameters are transmitted by each NB-IoT cell [14]. In Section 5.2, we present some of these MNO-defined parameters detected in Hong Kong's operational NB-IoT networks. SIB1-NB, SIB2-NB, and SIB3-NB messages were intercepted in the field with a Nordic Semiconductor nRF9160 Development Kit (DK) [35] using its modem trace capture function. The captured modem traces were analyzed using the *Wireshark* software package.

5.1.3 Cell Selection and Re-selection. To find a suitable cell to camp on, a UE performs a cell selection. After being powered on, the UE scans all E-UTRA Absolute Radio Frequency Channel Number (EARFCN) of the targeted Public Land Mobile Network (PLMN) [40]. Under the highest-scored EARFCN, the UE measures RSRP of all cells, detects the Master Information Block (MIB-NB) and SIB1-NB messages. The UE then camps on the cell that has the highest RSRP and also meets the criteria: RSRP and RSRQ are greater the thresholds specified in the SIB1-NB message.

Cell re-selection, on the other hand, is periodically performed after the first cell selection. This is to find other cells having stronger signal than that of a serving cell. However, our sensor node would not trigger a cell re-selection, since the modem is powered off completely after data transfer. The modem would never be left in an idle state where cell re-selection takes place.

5.2 Network Operator Configurations

As of October 2021, three MNOs provide city-wide commercial NB-IoT services in Hong Kong. Through scanning available networks on the nRF9160 DK, SIB1-NB messages from cells of the three MNOs were captured and analyzed. Table 3 tabulates some key parameters of the de-identified MNOs' NB-IoT network deployment.

⁸Signal measurements and the unique cell identity of the currently connected cell can be retrieved using the AT commands +CESQ and +CEREG?, respectively.

While all three operators offered NB-IoT services using LTE Band 3 (B3; 1800 MHz), LTE Band 8 (B8; 900 MHz) is activated by Operators A and B only. These two spectra were originally utilized to provide GSM and UMTS services, but they have been re-farmed in recent years to increase LTE capacity. By performing network scans with our sensor node in most of the participating households, we observed that the Operator A, which we subscribed to, primarily provides NB-IoT services in B8.

Hence, we have band-locked our sensor nodes to B8, in order to speed up the cell search process and to reduce energy consumption. Evidenced by the presence of the *eutraControlRegionSize-r13* and *nrs-CRS-PowerOffset-r13* attributes in SIB1-NB, deployment in B8 used in-band mode. Deployment in B3 is believed to be in guard-band mode, since Operator A's 1800 MHz spectrum is fully occupied for LTE. For Operator B, we believe that guard-band deployment is used for B3 (for the same reason as Operator A); deployment mode is uncertain for B8, as this operator has not yet discontinued GSM service in 900 MHz, meaning that either guard-band or stand-alone mode is possible. We have only detected Operator C to deploy NB-IoT exclusively in B3 using in-band mode. The RSRP and RSRQ threshold values for initial cell selection were also extracted from the SIB1-NB messages of the three MNOs.

5.3 Overall Observations

In Section 3.3, we described that each of our sensor node sends an hourly device health report, which includes instantaneous RSRP and RSRQ measurements, to the cloud database. These measurements were reported by the nRF9160 modem after establishing connection to a cell each hour. Device health reports generated from July 1 to September 30, 2021 were used to study the factors affecting RSRP and RSRQ in various urban environments. In total, 263,830 device health reports collected from the 123 sensor node installations in 20 households over a three-month period have been analyzed.

5.3.1 Effects of Building Density and Penetration Depth. To identify patterns of RSRP and RSRQ across the building density levels and penetration depth categories, each installation's median RSRP and RSRQ values during the three-month period are computed for comparison among its peers.

Fig. 9 presents how RSRP is varied by building density and penetration depth. Fig. 9(a) shows that, in general, RSRP improves as the building density goes from medium to very high; in other words, NB-IoT signal strength is higher in very dense environments than in the lower-density areas. While it appears to be counter-intuitive, this could possibly be explained by the fact that MNO has established more cells to serve the high-density areas. Due to the fact that cells are located in close proximity to each other, sensor nodes in the very dense environments perceived higher signal power levels. On the contrary, sensor nodes in lower-density environments might be connected to cells that are further away, hence suffering from more substantial path loss in open air. Fig. 9(b) illustrates that RSRP progressively weakens as it moves from outdoor to shallow indoor and deep indoor. With building structures and obstacles attenuating the signal, the trend shown by our empirical observation is consistent with the indoor loss (i.e., $0.5d$ as discussed in Section 2.2 and penetration loss models suggested in 3GPP TR 38.901 [2]). That is, the path loss model describes a logarithmic increase in path loss with the sensor nodes placed deeper indoor, as the distance to the cell increases and the probability of line-of-sight communication diminishes. Radio waves going through a variety of building materials introduces penetration loss. In particular, concrete walls and wooden obstacles (e.g., doors and furniture) have a stronger impact than that of non-infrared-reflective glass windows (as typically seen in domestic settings in Hong Kong). At 900 MHz, the material penetration losses of glass, wood, and concrete are modeled to be 2.27 dB, 4.96 dB, and 8.60 dB, respectively.

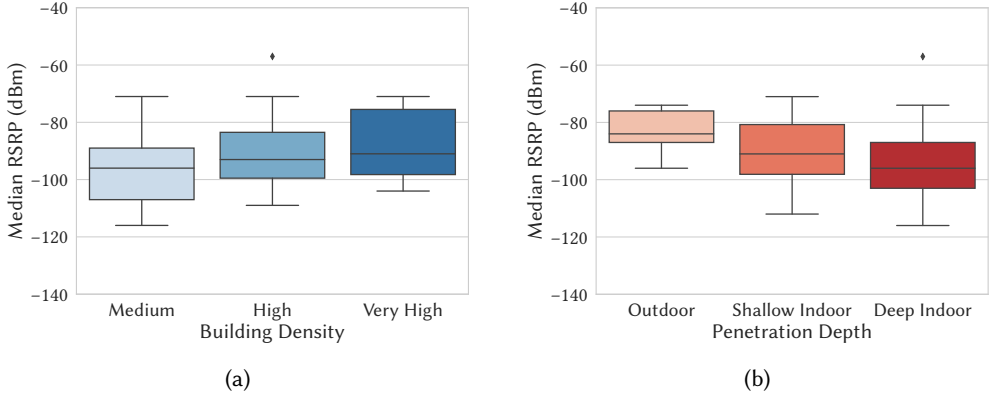


Fig. 9. Boxplots of RSRP against building density and penetration depth

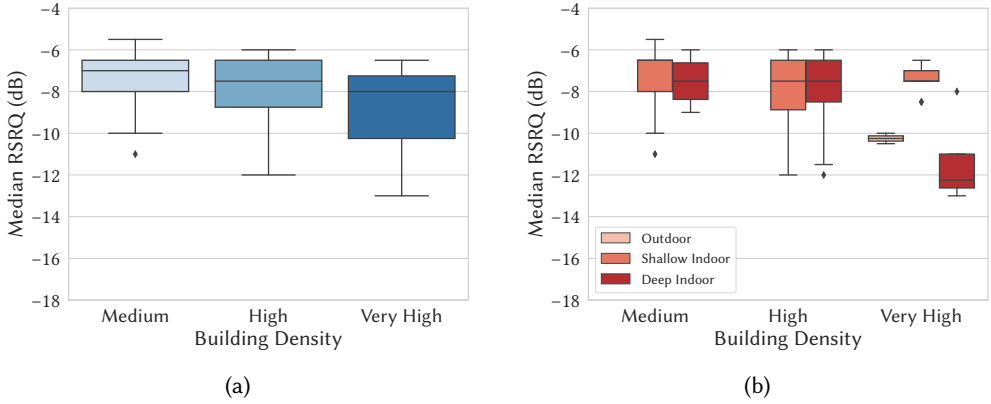


Fig. 10. Boxplots of RSRQ against building density and penetration depth

Fig. 10 presents the variation of RSRQ at different building density and penetration depth levels. Although Fig. 10(a) shows that the range of RSRQ spreads out more as the building density level increases from medium to very high. The median values of different density levels' are very similar though (at around -8.0 to -7.0 dB). The correlation between RSRQ and penetration depth is also unclear, as shown in Fig. 10(b). The substantially-lower RSRQ values in the very high building density category are inconclusive due to limited sample sizes (see Table 2 for detailed distribution): The deep indoor data points reflect only four installations in the same household. The worst three of them, which all registered RSRQ values of -12.0 dB or below, were placed between a concrete wall and (1) a ceramic toilet cistern; or (2) a washing machine, which, in essence, is a metallic structure. It is possible this very confined set-up with high penetration losses significantly reduced the signal-to-noise ratio. The two outdoor installations are located at separate geographical locations, but both could suffer from multi-path interference resulted from canyon-like environment surrounding the data collection sites.

5.3.2 Lack of Correlation Between RSRP and RSRQ. Fig. 11 presents all RSRP-RSRQ pairs in all 263,830 device health reports on a scatter plot, as well as the distributions of RSRP and RSRQ values. Except that RSRQ values below -14.0 dB are mainly clustered around weak RSRP values that are

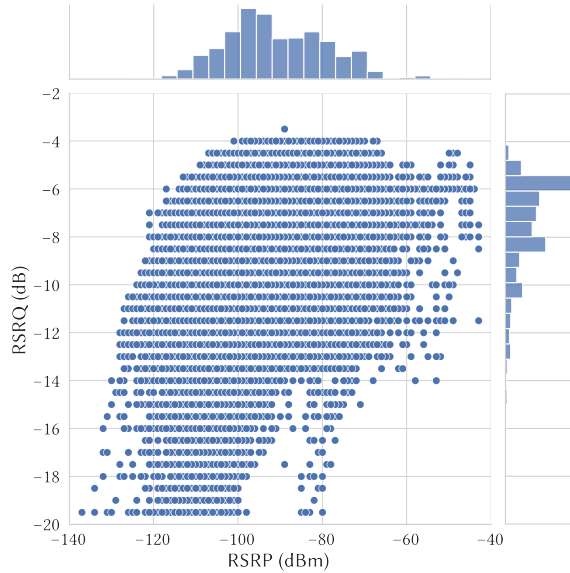


Fig. 11. Scatter plot of all RSRP-RSRQ measurement pairs and their distributions

below -100 dBm, no other obvious patterns regarding the distribution of RSRP and RSRQ could be observed. That is, a strong RSRP does not imply good RSRQ, and vice versa.

5.4 Transmission Failure

Next, we evaluate the reliability of NB-IoT in terms of success rate of uploading data to the cloud over HTTPS. As described in Section 3.3, in each hourly data transfer window, a sensor node generates a time-stamped device health report right before it attempts to upload data pages cached in the FIFO queue. In other words, the latest health report would be the last item in the FIFO queue. Hence, by comparing the time difference between health report generation and reception on the cloud database, we can deduce the status of the data upload attempt. If the time difference is within 10 minutes⁹, the transmission is considered a complete success. On the other hand, a time difference of an hour or longer indicates data upload failed partially or completely on the first attempt. The resilience protocol was invoked, and the health report was re-transmitted successfully in one of the subsequent hourly data transfer windows.

96.27 % of all 263,830 analyzed health reports were successfully transmitted at the first attempt. Only 3.73 % or 9854 of them experienced re-transmission¹⁰. We attributed the re-transmissions to potential NB-IoT transmission failure, which we considered as the weakest link of the data transfer. Server-side failure is unlikely because of the high availability of the public cloud provider's serverless computing and database services. Fig. 12(a) and 12(b) show the probability of transmission failure at different RSRP and RSRQ, respectively. The probability is calculated by the normalized ratio of failed-on-first-attempt to all health reports for each RSRP or RSRQ value. Apart from the fact that transmission always failed when RSRP is at -124 dBm or below, there is no

⁹Typically, the time difference would be within a couple of minutes; however, NB-IoT operations would be postponed if there is an on-going flow event, so we set 10 minutes as the success threshold.

¹⁰"Re-transmission" stands for repeated attempt of data upload over HTTPS built into the sensor node application logic, as discussed in Section 3.3. It should be emphasized that the use of "re-transmission" in this sub-section does not refer to similar concepts adopted in NB-IoT CEL, TCP, etc.

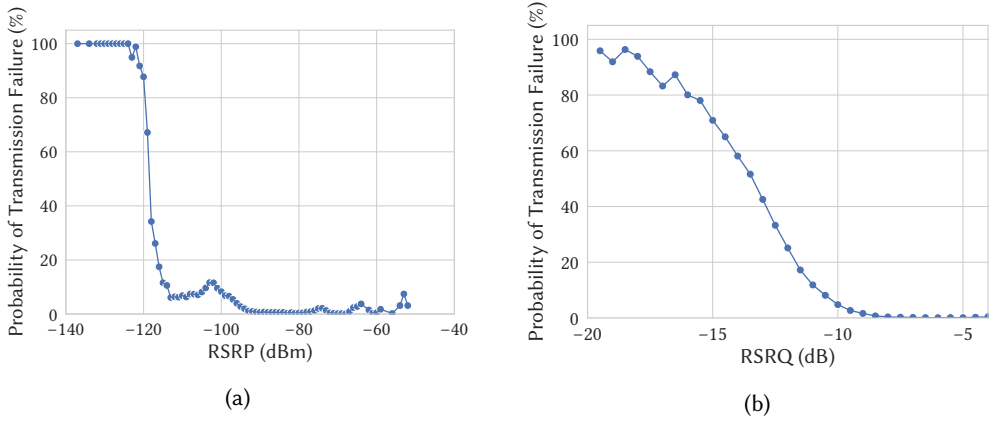


Fig. 12. Probability of transmission failure at different RSRP and RSRQ

certain relationship observed between RSRP and transmission failure, in view of the spikes at around -103 dBm and towards the highest RSRP values. Fig. 12(b) illustrates that the probability of transmission failure grows almost exponentially as RSRQ deteriorates beyond -9.0 dB. The failure probability stayed below 0.75% in the RSRQ range of -9.0 to -4.5 dB. At -13.5 dB and -16.5 dB, failure probabilities of 51.6% and 87.3% were registered, respectively. It is also noted that there were successful transmissions took place even when the NB-IoT modem reported a RSRQ below -19.5 dB, the lower bound of the modem's detection range.

We conclude that RSRQ is a more promising indicator for transmission reliability than RSRP, given the clear trend of failure probability and the observations in Section 5.3.2. On top of that, transmission is prone to fail (90% or higher failure rate) when RSRP is at -121 dBm or below.

5.5 Multi-cell Coverage Scenarios

In light of the unclear relationship between RSRQ and building density or penetration depth (Section 5.3.1), we have decided to gather more fine-grained NB-IoT signal measurements to seek explanations on factors affecting RSRQ. In October 2021, we gradually rolled out a firmware update over-the-air to 62 sensor nodes in nine selected households. This firmware update enables the sensor node to record the unique cell identity (CI) of the connected cell, alongside RSRP and RSRQ measurements in the hourly device health report. The CI is a hexadecimal concatenation of the eNodeB's unique ID and the cell's sector ID (the least significant 8 bit). We analyzed these data with cell information augmented over a 10-day period from October 20 to 29, 2021. The data revealed that most sensor nodes did not stay connected to the same cell over time. Those sensor nodes are within the coverage of multiple cells, and they might choose to connect to different cells during each hourly data transfer window. This sub-section presents our empirical observations in both scenarios of a sensor node with coverage by a single cell and by multiple cells.

5.5.1 Coverage by Single Cell and Multiple Cells. Only nine sensor nodes reported that they were exclusively served by a single cell throughout the 10-day period. Those nine sensor nodes were placed in sites of medium and dense building density (one sensor node was placed in an urban environment of medium level of building density; the other eight operated in dense neighborhoods). Three sensor nodes were put in shallow indoor while six were put in deep indoor environments. Fig. 13 shows three of such sensor nodes in different household environments (building density and penetration depth indicated in the legend). In the single-cell scenario, RSRP remained stable

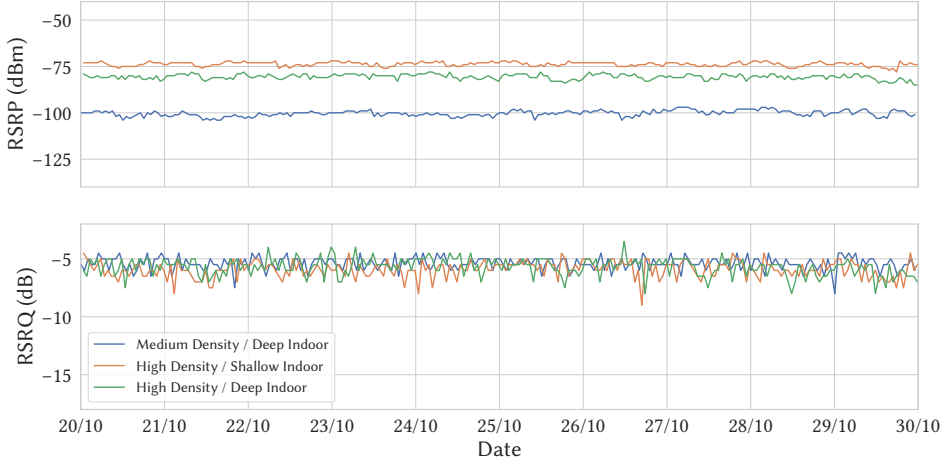


Fig. 13. RSRP (top) and RSRQ (bottom) time series of three individual sensor nodes in different households

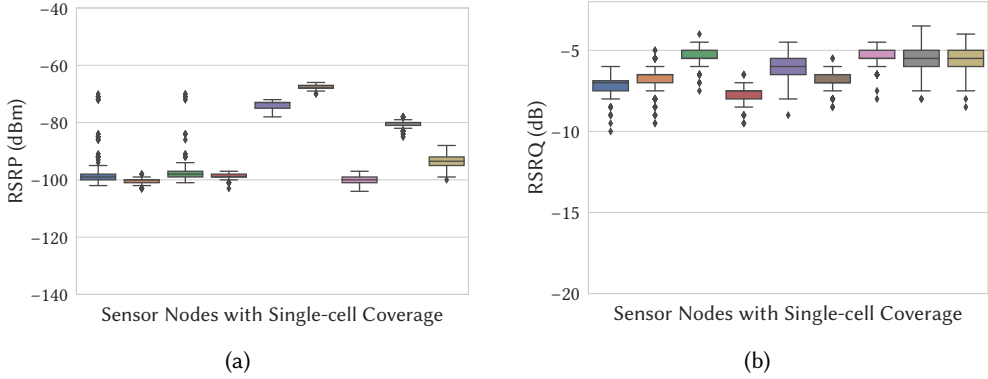


Fig. 14. Boxplots of RSRP and RSRQ of all nine sensor nodes in single-cell coverage environments

over time, implying that the signal carried NRS symbols traversed the same path to the UE. Despite minor fluctuations, RSRQ persisted above -10 dB, which hints minimal probability of transmission failure, regardless of RSRP. This pattern was observed over all nine sensor nodes with single-cell coverage at different building density levels, as shown in Fig. 14. In addition, these sensor nodes did not experience any transmission failure.

Scenarios involving sensor nodes connected to two or more distinct cells, observed in the rest of 53 installations, are more fuzzy. We identified three main types of patterns with sensor nodes connected to different cells. In the following, we first study these three types of scenarios with RSRP and RSRQ time series obtained from several sensor nodes in different households.

5.5.2 Scenario 1: Temporarily Unavailable Cell. The first type refers to a sensor node generally stay on the same cell, but it could occasionally switch to another cell in isolated incidents. Fig. 15 shows an example of UE1-1¹¹, a Flush Logger installed at a high building density, shallow indoor environment

¹¹To avoid confusion across examples, we denote UEs and eNodeBs in the format of $x-y$ where x is the household code, and y is the UE code (numeric) or eNodeB code (alphabetic) associated with the household.

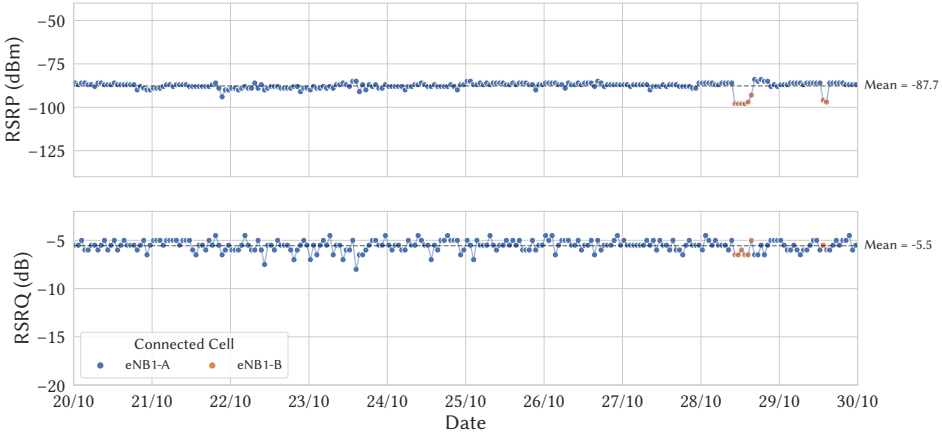


Fig. 15. RSRP (top) and RSRQ (bottom) time series of UE1-1 which experienced temporarily unavailability of eNB1-A

of household 1 (HH1). Out of 240 data transfer windows across 10 days, UE1-1 connected to eNodeB 1-A (eNB1-A) for 96.7 % of the time; however, on October 28 and 29 afternoons, it connected to eNB1-A for six and two consecutive hours, respectively. We believe that eNB1-A was temporarily offline during these periods, since we observed a similar pattern on other sensor nodes inside the same household. The dips in RSRP could be explained by UE1-1 chose to connect to the next available cell at eNB1-B, which is possibly farther away and hence received lower signal power. RSRQ when connected to eNB1-B, nevertheless, kept at a high level comparable to eNB1-A. This type resembles the characteristics of single-cell coverage scenario, as there is effectively only one “strong” cell in range. In particular, minimal fluctuation of RSRQ was observed.

5.5.3 Scenario 2: Competing Neighbor eNodeBs. The second type of scenarios involves the presence of multiple eNodeBs in vicinity. Fig. 16 presents an example captured by UE2-1, a Tap Sensor installed deep indoor (deep inside a kitchen cabinet) in HH2, which is situated in a high building density urban area. UE2-1 appears to be toggling between eNB2-A and eNB2-B, two geographically separated cells, while RSRP was kept rather stable at an average of -87.2 dBm. This might hint that eNB2-A and eNB2-B were in similar ranges to UE2-1, resulting in similar path losses and hence perceived signal power levels. On the other hand, fluctuation of RSRQ was more significant in this scenario than the single-cell scenarios, irrespective of the connected cell. We consider this pattern as neighboring cells of different eNodeBs competing with each other.

5.5.4 Scenario 3: Competing Sectoral Cells. In addition, we also frequently observed cases of sensor nodes connected to multiple cells over time, but these cells were under the same eNodeB. Fig. 17 shows an example of UE3-1, a Tap Sensor in HH3’s kitchen cabinet (high building density, deep indoor environment). UE3-1 stayed with the same eNB3-A all the time, but occasionally, it switched to different sectors. These sectoral cells are co-located at eNB3-A, distinguished by directional antennae facing different directions. While we are uncertain why UE3-1 opted not to connect to the most favorable sector S106 occasionally, we observed that connecting to eNB3-A’s other sectors (i.e., S102, S104, and S105) resulted to deteriorated RSRP and RSRQ. In particular, RSRQ with S104 (after midnight of October 28) could deviate from S106’s average by 10 dB. Fig. 18 shows the approximate locations of eNB3-A and UE3-1 via an aerial view. eNB3 employed multi-sectoral antennae on the building rooftop, according to our visual observation on site. It is possible that

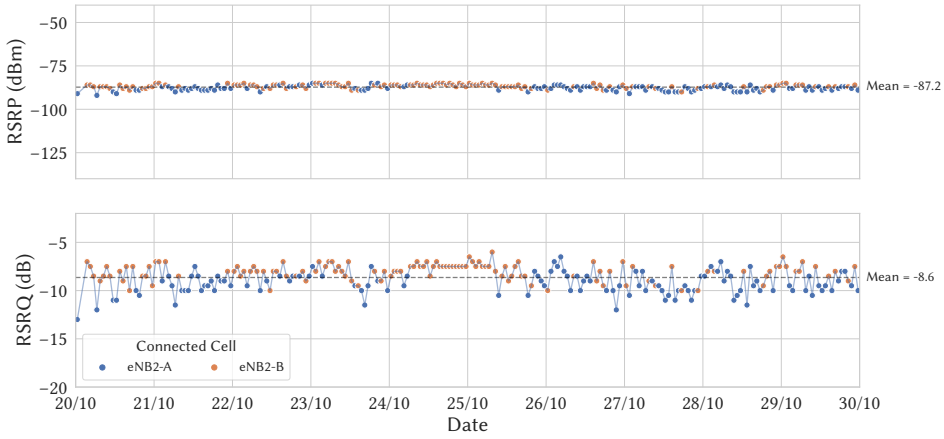


Fig. 16. RSRP (top) and RSRQ (bottom) time series of UE2-1 covered by competing neighbor eNodeBs with similar RSRP

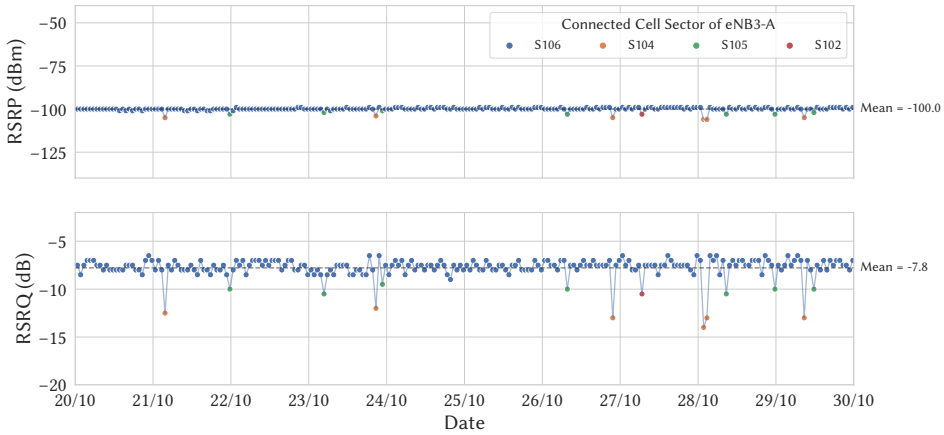


Fig. 17. RSRP (top) and RSRQ (bottom) time series of UE3-1 covered by competing multi-sectoral cells with similar RSRP

UE3-1 received stronger signals from the high-gain main lobe of S106's directional antenna, but it could only receive from the weaker side lobes of other sectors caused the deviation in RSRP and RSRQ. Furthermore, this observation affirmed that directional antennae are used in NB-IoT deployment in Hong Kong's dense urban environment, as opposed to omnidirectional coverage in Oslo reported by [5].

5.5.5 Complexity in High Building Density Environments. Indeed, the three examples discussed above belong to the least complicated scenarios in our dataset. They captured the essence of different possible cases of multi-cell coverage, but in reality, scenarios can be much more sophisticated involving complications contributed by multiple factors. We present two of the most complex cases among our dataset in Fig. 19, both obtained from a bathroom in HH2. Fig. 19(a) and 19(b) show

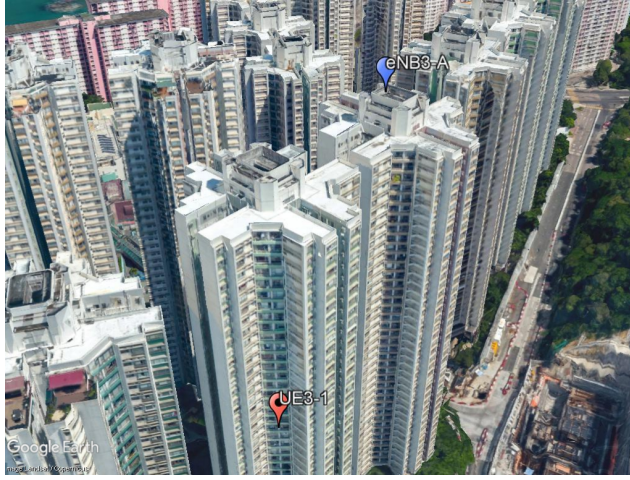


Fig. 18. Approximate locations eNB3-A (on rooftop) and UE3-1 (deep inside the apartment) indicated in aerial view

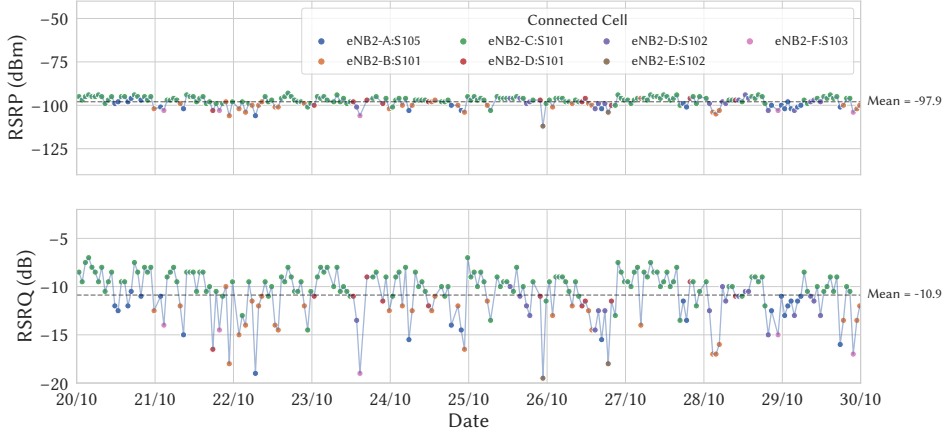
UE2-2 installed at the shower stall (shallow indoor) and UE2-3 installed at the basin cabinet (deep indoor), respectively. They were physically separated by less than two meters.

Both UE2-2 and UE2-3 experienced frequent changes of connected cell over time. UE2-3 registered a slightly lower RSRP level than UE2-2, possibly explained by the material penetration loss through the cabinet; however, each sensor node's RSRP kept within similar ranges, which is a sign of competition among neighboring cells, as we discussed above. Sharp fluctuations in RSRQ were also observed from both sensor nodes. Interestingly, despite their proximity, UE2-2 and UE2-3 connected to different cells even during the same hour¹². This may indicate very dynamic radio channel conditions surrounding this environment, which we seek to explain in Section 6.1.

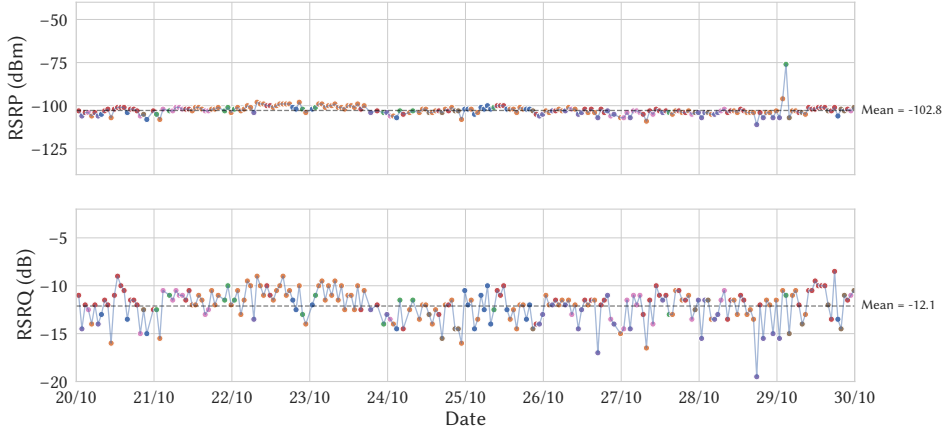
5.5.6 Influence on RSRP and RSRQ Fig. 20(a) shows how RSRP varies in single- and multi-cell coverage environments, categorized by how many distinct cells a sensor node connected to over the 10-day period, or in other words, the number of cells available for selection (N_{cell}). Similar to Section 5.3, we calculated the median RSRP (and RSRQ) values of each sensor node over time for these boxplots. As expected from previous case studies, there is no relationship between RSRP and N_{cell} . Fig. 20(b) re-affirmed the observation that deep indoor installations perceived lower signal power than shallow indoor ones, due to attenuation in penetrating through obstacles.

Meanwhile, a strong inverse relationship between RSRQ and N_{cell} was found. A clear trend of high N_{cell} leading to deteriorated RSRQ is observed in Fig. 21(a). This empirical evidence suggests that more cells in vicinity would cause greater interference in the channel, hence degrading the NB-IoT link quality. Also, under single-cell coverage, RSRQ remained at a high level despite varying RSRP. Moreover, Fig. 21(b) shows an interesting pattern that, at each N_{cell} level, deep indoor installations had slightly better RSRQ than the shallow indoor counterparts. A likely explanation is that, as the signal power attenuates when penetrating through obstacles, the interference and noise power (at the same frequencies) experienced almost the same degree of attenuation. Proportionally, the reduction in noise floor is greater than that of the useful signal, thus an improved RSRQ.

¹²The hourly data transfer window among sensor nodes are staggered by design to avoid congestion and interference among sensor nodes in the same household, as mentioned in Section 3.3. In the case of UE2-2 and UE2-3, their hourly windows separated by five minutes.



(a) UE2-2 in bathroom shower stall (shallow indoor)



(b) UE2-3 in bathroom basin cabinet (deep indoor)

Fig. 19. RSRP and RSRQ time series of sensors in HH2 under complex multi-cell coverage scenarios

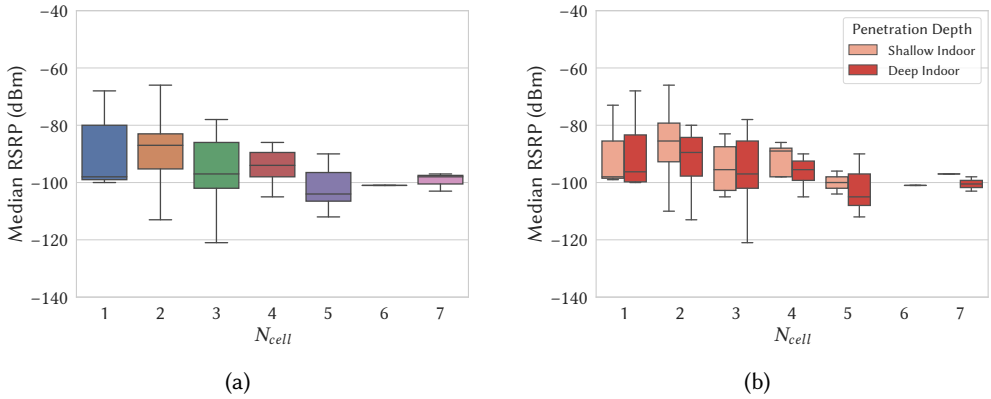


Fig. 20. Boxplots of RSRP against number of distinct cells available for selection

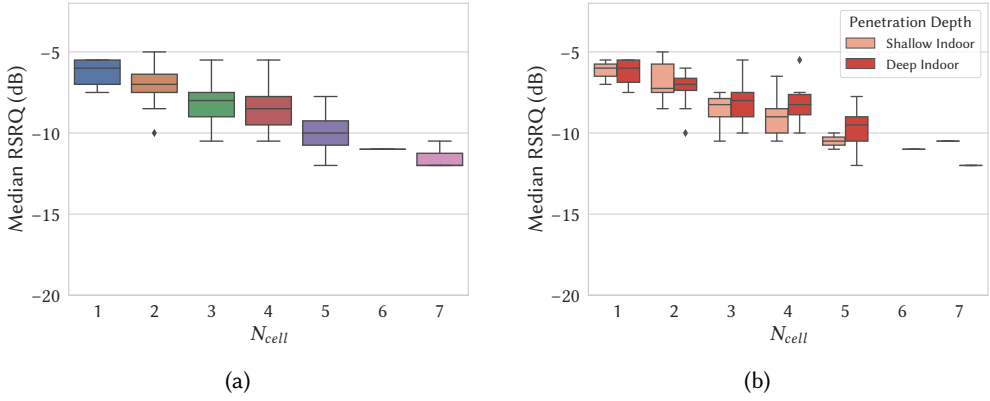


Fig. 21. Boxplots of RSRQ against number of distinct cells available for selection

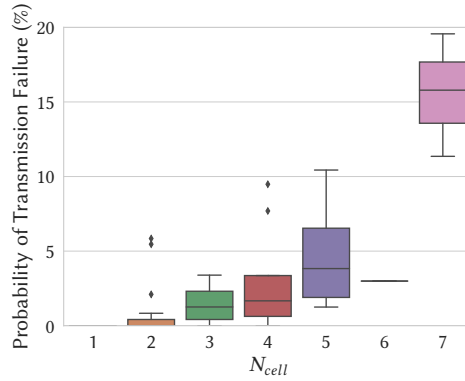


Fig. 22. Boxplot of probability of transmission failure against number of distinct cells available for selection

Last but not least, the probability of transmission failure in relation to N_{cell} is presented in Fig. 22. This empirical observation is consistent with our derivation in Section 5.4: As higher N_{cell} leads to lower RSRQ, the probability of transmission failure hence increases. Sensor nodes under single-cell coverage in the 10-day period reported no failure, while the failure rate of the worst-case multi-cell coverage ($N_{cell} = 7$) peaked at around 20 %.

5.6 Summary of Empirical Measurements

In summary, we utilized over 120 NB-IoT sensor nodes deployed in more than 20 sites in the dense urban environment of Hong Kong to obtain longitudinal measurements of hourly RSRP and RSRQ values. Through analyzing these empirical data, we have found out that:

- (1) RSRP provides good indication on signal attenuation due to penetration through building materials and obstacles.
- (2) RSRQ accurately reflects the link quality, indicated by the rate of successful data transmission, and is mostly independent of RSRP.
- (3) Single-cell coverage scenarios usually result in better RSRQ.
- (4) Multi-cell coverage negatively affects RSRQ and successful rate of data transmission, with the severity increases with more cells in the vicinity.

6 FINDINGS AND DISCUSSION

We have quantitatively analyzed empirical NB-IoT signal measurements collected by our sensor nodes in actual household environments. In this section, we carry on the discussion of the unfavorable signal coverage conditions and their implications for NB-IoT sensing applications. Then we present the initial high-resolution water flow data collected by our sensor nodes, and evaluate the applicability of NB-IoT in such kind of sensor network applications.

6.1 NB-IoT Coverage in a Dense Urban Environment

Longitudinal signal measurements in Section 5 have revealed the heterogeneity of NB-IoT coverage conditions in Hong Kong. Particularly, we identified multi-cell coverage as a common phenomenon in high building density areas. Thus, a dense urban environment, arguably, has adverse impacts on link quality. This sub-section further explores its plausible causes, discusses potential implications on sensor network reliability and resilience, and suggests possible mitigation techniques for IoT application designers and system integrators.

6.1.1 Channel Dynamics and Interference. Empirical measurements in Section 5.5 indicated the correlation between degraded RSRQ and the presence of multiple neighboring NB-IoT cells. This degradation appeared to worsen with more cells in the vicinity. This could be attributed to an increasingly dynamic channel conditions, such as noise and interference caused by some combinations of neighboring cells, NB-IoT and LTE UEs. Spurious emissions from household appliances, which we could neither prove nor disprove in this work, is a plausible reason as well. While it was impractical to perform detailed analysis (e.g., monitoring channel conditions with a spectrum analyzer) in our volunteer households to hunt down the sources, we attempt to look for an answer from available literature.

Our measurements detected all NB-IoT cells operated at the same downlink and uplink frequencies, evidenced by the modem reporting an identical EARFCN. Hence, we speculate that co-channel, inter-cell interference (ICI) is one of the plausible causes of degraded link quality in multi-cell coverage scenarios. ICI, in the context of LTE and NB-IoT, has been studied in [11, 15, 16, 24, 27]. The underlying reasons of ICI may be threefold:

Firstly, neighboring cell(s) might concurrently transmit or receive signals from other NB-IoT UEs. Inter-cell interference coordination (ICIC) was introduced for LTE [15]. ICIC provides a mechanism for eNodeBs to negotiate usage of different PRBs, via the X2 inter-eNodeB interface, to minimize ICI experienced by UEs in cell-edge scenarios. However, it is not applicable to NB-IoT, as the same PRB in the frequency domain is shared among all cells [24]. Therefore, we argue that ICI, as a result of NB-IoT traffic from neighboring cells, may exist. [24] also suggested that re-transmission due to higher CEL may intensify the traffic in the NB-IoT channel, increasing the probability of this type of ICI.

Secondly, interference might arise from partial NB-IoT deployment. Under this partial deployment strategy, some cells would have NB-IoT-plus-LTE enabled, while the rest remain LTE-only. While this strategy could help better utilize radio resources for LTE customers, [27] argued that PRB dedicated to NB-IoT traffic might interfere with traffic associated with LTE-only cells. The MNO we used reportedly have deployed NB-IoT only in outdoor cells, leaving its other cells (e.g., microcells and picocells for providing indoor coverage, which are prevalent in dense urban environments) in LTE-only mode. Thus, we consider this is a possible mode of ICI.

Thirdly, in-band deployment might be problematic, despite its co-existence design. [16] performed extensive empirical signal measurements of two NB-IoT networks in Oslo, and suggested that in-band deployment is more susceptible to interference by LTE traffic than guard-band deployment.

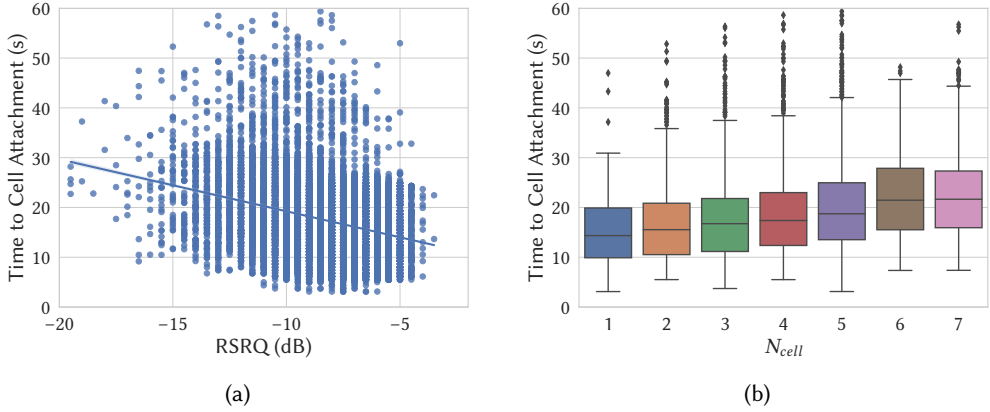


Fig. 23. Effects of RSRQ and multi-cell coverage on modem connection time

6.1.2 Reliability and Resilience Implications. Regardless of the exact causes of ICI, empirical data proved that multi-cell coverage generally leads to worse link quality, which in turn, results in a substantially higher transmission failure rate (Section 5.5). This negatively impacts the reliability and resilience of the sensor network in three ways:

- (1) Transmission failure leads to potential data loss (if a resilience protocol like Section 3.3 is not implemented), or increased delays in retrieving the data collected from the field.
- (2) Data re-transmission(s) are necessary to recover from transmission failures, which consume extra energy and shorten battery life.
- (3) NB-IoT services are often billed to a quota of data usage. A partial transmission failure (e.g., successful uplink but failure to receive acknowledgment in downlink) may be counted towards the data usage and have operational cost implications.

Although a thorough investigation into energy consumption of our sensor nodes is beyond the scope of this article, we could still make use of modem connection time as a proxy indicator to infer the impact of NB-IoT channel conditions on battery life. In addition to connected cell information, we have also logged the time taken from modem power-up to successful cell attachment in each sensor node's hourly data transfer window. The longer the connection time spent on attaching to cell, the more the battery energy wasted. Fig. 23(a) shows a regression plot of time to cell attachment against RSRQ. Although the data points are spread out, a weak to moderate correlation between improved RSRQ and reduced connection time can be observed. Fig. 23(b) also shows that the connection time in single-cell environment is slightly shorter than multi-cell environment. For instance, the median connection time for $N_{cell} = 1$ and $N_{cell} = 7$ are 14.3 s and 21.6 s, respectively. This implies an approximately 50 % difference in energy consumption¹³ due to the cell attachment process alone¹⁴, and a substantial reduction of battery life. This demonstrates that inter-cell interference due to multi-cell coverage, manifested by low RSRQ, might reduce battery life and threaten the sensor network's reliability and resilience.

6.1.3 Cell Selection Revisited. Section 5.1.3 introduced that a UE camps on a cell based on the MNO-defined RSRP and RSRQ thresholds broadcast in the SIB1-NB message. Comparing the values

¹³This assumes the modem runs with the same level average current during cell search in both cases. In actual implementation, the modem might use different transmission power and repetitions for different CELs, determined by RSRP [14]. The power consumption profile differs in various CELs.

¹⁴We have yet to analyze the difference in time and energy usage for data transfer under varying signal conditions.

proposed by three different MNOs (Table 3) and our derivations on transmission failure (Section 5.4), we found that the MNO-defined thresholds may be incapable of ensuring a UE's quality of service. For instance, the MNO which we subscribed to, set the cell selection thresholds for RSRP and RSRQ as -140 dBm and -23 dB, respectively. This configuration means that a UE can select virtually any cell it could detect, as the thresholds are beyond the UE's minimum reportable value.

On the other hand, we deduced from our empirical measurements that data transfer in our application always failed if RSRP is at -124 dBm or below. The discrepancy between the RSRP thresholds for MNO-defined cell selection and our empirical observation for successful transmission suggested that the MNO-configured thresholds may be sub-optimal. For instance, in an extreme case, a UE detects only one cell over long distance with a RSRP in the range of -124 to -140 dBm. Based on the MNO configuration, the UE would choose to connect to this weak cell. The UE's ability to perform network functions, nevertheless, could be limited severely. It is understandable that MNOs would set lenient thresholds to maximize coverage for the majority of their customers. However, this set-up could be undesirable for NB-IoT applications which demand high reliability and energy efficiency. Since the NB-IoT network is a shared resources among multiple customers, it is unlikely that a MNO could alter the parameters to cater for specific customer(s). Therefore, it is often the system integrators' responsibility to engineer their devices and applications in a way that are resilient to such limitations.

6.1.4 Minimizing Energy Wasted in Transmission Failures. For instance, if a sensor network application emphasizes battery life, it has to minimize transmission failures, and thus energy depletion. Having each sensor node to learn its parameters of unsuccessful transmission is a possible approach to mitigate the unfavorable coverage scenarios discussed above. Algorithm 1 is a low memory footprint way to enable a sensor node to predict whether a data upload operation via the connected cell would be successful or failed, given the instantaneous RSRP and RSRQ measurements. Upon each NB-IoT transmission, RSRP and RSRQ measurements of the currently connected cell (identified by CI) are obtained after modem initialization. If the CI is not registered in the RSRQ thresholds map (of all previously connected cells), the cell-specific RSRQ threshold is firstly set to -19.5 dB, which is the lower bound of the RSRQ range. The criteria on line 9 predicts the outcome of this transmission: If the instantaneous RSRP is less than or equal to -124 dBm, the empirically observed threshold of 100 % failure, or that the instantaneous RSRQ is weaker than the learned cell-specific abort threshold, the sensor node would abort this transmission due to high probability of failure; otherwise, the sensor node would proceed to a data upload attempt. When the transmission fails, the cell-specific abort threshold used for predicting transmission failure is updated to the exponentially weighted moving average (EWMA) between the instantaneous RSRQ (that led to this transmission failure) and the previous threshold value. In this way, the cell-specific abort threshold would gradually converge to a level that could indicate a high chance of transmission failure. The learning rate is determined by the smoothing factor $\alpha \in [0, 1]$.

We evaluated the effectiveness of this EWMA predictor with the NB-IoT signal measurements and transmission failures data captured by sensor nodes deployed in actual household environments. Three sensor nodes that were relatively prone to transmission failures among the fleet were selected for evaluation. Their hourly data collected between October 20, 2021 and January 7, 2022 (80 days in total) were fed into a simulation program based on Algorithm 1, to compute the abort decision at each data transfer window iteratively. Table 4 presents the predictor performance in conjunction with data on actual transmission failures. By incorporating the proposed transmission decision algorithm, we assume that a sensor node turns on its modem in every (hourly) data transfer window to make an upload-or-abort decision, and thus, incurred a fixed energy cost. The *energy wasted* by each sensor node attributes to the energy depleted by the failed data upload process (i.e., excluding

ALGORITHM 1: Transmission decision algorithm based on the cell-specific EWMA of historical RSRQ values

```

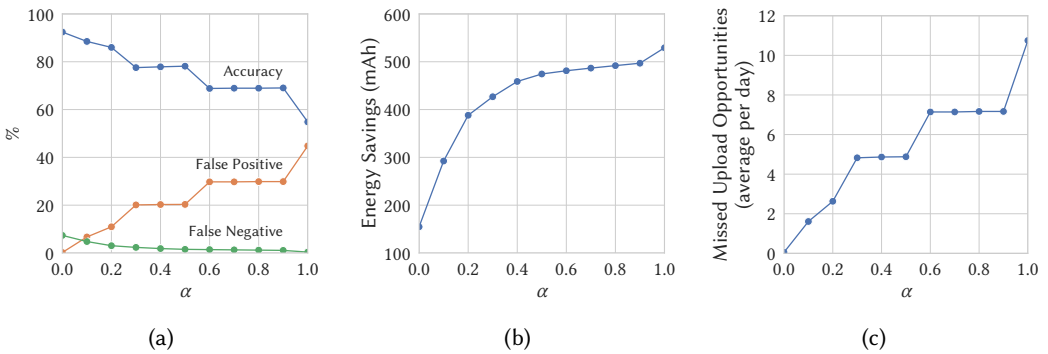
1   $RSRP_{threshold,abort} \leftarrow -124$  dBm;
2  Initialize an empty map  $RSRQ_{thresholds,abort}$ ;
3  foreach Transmission do
4      Abort  $\leftarrow$  FALSE;
5       $(CI, RSRP, RSRQ) \leftarrow \text{InitializeModem}()$ ;
6      if  $RSRQ_{thresholds,abort}[CI] = \text{NULL}$  then
7           $RSRQ_{thresholds,abort}[CI] \leftarrow -19.5$  dB;
8      end
9      if  $RSRP \leq RSRP_{threshold,abort}$  or  $RSRQ \leq RSRQ_{thresholds,abort}[CI]$  then
10         Abort  $\leftarrow$  TRUE;
11     end
12     if Abort = FALSE then
13         Result  $\leftarrow$  AttemptToUploadData();
14         if Result = FAILED then
15              $RSRQ_{thresholds,abort}[CI] \leftarrow \alpha \times RSRQ + (1 - \alpha) \times RSRQ_{thresholds,abort}[CI]$ ;
16         end
17     end
18 end
  
```

the energy spent on modem initialization). This amount of energy was measured by an onboard battery fuel gauge enabled on the selected sensor nodes, and summed across all failures over the 80-day period. *Accuracy* indicates the percentage of correct prediction (transmission failure and success). *False positive* and *false negative* refer to a misprediction of a transmission failure: The former means that the cell-specific RSRQ abort threshold was too stringent, and the transmission would have been successful if an abort was not invoked; the latter indicates that the transmission failed with a RSRQ measurement above the current threshold, and a new abort threshold would be re-evaluated. In other words, a high false positive rate leads to more *missed opportunities* of successful transmission, and reduces the timeliness of data transfer. Supposedly, if a resilient data transfer protocol (as discussed in Section 3.3) is in place, there would not be data loss or extra energy usage. Meanwhile, a high false negative rate results in wasting of more energy. By subtracting the energy wasted due to false negative from empirical data collected on total energy wasted, we can estimate the *energy savings* brought by the transmission decision algorithm. UE2-2 (a case discussed in Section 4.2.1), UE4-1, and UE5-1 demonstrated different levels of transmission failure rates ranging from 1.5 to 10.1 %. At $\alpha = 0.5$, UE4-1 would have managed to conserve 474.4 mAh through the transmission failure prediction algorithm. This is a substantial energy savings equivalent to about 12 % of the battery capacity, which could provide a significant lifetime extension.

The determination of the smoothing factor α is a compromise between data transfer timeliness and energy savings. Fig. 24 illustrates the effect of α on the various aspects of the EWMA predictor's performance: Fig. 24(a) shows that the accuracy deteriorates as α increases. A large value of α means that the abort threshold rapidly converges to the RSRQ level when it first encounters a failure on a specific cell. This leaves no room for the threshold to correct itself in subsequent upload attempts, which in turn leads to a high false positive rate. However, this over-zealous threshold would minimize false negatives. Consequently, a large value of α tends to offer more energy savings,

Table 4. Simulation Results for Transmission Failure Prediction

Sensor Node	Failure Rate (%)	Energy Wasted (mAh)	EWMA Predictor ($\alpha = 0.5$)				
			Accuracy Rate (%)	False Positive (%)	False Negative (%)	Energy Savings (mAh)	Missed Upload Opportunities (average per day)
UE4-1	10.1	550.9	78.1	20.3	1.6	474.4	4.9
UE2-2	7.4	245.2	78.5	19.0	2.5	165.6	4.6
UE5-1	1.5	69.3	98.7	0.4	0.9	28.4	0.1

Fig. 24. Effect of α on EWMA-based transmission failure predictor performance

at the expense of reduced timeliness (i.e., more missed opportunities) of data upload. Fig. 24(b) and Fig. 24(c) visualize how the energy savings and missed upload opportunities increase with α , respectively. Through these simulation results, we showed that it is possible for a sensor node to locally learn from the RSRQ measurements, and then to optimize for battery life under challenged NB-IoT coverage scenarios.

6.2 Creating AI-enabled Smart Applications with NB-IoT Sensor Networks

Our NB-IoT sensors system has been deployed in 21 households to collect ground truth water-use data since early May 2021. The decision to change from a Wi-Fi sensor node to an NB-IoT sensor node has minimized the level of inconvenience to participating households significantly. None of the participating households dropped out from the study during the data collection exercise. Over a six-month period, our Tap Sensors collected 401,772 labeled tap-based flow events from 21 households. Among all the events, 356,422 were recorded from faucets (i.e., basin taps and kitchen taps), 26,140 from showerheads and bathtubs, and 19,210 from washing machines. This unprecedented high-resolution ground truth dataset enabled the research team to examine the water-use patterns of actual households in Hong Kong. In the process, we identified two salient characteristics that are important for training of an accurate machine learning model for water end-use classification:

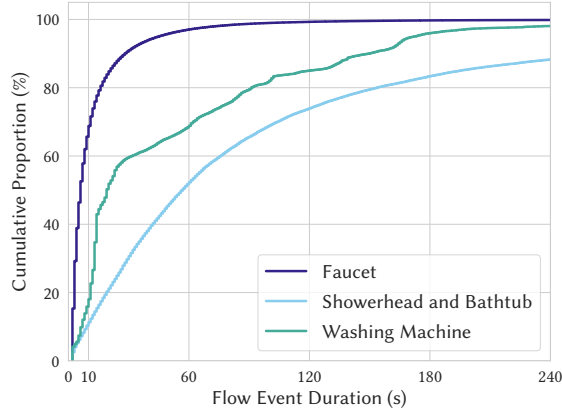


Fig. 25. Cumulative distribution of flow events duration by end-use category

- (1) Faucet usage has accounted for the majority of flow events incurred in a domestic setting (over 88 % in our dataset). Consequently, to prevent biases towards faucet classification, proper weights have to be applied to each category when training the model.
- (2) Fig. 25 shows the cumulative distribution of the three end-use categories. We found that 70 % of the faucet events lasted less than 10 s; 50 % of showering events and 70 % of washing machine events are shorter than 60 s. The predominance of short-duration flow events has justified the necessity of collecting fine-grained water-use data: The shorter the sampling interval, the more the water flow features can be extracted to improve classification accuracy. The curve showing the cumulative distribution of washing machine events, as shown in Fig. 25 is a rugged one, indicating an uneven distribution of flow event duration. We have analyzed those events, and interesting patterns in water usage in laundry cycles were discerned. A laundry cycle is composed of a sequence flow events recorded at a washing machine during its wash and rinse program. Fig. 26 plots laundry cycles selected from two households. Initially, we had an impression that washing machine usage is typically of long duration events with stable and repetitive patterns, such as the example shown in Fig. 26(a). However, empirical data from 21 households reveal the otherwise. Some washing machines generated frequent events of very short duration, as shown in Fig. 26(b). No repetitive pattern can be found. It is believed that newly-released washing machine models have incorporated more sophisticated sensors and algorithms for estimating the most optimal laundry program to save energy and water, hence resulting in very dynamic water-use patterns. With a fine-grained dataset, support-vector machine (SVM) [10, 45] can learn the nuanced differences among different short-duration events contributed by faucets and washing machines, by extracting features such as gradients of flow profiles. This minimizes misclassification of washing machine events.

The availability of longitudinal ground truth data enabled us to train a water end-use classification model based on SVM. We split our large dataset using a 80:20 train-test ratio. The model is also trained to accommodate the aforementioned empirically observed features. Our model attained a flow event classification accuracy of 83.5 %, when the flow rate sampling interval of 1 s is used. If the sampling interval is stretched to 10 s and 60 s, the classification accuracy deteriorates to 78.0 % and 75.7 %, respectively. These results are consistent to the findings of our previous work [22].

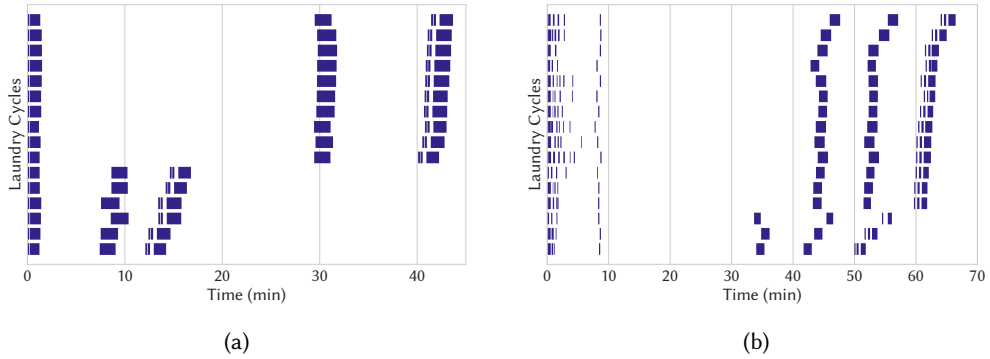


Fig. 26. Visualization of laundry cycles recorded in two households with different washing machine types (Each row along the vertical axis denotes a laundry cycle, where each colored block notates a flow event)

In our experience of developing a machine learning model for water end-use classification, we demonstrated that fine-grained ground truth data are crucial to feature extraction, and hence, classification accuracy. Compared to alternative LPWAN technologies, NB-IoT offers unmatched capabilities of managed city-wide coverage, deep penetration in dense urban environments, and less restricted uplink data size. These capabilities are key to collecting necessary data for building machine learning models in AI-enabled IoT applications. Apart from our Smart Water Auditing system, we believe that high-fidelity real-world data collected by NB-IoT sensor network can be utilized in many other AI-powered smart infrastructure projects to enhance operational efficiency and achieve sustainability goals, for example, power grid management [13] and air pollution monitoring [39].

7 CONCLUSION

This article presents the results of a large-scale empirical study on NB-IoT coverage and connectivity in Hong Kong, a city well known of her high building density. We have designed and developed a NB-IoT sensor network for measuring domestic water consumption in high-rise residential buildings. Our purpose-built sensor node enables the collection of high-resolution tap-based water flow rate data sampled at 1 s interval, which are necessary for the training of high-accuracy machine learning models for water end-use classification. We have deployed 130 NB-IoT sensor nodes in 21 households located in different districts of Hong Kong for over six months since May 2021. In addition to water-use data, we have also gathered NB-IoT signal measurements for over three months. Through analyzing these longitudinal signal measurements, we revealed interesting patterns of NB-IoT coverage and connectivity. We found that signal strength and link quality are affected by different levels of building density and penetration depth. The correlation between signal quality and transmission failure was also identified. More notably, we observed that inter-cell interference in dense urban environments has adversely impacted link quality in NB-IoT network. The plausible causes of these phenomena have been discussed in this article. Building on these empirical observations, we proposed a transmission decision algorithm for a sensor node to locally learn from its historical signal measurements and predict transmission failures due to adverse signal coverage conditions. By minimizing energy wasted in transmissions failures, this algorithm could enable substantial energy savings, according to our simulation results. Furthermore, we presented our initial results of the water end-use classification SVM model, which attained 83.5 % accuracy via training with six months of high-resolution water-use data. We demonstrated that NB-IoT radio

technology, coupled with meticulously engineered resilience design on sensor nodes, enable highly reliable fine-grained data collection applications. Such applications are vital to the development of AI-enabled smart infrastructure.

We will extend our work and utilize our fleet of over 100 sensor nodes to further evaluate NB-IoT performance in real-world environment. In particular, we plan to investigate energy consumption and battery life of sensor nodes under different coverage conditions, as well as the efficiency of various IoT-oriented networking protocols in practical sensing applications.

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Icons of network equipment and household appliances depicted in Fig. 2 are designs from VRT Systems¹⁵ (CC-BY-SA 3.0) and Freepik.com¹⁶, respectively. Aerial views and satellite images used in Fig. 5, 6, and 18 were retrieved from Google Earth.

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