Multi-Network Provisioning for Perpetual Operations in IoT-Enabled Smart Spaces

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***Abstract*— The IoT revolution has enabled perpetual continuous monitoring of spaces, people and events. Data thus generated can be used to create knowledge for diverse ubiquitous services. Today, IoT platforms are key technology substrate for smart homes/buildings that are equipped with heterogeneous devices and diverse (often multiple) network interfaces. In this paper, we address a key challenge in perpetual smartspace applications, i.e. that of energy cost associated with continuous sensing and communication. Diverse applications utilize data at different levels of quality; we exploit these quality tolerances by modeling them as "space-states" and intelligently leverage the dynamic space-states to select and provision resources (access networks, device capabilities) to reduce energy overhead while ensuring application quality. We propose efficient IoT provisioning algorithms that trigger actions and space-state shifts to drive energy-optimized sensor/network activations. To validate our approach, we derive usecases from real-world assisted living smarthomes with multiple personal and in-situ devices and target applications such as elderly fall detection. Through detailed testbed measurements and larger simulated scenarios, we show that adaptive provisioning techniques that use state-spaces and their semantics can achieve greater than 3X reductions in energy dissipation and reduce active devices without loss of sensing accuracy.**

I. Introduction

The growing Internet of Things (IoT) ecosystem with over 50 billion connected devices is accelerating the pace of IoT deployments that can offer diverse services in cyberphysical spaces such as smart homes and buildings. These deployments encompass pervasive sensing, intelligent interaction, smart control and enable continuous monitoring of spaces, people, activities and events. This paper focuses on perpetual systems, which are sensing systems that can continuously monitor the underlying space and provide key insights and services in the smartspace without interruption. Application domains for perpetual systems can range from societal services such as public safety, assisted living and healthcare, industrial monitoring and control, safe operation of mission-critical facilities (e.g. nuclear power plants) and inventory management for enterprises.

For instance, a home-based healthcare monitoring deployment can capture the resident's Activities of Daily Living(ADLs) to facilitate patient tracking, health assessments and emergency response services in a manner that is easier, quicker and safer. Such services enable seniors (or individuals with disabilities) to live independently; it can be used to provide assurance to family members/caregivers who cannot be available to provide care 24/7. Perpetual health monitoring is also useful in nursing care and rehabilitation facilities that are facing a shortage of qualified nurses/doctors to monitor patients with chronic diseases [1]–[4]. A rather different usecase is that of a smart campus with IoT-instrumented buildings [5] which offer a novel range of services - smart classrooms/meeting spaces that are able to capture activities and interactions to improve educational outcomes, public safety/environmental monitoring for health/safety, building energy management for sustainability etc. Consider, next, a smart retail with autonomous inventory monitoring [6, 7] and checkout systems in physical retail stores. Studies indicate that the growing cost of human labor is unable to sustain traditional manual approaches to inventory inspection and tagging of items - about 4% of sales are lost due to an average 5-10% out-of-shelf stock-out rate. Experts argue that the design of reliable/accurate automated inventory monitoring and checkout systems can revolutionize physical retail by bringing down operating costs.

While the above IoT deployments hold significant promises to improve the quality of life, several limitations arise in operating these IoT deployments in a scalable, resilient manner over time. Perpetual monitoring systems are expected to operate 24/7, to deliver services/detect events. A key operational challenge here is the energy consumption associated with continuous IoT sensing/communication operations. These challenges that arise are both at the device scale and in a broader sense, at the systemic level. First, IoT devices are often wireless and small with restricted resources including limited compute power, battery and storage capability. Continuous operation implies increasing plug-loads, frequent data uploads and battery replacements. The huge scale of deployment raises questions on the total energy impact when numerous devices must operate perpetually; indeed the carbon footprint caused by the IoT industry is non-trivial. According to a recent IEA report [8], the total additional energy consumption that results from connecting devices to a communications network is expected to increase from 500 TWh in 2010 to 1,150 TWh by 2025; note that this projected number for communication energy does not include the energy use of the equipment operation.

In this paper we aim to optimize the energy consumption of IoT-based perpetual systems in smart space settings by reducing the overhead of sensing/communication energy cost (of mobile and insitu IoT devices) while supporting essential QoS of running applications. Our key idea is to exploit the heterogeneity of IoT device/communication technologies, and the dynamic space-states to create a context-aware energy-efficient IoT system without loss of service quality.

Key contributions of this paper include:

- Modeling data collection needs of dynamic smartspace applications using a novel space-state abstraction.
- Formalizing energy-efficient multi-network IoT provisioning with space-states as a constrained optimization problem, shown to be NP-hard.
- Implementing near-optimal algorithms for IoT provisioning that leverages semantics of tasks and spaces. The phased approach involves floor-plan segmentation, space-state classification based on events, and energy optimization; exploits heterogeneous IoT device/ network.
- Validation of our approach using a real prototype testbed for assisted living called SAFER [2]
- Conducting an in-depth measurement study to characterize accuracy/energy cost tradeoffs with multiple devices and network interfaces, that are used to drive emulated scenarios in assisted living.
- Extensive evaluations to study the scalability and effectiveness of our algorithms/approach using simulation studies using real assisted living layouts.

II. Energy Efficiency and Perpetual IoT

In this section, we describe the unique aspects of energy optimization in the perpetual IoT multi-network setting and design a space-state strategy.

A. Problem Description

We characterize the energy efficiency problem in the indoor context where IoT devices are scattered in a home/building to enable indoor event detection tasks. Specific sensors include wearable devices with motion/accelerometers/GPS, ambient sensors to capture environment such as humidity/temp/gas and audiovisual sensors that capture voice/video etc.) These IoT devices have varying capabilities: processing, power source 'battery or wall-powered', reliability, accuracy and are interconnected using diverse (sometimes multiple) network interfaces. Recent advances in IoT communication technologies have created a variety of low-power connectivity options, such as NB-IoT, LTE-M, LoRa, Zigbee, etc, with different network characteristics. NB-IoT and LTE-M are recent protocols for low bandwidth cellular communications that connect inexpensive internet devices with small data transmission rates and smaller power consumption, i.e. higher battery life [9]. Consequently, IoT devices are today equipped with multiple network interfaces that can be customized and configured to support tradeoffs - e.g. larger datarates for communication energy consumption based on usage needs.

This feature is handy with perpetual services to detect critical anomalous events such as elderly falls; event likelihoods can help us tune the choice of sensors, data rates and network interfaces for better situational awareness. Table I depicts variations in service accuracies and data rates required that fluctuate based on the current activity performed in the monitored space. These measurements can guide the choices made to achieve the highest accuracy possible while ensuring energy efficiency.

IoT Node Sensors /Network Interfaces/	**Battery capacity**	**Configurations Examples**	**Power consumption**	**Performance accuracy**
Mobile phone Microphone Accelerometer Gyroscope /Bluetooth, Wi-Fi, LTE/	**8**Wh	All sensors/Wi-Fi	2249 mW	70%
		Microphone/Wi-Fi	1920 mW	45%
		Accelerometer,Gyroscope/Bluetooth	1172 mW	60%
		Accelerometer/Bluetooth	1050 mW	40%
		Idle	28 mW	0%
Wearable device Accelerometer Gyroscope /BLE, Zigbee/	**0.72**Wh (CR2032) **3**Wh (2XAAA)	All sensors/BLE	226.5 mW	40%
		Accelerometer/BLE	112.48 mW	30%
		Idle	1.32 mW	0%
Smart pad Pressure matrix Motion Acoustic sensor Camera /Bluetooth, Wi-Fi, NB-IoT, LTE-M/	**18**Wh ∞	All sensors/Wi-Fi	3.1 W	90%
		Motion, LQ camera/Bluetooth	1.74 W	75%
		Motion, Pressure matrix/Bluetooth	1.32 W	70%
		Acoustic/LTE-M	740 mW	45%
		Motion/NB-IoT	650 mW	20%
		Idle	330 mW	0%

TABLE I: IoT Configurations in the SAFER Prototype

For example, in the SAFER assisted living context[2], activating all platform IoT nodes for a fall detection service will offer above 90% accuracy. This high level of accuracy is wasteful at times of low activity (during night time) when lower levels of sensing/transmission are adequate. However, higher accuracy is required during the wake-up times; studies indicate that 70% of elderly falls happen during this time. This illustrates the need to provide abstractions that capture the dynamicity of the underlying space into multiple modes that can then be used to trigger increased sensing based on event shifts.

We introduce a key abstraction for exposing indoor space dynamicity in IoT deployments to build more reliable and energy-efficient systems. For this, we observe that there are 3 key modes that the physical space shifts between based on the occurrence of events, We refer to these settings as *space-states*. The three modes **Normal, Anomaly, and Emergency** modes capture different conditions and vary in the amount/quality of data that needs to be sensed and transmitted. Ambient sensing at low datarates occurs in the *normal* mode. Upon sensing a potential gas leak. the system switches to the anomaly space-state; more data to identify the causes and actions; a latency tradeoff occurs to capture more information in the anomaly mode. In a fire event (smoke, heat, gas detection), the space-state shifts to the emergency state where low latency and high data quality are needed - we enable more sensors, high bandwidth interfaces to detect the causes of fire/recommend evacuation routes [10].

In each mode, knowledge of device capabilities can be used to activate an adequate subset of data sources to meet the accuracy/latency levels based on the space-state. Available connectivity's options have varying characteristics and energy cost that can be leveraged as Wi-Fi module is the most energy-hungry [11], this can be utilized in such a dynamic space to activate the network interface that accommodates the streaming data rate. Battery-powered devices such as mobile/wearables dissipate power quickly and need to be recharged. Furthermore, we noticed that one can designate areas in the floor plan to be used to identify event patterns; i.e. not all wall powered IoT devices are utilized all the time. Knowledge of the space-state and activities of daily living (ADLs) of a resident can provide us with semantic information about the location, activity type, duration, etc.; this can be utilized intelligently to minimize energy dissipation in the integrated system. Given the above observations, our goal is to minimize energy consumption of the integrated IoT deployment to enable long-term operation while meeting accuracy threshold demands.

B. *Related Work*

Perpetual monitoring systems are becoming common in multiple contexts [1]–[7]; however, continuous sensing/transmission and processing for operational purposes in such settings have cross-layer concerns at multiple levels of the system (devices, networks, data etc.). One of the main concerns that gained attention from research communities, is the energy consumption that increases the operation costs and affects the system lifetime; novel techniques have been proposed to reduce energy consumption in sensor networks at the device, communication/network and system levels.

At the *device level*, engineers look into circuit and hardware optimization to reduce power consumption through energy harvesting (motion, thermal, wireless [12]–[16]), wake-up receivers, duty-cycling methods to maximize the devices' lifetime.

At the *communication level*, standardization associations (IETF, IEEE, 3GPP etc.) have specified and developed protocols to enable energy efficient IoT by reducing communication overheads. They focused on optimization of access technologies, and create different options (BLE, NB-IoT, LTE-M, Zigbee, LoRa, etc.), on adaptation of IP protocols to extend the web architecture to the most constrained sensors, and developing lightweight protocols enabling the connection of everything to the cloud (MQTT, etc.). Each option offers different bandwidth, range, energy, reliability, etc. [9, 17]–[19]. Also, studies such as [20], focuses on the *access network* power consumption for a range of IoT traffic levels.

Earlier literature in *system level* is based on wireless sensor networks which can be classified into three approaches *duty cycling*, *data-driven* and *mobility* [21]. *Duty cycling* [22, 23] focus on optimizing the subsystem by exploiting active/sleep/node redundancy. In early techniques, sensor nodes, transmission are homogeneous(limited heterogeneity [24]) and energy is constrained, e.g. LEACH [22]. *Data-driven* [25, 26] focus on reducing data sampling/transmission by exploiting data aggregation, compression, or prediction. *Mobility* [21] focus in mobile entities, which can be the sink. The IoT ecosystem, large level of heterogeneity/dynamicity/scalability that integrates several technologies, e.g. wireless sensor networks. It includes devices with varying capabilities; these devices use diverse communication protocols and direct connections to local or cloud platforms.

Recent methods to tackle energy efficiency in IoT vary; several efforts to modify *IoT sensing* behavior based on the application requirements to conserve energy. The tradeoff between energy and performance metrics [27]–[29], by designing scheduling/activation algorithms with the consideration of QoS. As some IoT applications incur high communication/energy costs, managing IoT devices to reduce network overhead is critical and number of studies consider *transmission scheduling*. They argue that devices consume more energy in communication; their technique is a self-adaptive that aims to minimize the energy by harvesting in significant manner on IoT; range from modifying scheduling strategy with traffic streams, optimizing graphs using critical path elimination, building mini clouds at relays/coordinator/gateways and reduced number of hops in IoT network, integrating routing and node placement techniques in a single network architecture [30]–[32].

III. The Energy Optimization Problem for Multi-Network IoT Platforms in Smart Spaces

In this section, we first introduce various terms comprising of our problem (the IoT multi-network energy problem) then discuss our assumptions about the system; formulate the problem as an optimization problem.

A. *Terms and assumptions*

We assume that in each building there is a *local controller* that connects with all IoT devices (*nodes*) to track their status. Each node has one to many network (*interfaces*) to communicate and send their data. Each node comprises one to many sensors (*data sources*) that feed data to a designated service. We also assume that each node can choose at most one interface at any given time out of its available network interfaces.

We assume *applications* are part of smart building/home systems that deliver multiple *services*. For example, smart meeting application (e.g., Noodle in TIPPERS [5]) in a building can deliver services such as recording audio/video and speech recognition/translations. For a given service, a set of sensors belonging to a certain set of nodes are required to send data for the particular service to be realized. For example, for the fall detection service for an elderly individual, data from floor mat sensors and cameras around the subject's current location is preferred rather than pulling data from all over. We classify nodes into two groups in terms of their source of energy/power: unconstrained *wall-powered devices* and constrained *battery-powered* devices. Obviously, trade-off exists between the energy consumed by a node and its different network configurations and their bandwidth and latencies. Lower Latency is desired but only at the cost of higher energy consumption, which leads to shorter system lifetime. Higher bandwidth interface (e.g., Wifi) can be chosen only if the data volume is high; otherwise, a lower bandwidth interface may be preferred. Sending an adequate amount of data through an appropriate network interface results in an energy-optimized sustainable IoT system.

B. Problem Statement and Formulation

We formulate energy optimization for IoT multi-network problem as a constrained optimization problem. Let us denote I to be the set of all candidate nodes (indexed by i) in a certain segment/building at a given time, J be the set of all types of data sources/sensors in the system (indexed by j), and K be the set of all available interfaces (indexed by k). Obviously, not all nodes will have all sensors, nor all interfaces. Consequently, we denote a binary indicator p_{ij} to denote if node i contains data source type j onboard, s_{ij} to denote if data source j at node i is required for the service at hand, and q_{ik} to denote if node i has interface k onboard. Given these (with the associated attributes described later), we are required to find two sets of binary decisions: (i) x_{ij} indicating if data source j on node i to be selected for the service, and (ii) y_{ik} indicating if node i chooses interface k to transmit data at that time interval. The objective is to minimize the overall energy consumption subject to latency and accuracy constraints. This selection of sensors/interfaces happens periodically at an interval denoted by T.

Each sensor type j has these attributes: the data generation rate (denoted by dr_j, measured in bytes per sec) and the energy consumption rate, $e_i j$, at which energy get depleted when the sensor gets activated at node i. Admittedly, different data sources such as video, audio, and motion generate data in different rates and consequently consume different amount of energy. Again, a data source on a certain node has certain accuracy to contribute towards its service, denoted by a_{ij}. Finally, each interface k has these attributes: energy consumption rate (e_k, measured in Joules per byte), bandwidth of the interface (bw_k, measured bytes per second), and the propagation delay/latency of the interface (pl_k). Note that the propagation delay accounts for the signal propagation delay from the transmitter to the receiver, but the actual end-to-end delay (latency) depends on, in addition to the propagation delay, to the volume of data being sent over the interface, which in turn depends on which data sources are chosen and the bandwidth of the interface. Consequently, the effective end-to-end latency l_{ik} (at node i for sending data on interface k) is given by:

$$l_{ik} = pl_k + \left(T \cdot \sum_j x_{ij} dr_j \right) \cdot \frac{1}{bw_k} \tag{1}$$

As noted earlier, the service in question has two constraints: *latency constraint* and *accuracy constraint*. The latency constraint dictates that the end-to-end latency of collecting data from all of the chosen data sources should not exceed a certain bound. This bound is called the *latency demand* and is denoted by τ. Interestingly, the latency demand can be a variable (rather than being a constant) that may change over time depending on the service operation and its space state. For example, τ can take a lower value for a time-critical service (when quicker responses are demanded) than a normal service when the latency demand can be relaxed (by setting τ to a higher value).

The second constraint, the accuracy one, asks for certain accuracy of the service. We argue that when data from multiple sources are combined for a given service, the accuracy of the service should increase. By defining accuracy as the probability of detecting some event of interest, we can use a soft OR operator to combine accuracy when data from multiple data sources is utilized as follows: if one source gives accuracy a_1 and another source one gives a_2, the combined accuracy is given by: $1-(1-a_1)(1-a_2)$ (probability that at least one of the two sources detects the event), or more generally, $1 - \prod_m (1 - a_m)$ for relevant m's.

The accuracy constraint dictates that the combined accuracy over all collected data from the chosen data sources should exceed a threshold, called the *accuracy demand* (denoted as α). Like the latency demand, the accuracy demand can also be a variable that may change over time depending on the service space state. For example, when the service detects an anomaly, the accuracy requirement becomes higher compared to when the service was running as normal.

As stated above, our objective is to minimize the overall energy consumption for collecting and sending data over the interfaces across all nodes. We also want to extend the lifetime of battery-powered devices, so we should consider the remaining battery capacity of those devices. Considering this, we define *energy-cost*, denoted by c_{ik}, for each interface choice per node as follows:

$$c_{ik} = T \cdot \eta_i \sum_j x_{ij} \left(e_k \times dr_j + e_{ij} \right) \tag{2}$$

The cost is proportional to the amount of energy consumed by the interface, which is e_k times the data volume generated by the sensors chosen at the node, plus the amount of energy consumed by the node for activating those sensors (e_{ij}'s). The cost also takes into account the fact that operating a battery-operated device is costlier than an equivalent wall-powered device, when they both consume the same amount of energy. The operation arguably gets costlier when the remaining battery capacity becomes low. To reflect this, we multiply the base energy consumption with an adjustment factor, η_i, which is given by (the expression is adopted from [2, 3]):

$$\eta_i = 1 + \beta \cdot \exp\left(-\frac{r_i}{r_i^0} \right) \tag{3}$$

where r_i^0 denotes the initial battery capacity of the node, r_i is the current remaining energy, and β is a tune-able parameter to adjust the effect.

We, therefore, have the following optimization: find x_{ij} and y_{ik} so as to—

$$
\begin{aligned}
\text{minimize} \quad & \sum_{i\in I}\sum_{k\in K} y_{ik}\cdot c_{ik} && (4)\\
\text{subject to} \quad & \sum_{i\in I}\sum_{j\in J} x_{ij}\cdot \log(1-a_{ij}) \le \log(1-\alpha) && (5)\\
& y_{ik}\cdot l_{ik} \le \tau, \forall i,k && (6)\\
& y_{ik} \le \sum_{j\in J} x_{ij}, \forall i,k && (7)\\
& \sum_{k\in K} y_{ik} \le 1, \forall i && (8)\\
& x_{ij} \le p_{ij}\cdot s_{ij}, \forall i,j && (9)\\
& y_{ik} \le q_{ik}, \forall i,k && (10)\\
& \forall x_{ij}, y_{ik} \in \{0,1\}, \forall i,j,k
\end{aligned}
$$

The objective (4) is to minimize the total energy cost for all nodes for the chosen associated interfaces. Eq 5 is actually a rewritten expression (taking log in both sides with some adjustments) of the following:

$$1-\prod_{i\in I}\prod_{j\in J}\left(1-x_{ij}a_{ij}\right)\ge\alpha \quad (11)$$

which ensures that the effective accuracy accumulated over all data sources remains higher than the accuracy demand, α. Eq 6 is to meet the latency constraint so that the latency of *all* data sources remains within τ. Eq 7 ensures that an interface on a node is activate (at most once, Eq 8) only if some sensors on the node is chosen. The last two constraints allow only onboard data sources and interfaces to be chosen for a given node.

The IoT multi-network energy optimization problem as formulated above is an NP-hard problem that can be reduced from the minimum multidimensional multiple-choice knapsack problem [33].

Looking closely at the formulation, it reveals that for each node, we are required to find two things: the subset of data sources to be chosen (x_{ij}) and the network interface to be used (y_{ik}). We can combine these two selections into one as follows. For each node, we construct a list of *choices* where each choice is a tuple in the form of (S,k) where S is some *subset* of data sources for some choice of interface k. Ideally, this list may contain all possible combination of choices over the set of data sources and interfaces that the node has. But the choices for which the associated latency exceeds τ can be treated as invalid because they violate the latency constraint and hence can be dropped. In addition, there can be an *empty* choice denoted as $(\emptyset, \text{null})$ (no sensors and no interface are chosen). With this transformation, we are now required to choose *exactly* one choice per node that minimizes the total energy cost subject to the accuracy constraint. This is effectively an instance of the classical Multiple-Choice Knapsack Problem (MCKP) and we use the classical MCKP heuristic to solve this. Since the number of interfaces and data sources per node, in practice, is small (in the order of 10 or fewer), the total number of choices are rather bounded and an efficient algorithm can be devised (refer to the next section).

IV. Algorithms and Heuristics for Energy Optimization in Multi-Network IoT Platforms

In the following sections, we will propose a description of set of feasible design intuitions along practical algorithms based on aggregated resources to optimize energy efficiency in IoT platforms over heterogeneous networks.

A. Design intuitions

We have considered the following intuitions in our solution: *Location-aware space segmentation:* partitioning is a viable strategy of overall system energy efficiency, scalability, and performance. *Exploiting space-state modes:* aggregating multiple low cost sensor as a base-line ambient sensing including (motion, door sensors, temperature, etc.) to detect ambient events/activities such as ADLs (activities of daily living) and occupancy information, that shift the space-state modes (normal, anomaly, emergency) is beneficial. These base-line sensors can be wired or wireless with a slow-battery-drain and consume power at a very low rate, such as less than 8 watts consumption in layout of the 39 sensors (31 motion, 4 door, and 4 temperature) deployed on the 900 ft^2 home, as shown in Figure 3; that have been used for daily activity/space-state recognition [4, 34].

B. Framework and Algorithms

Developing an optimal energy efficient system for perpetual and heterogeneous IoT operation needs comprehensive knowledge about the floor-plan architecture, space-state, semantics patterns, and IoT device profiles/status. To handle the complexity that arises due to the dynamic nature and the diversity of the underlying infrastructure, we propose a three-phase system framework that utilizes the design intuitions mentioned above as illustrated in Figure1.

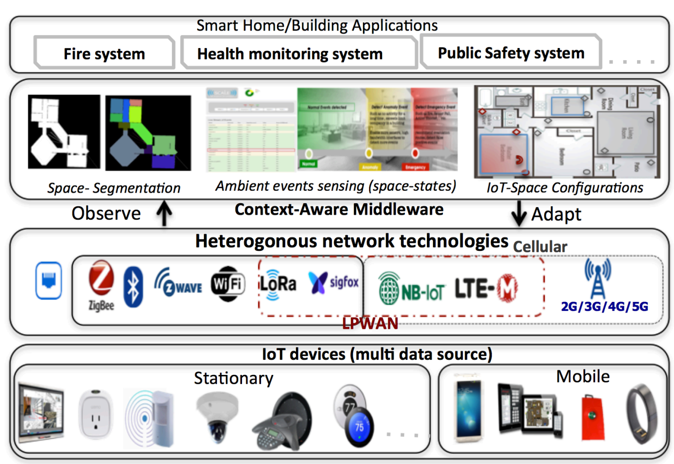


Fig. 1: The proposed system architecture

Algorithm 1: *System-Wide-Greedy*(α)

$ChoicesList_i(\{S\}, k) \leftarrow$ all combinations of available IoT nodes(i)with its feasible $sensors\{S\}$subset associated with k *interface*
$ChoiceResult_i \leftarrow \text{Empty}_{set}(\{\}$,null)
$CombinedAccuracy = 0$;
while ($CombinedAccuracy \leq \alpha$) **do**
  foreach i **do**
    $\Delta EnergyCost = ECost_{next}(i) - ECost_{current}(i)$
    $\Delta Accuracy = Accuracy_{next}(i) - Accuracy_{current}(i)$
    $CalculateSlop(\{i\})(\Delta EnergyCost/\Delta Accuracy)$
  end
  Select i with the largest slope;
  $Choice - Result_i = Choices - list_i(next)$;
  $CalculateCombinedAccuracy$;
end

1) Base-line algorithms: We activate all IoT nodes that are needed by the service at hand (e.g., fall detection), which are enabled with all data sources (sensors) required by the fall detection service, such as smart pad, audio, and video cameras, with the highest bandwidth network interface available, Wi-Fi.

Location-Aware algorithm: In this approach, we activate the IoT nodes that are present in the segment area where the user is currently located based on the feeds from the ambient sensing. The scheme chooses the highest data rate to get the highest accuracy with the highest bandwidth network interface available.

Context-Power-Aware algorithm: In this approach, we take into the consideration the space-states (normal, anomaly, emergency) and the demanded accuracy of operation; each space-states mode requires different level. Also, it maximizes the system lifetime by activating the wall-powered devices first, then choose the battery-operated devices in descending order of their remaining battery capacity until we exceed the current space-state's accuracy threshold.

2) Greedy Algorithms: In this subsection, we outline greedy heuristics for the selection of data sources (sensors) and network interfaces per node. As per the formation outlined in the earlier section, we are required to find the best *choice* for each node, that is, the best (S, k) tuple per node that optimizes the total energy cost subject to the accuracy constraint. For the n-th choice at node i, we compute the following two quantities: *energy(i, n)* and *accuracy(i, n)*, the total energy cost and the combined accuracy, respectively, associated with the choice of data sources and the interface. Given these, we can construct a selection in the following two ways:

Node-approximation: For each choice (i, n), we compute the ratio of *energy(i, n)* to *accuracy(i, n)* and then rank the choices per node in ascending order this ratio (0/0 is assumed to be 0). Once the choices are ranked, the algorithm builds the solution as follows. It starts by taking the first choice (the empty choice) from each node (zero energy cost with no interface is chosen) and then progressively moves to the next *immediate* choice per node (one node at a time) and compute the combined accuracy with the associated choices across all nodes (using the soft OR operation described before). The algorithm ends when the accuracy demand is met (combined accuracy exceeds α) or the solution cannot be improved any more.

System-wide greedy: In this approach, the search iterates over the entire (i, n) space instead of doing it per node. This approach uses the classical gradient-based MCKP heuristic [35]. The choices per node are ranked in the ascending order of accuracy (for the choices having the same accuracy, only the lowest energy choice is kept). The algorithm, starting with an empty choice, makes a sequence of changes in which the current choices from each node are upgraded to the next best based on the gradient of energy cost change to accuracy change, given by the ratio $\frac{\Delta energy}{\Delta accuracy}$, with worst-case time-complexity $O(n.i)$. The goal is to move toward the choice that offers lower change in energy cost compared to a big change in accuracy. The process continues until the accuracy demand is achieved (Algorithm 1).

V. Performance Evaluation and Results

The perpetual IoT platform is derived from our existing community-oriented IoT deployments in SCALE [1] that was deployed in Victory Court Senior Apartments in Montgomery County, MD. Leveraging that, we developed SAFER [2], an elderly fall detection system, that helped us to explore challenges arising in real world deployments and to collect measurements varying and realistic combinations of sensors to drive our simulations.

A. Prototype Platform and Measurement Study

We aim to investigate the energy consumption of various IoT access network technologies, such as Wi-Fi, Bluetooth, NB-IoT, and LTE-M, to present their average energy consumption based on our measurements and datasheets [11, 18, 19, 36]–[39]. *SAFER: prototype platform and testbed:* The smart pad, shown in Figure 2, is comprised of multiple data sources (matrix of Square Force-Sensitive Resistor sensors, motion, camera, acoustic sensor) with multi-connectivity options: Wi-Fi (Edimax EW-7811Un), Bluetooth, NB-IoT, and LTE-M (Cellular IoT Application Shield).

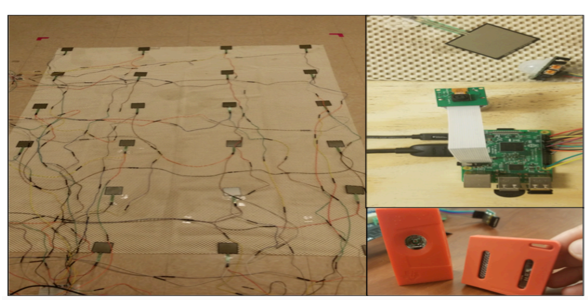


Fig. 2: The SAFER platform devices

Communication Technology	Maximum bandwidth	Transmission range	Latency	Avg. Power Consumption	The communication energy efficiency based on data rate			
					100 bps	100 kbps	1Mbps	10Mbps
Wi-Fi (+router)	54 Mbps	< 300 feet	2-3ms	1800 mW	18.00 mJ/b	18.00 µJ/b	1.800 µJ/b	0.1800 µJ/b
Bluetooth (+gateway)	3 Mbps	300 feet	100ms	1000mW	10 mJ/b	10 µJ/b	1 µJ/b	N/A
NB-IoT (Cat-NB1)	250 kbps	6 miles	1.5-10s	480 mW	4.8 mJ/b	4.8 µJ/b	N/A	N/A
LTE-M (Cat-M1)	1 Mbps	1-3 miles	50-100ms	500 mW	5.7 mJ/b	5.7 µJ/b	0.57 µJ/b	N/A

TABLE II: Comparison of some access network technologies that have been used in our platform [11, 18, 19, 36]–[39]

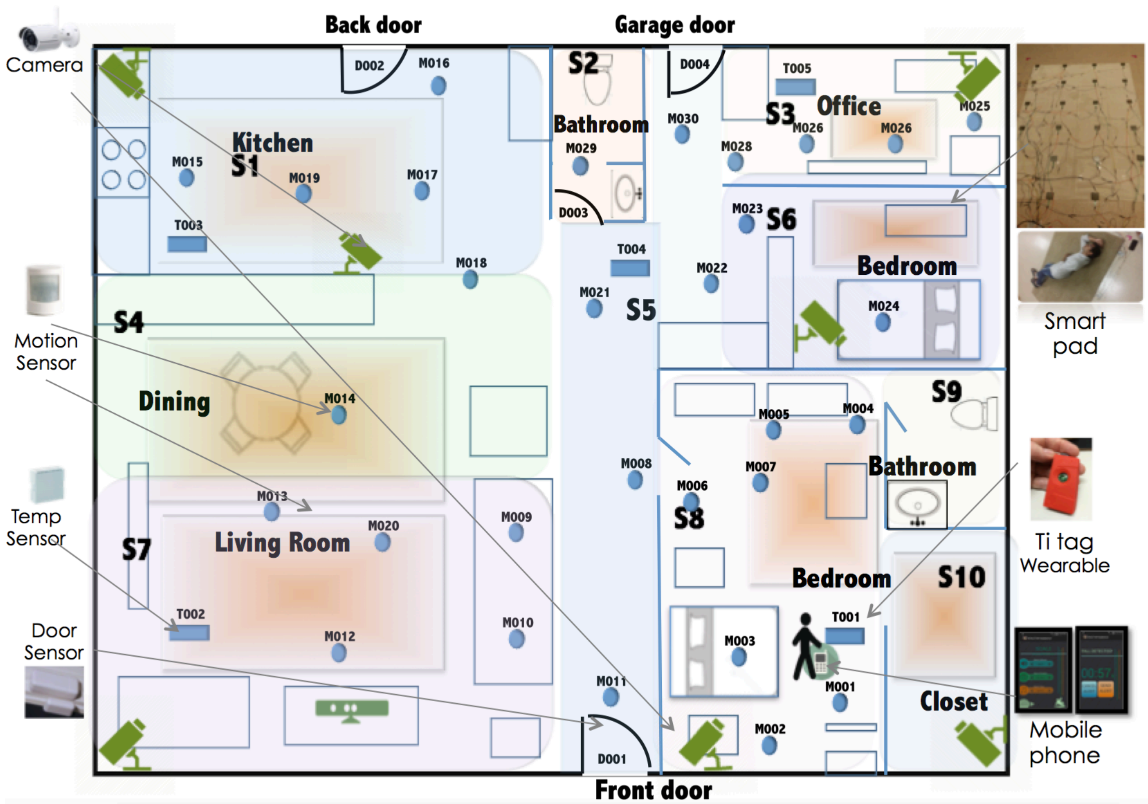


Fig. 3: Segmented floor-plan for an assisted living setting (SAFER with base-line ambient sensing) [34]

The wearable sensor (Ti SensorTag CC2541), Figure 2, incorporates up to 10 sensors: light, digital microphone, magnetic sensor, humidity, pressure, acc., gyroscope, magnetometer, object temperature, and ambient temperature. It includes interfaces BLE, 6LoWPAN and ZigBee. The setup also has a mobile phone with a set of onboard sensors.

The measurements shown in Table I include the transmission range, bandwidth capacity in bits per second and power consumption. We observe that energy cost per bit is higher if a small amount of data is sent over a higher energy interface with higher bandwidth.

According to [38], Bluetooth uses nearly 3% of Wi-Fi's energy; for example, sending data at the rate of 75 bytes/sec over Wi-Fi requires 80 mW whereas Bluetooth consumes only 2mW. In NB-IoT, however, the data rate does not directly impact the power consumption [18], similar to WiFi radio [38].

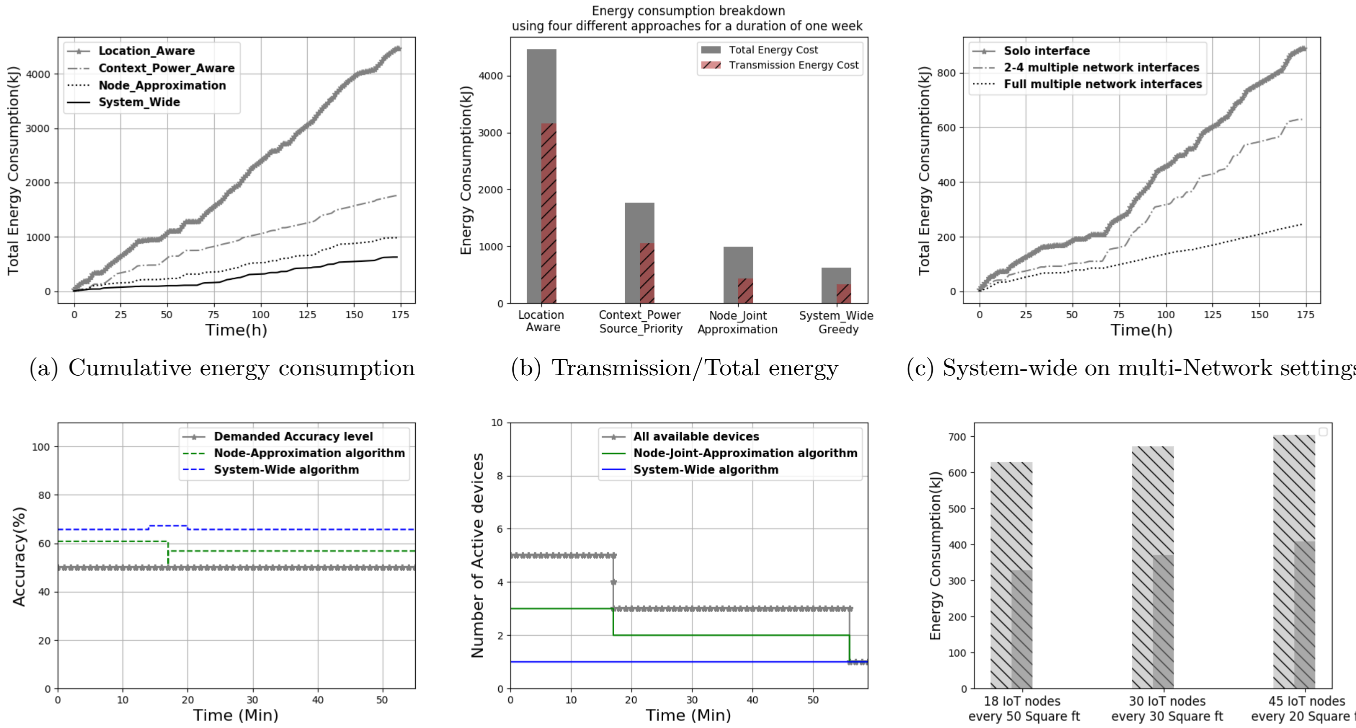
We, therefore, calculate energy efficiency (in Joules per bit) of different network interfaces at various data rates. It is also observed that data sources have varying data generation rates (e.g., sensors like humidity/temperature/GPS produce 120-200 bps whereas video can reach up to 10Mbps).

B. *Experimental Setup - Simulation Studies*

To conduct further experiments, we developed a fixed-time interval simulator and created multiple test cases at different scales/devices intensities based on real-world layout of elderly living options. The floor-plan includes 2 bedrooms, a living room, kitchen, office and 2 bathrooms with a space of $900ft^2$ (Figure 3).

With a density of 1 IoT device per 50 ft^2, we considered a total of 18 devices (15 static wall-powered devices and 3 mobile battery-powered devices).

We also considered two more settings with density 1 node per $30ft^2$ and 1 node per $20ft^2$, respectively. We execute our simulations on the CASAS trace dataset obtained from [34] that contains the activities of daily living of an individual in an assisted living setting for a week (ADLs are used to switch between space-states).



(a) Cumulative energy consumption (b) Transmission/Total energy (c) System-wide on multi-Network settings

(d) Accuracy comparison (e) Number of available/active devices (f) System-wide on Multi-scale settings

Fig. 4: Simulation Results

We use the following performance metrics.

Cumulative energy consumption: the total energy consumption can be used as a benchmark to evaluate the energy optimization algorithms.

Sensing and transmission energy consumption: we examine the effect of different algorithms in the ratios of sensing and transmission energy consumption.

Number of active/idle IoT nodes: intuitively, an optimized algorithm should reduce the number of active IoT nodes while attaining the demanded accuracy.

C. Experimental Results

Comparing Energy Optimization Algorithms:

Figure 4a shows the cumulative energy consumption of different algorithms. As we can observe, activating sensors based on space-state demanded accuracy that has been considered in Context-Power-Aware algorithm reduces energy consumption by half compared to the case when all IoT devices in the location are running. On the other hand, the Node-approximation algorithm saves nearly 75% of energy, then, System-wide greedy algorithm consumes little less energy as it takes into consideration the best choice to activate across all devices.

Figure 4b shows the comparison among different algorithms in terms of the ratio of energy consumed for transmission compared to the total energy cost. The resulting measurements indicate that a significant component of the total energy cost is consumed for communication activities.

We next study the effect of using multiple network interfaces on the overall energy consumption. Figure 4c illustrates the energy consumed by the system-wide greedy algorithm under three settings (only 1 interface for each IoT node(Wi-Fi); from 2-4 interfaces; the extreme case where all nodes have 4 interfaces (Wi-Fi,Bluetooth,NB-IoT, LTE-M). As can be seen, increasing the connectivity options allows the System-wide greedy algorithm to reduce the energy dissipation over time.

IoT Density and Scalability Studies:

Given that the above results that indicate the efficacy of the proposed greedy techniques, we explore the scalability of our approach in the context of the two greedy algorithms - Node-approximation and System-wide algorithms. Specifically, we focused on a one-hour window, where we observe that both techniques deliver near demanded accuracy - Figure 4d. An interesting result can be seen in Figure 4e where the total number of available IoT nodes in the one-hour segment is five.

The Node-approximation algorithm activates 3 out of 5 nodes to reach the demanded accuracy. In comparison, the System-wide algorithm activates only 1 out of the 5 nodes. An indirect consequence of using fewer nodes without sacrificing accuracy is that the System-wide algorithm can support longer operational lifetimes and hence increase reliable operation of the desired service. In the next experiment, we studied the effect of node density. As seen in Figure 4f, the System-wide greedy algorithm bounded the energy cost even with a dense IoT deployment, which is again beneficial in terms of system reliability and sustainability.

VI. Conclusion

In this paper, we studied techniques to ensure energy efficient perpetual IoT applications in smartspaces while ensuring application service quality. In particular, we considered how best to exploit the presence of multiple sensing modalities and multiple network interfaces along with knowledge of the application needs in the underlying space to intelligently activate the underlying system configuration.

In mission-critical environments (e.g. hospitals, chemical facilities, nuclear power plants), perpetual monitoring is critical to ensure safe operation; the extraction and exploitation of current operating context is critical for timely response. The notion of space-state based monitoring and activation in this paper is a starting point to support both efficiency and safety in these settings.

The ability for such cross-layer coordination (application, networking and devices) is of increasing importance as the number of IoT devices and connectivity choices increase - such flexibility also enables providers to expand on existing deployments as new technologies emerge. In future work, we will scale-up this approach by considering multiple people in the space, multi-service resource provisioning.

References

[1] M. Y. S. Uddin *et al.*, "The SCALE2 multi-network architecture for iot-based resilient communities," in *IEEE International Conference on Smart Computing*, 2016, pp. 1–8.

[2] N. Alhassoun, M. Y. S. Uddin, and N. Venkatasubramanian, "Safer: An iot-based perpetual safe community awareness and alerting network," in *IGSC*, Oct 2017, pp. 1–8.

[3] N. Alhassoun, M. Y. S. Uddin, and N. Venkatasubramanian, "Context-aware energy optimization for perpetual iot-based safe communities," *SUSCOM*, vol. 22, pp. 96–106, 2019.

[4] A. S. Crandall *et al.*, "Casas: A smart home in a box," *Computer*, vol. 46, pp. 62–69, 2013.

[5] http://tippers.ics.uci.edu/.

[6] C. Ruiz *et al.*, "Autonomous inventory monitoring through multi-modal sensing (aim3s) for cashier-less stores," in *BuildSys '19*, 2019, p. 395–396.

[7] C. Ruiz, J. Falcao, S. Pan, H. Noh, and P. Zhang, "Aim3s: Autonomous inventory monitoring through multi-modal sensing for cashier-less convenience stores," in *6th ACM BuildSys*, 2019, p. 135–144.

[8] A. W. Paul Ryan, Terence Smith, "Total Energy Model for Connected Devices," IEA 4E EDNA, Tech. Rep., June 2019.

[9] E. . C. F. . M. F. Mekki, Kais Bajic, "A comparative study of LPWAN technologies for large-scale IoT deployment," *ICT Express*, 2019.

[10] V. Nguyen *et al.*, "A scalable approach for dynamic evacuation routing in large smart buildings," in *SmartComp*, 2019.

[11] C. A. Gray, "Energy consumption of Internet of Things applications and services," Ph.D. dissertation, may 2019.

[12] F. Aoudia *et al.*, "Leveraging Energy Harvesting and Wake-Up Receivers for Long-Term Wireless Sensor Networks," *Sensors*, vol. 18, p. 1578, 2018.

[13] P. Kamalinejad *et al.*, "Wireless energy harvesting for the internet of things," *IEEE Communications Magazine*, vol. 53, no. 6, pp. 102–108, June 2015.

[14] T. Ruan, Z. J. Chew, and M. Zhu, "Energy-aware approaches for energy harvesting powered wireless sensor nodes," *IEEE Sensors Journal*, vol. 17, no. 7, pp. 2165–2173, 2017.

[15] M. Gorlatova, J. Sarik, G. Grebla, M. Cong, I. Kymissis, and G. Zussman, "Movers and shakers: Kinetic energy harvesting for the internet of things," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 8, pp. 1624–1639, 2015.

[16] C. Choi, J. Jeong, I. Lee, and W. Park, "Lora based renewable energy monitoring system with open iot platform," in *2018 International Conference on Electronics, Information, and Communication (ICEIC)*, 2018.

[17] M. Lauridsen, R. Krigslund, M. Rohr, and G. Madueno, "An empirical nb-iot power consumption model for battery lifetime estimation," in *2018 IEEE 87th Vehicular Technology Conference (VTC Spring)*, 2018, pp. 1–5.

[18] " Cellular system support for ultra-low complexity and low throughput Internet of Things (CIoT)," 3GPP, TR 45.820, Tech. Rep. 11, 2015.

[19] " Evaluation of LTE-M towards 5G IoT requirements for Category-M1 Devices ," Tech. Rep., December 2017.

[20] C. Gray, R. Ayre, K. Hinton, and R. S. Tucker, "Power consumption of iot access network technologies," in *2015 IEEE International Conference on Communication Workshop (ICCW)*, 2015, pp. 2818–2823.

[21] G. Anastasi *et al.*, "Energy conservation in wireless sensor networks: A survey," *Ad Hoc Netw.*, vol. 7, no. 3, 2009.

[22] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, 2000, p. 10 pp. vol.2.

[23] A. Warrier *et al.*, "How much energy saving does topology control offer for wireless sensor networks? - a practical study," *Comput. Commun.*, vol. 30, no. 14-15, pp. 2867–2879, 2007.

[24] Mao Ye, Chengfa Li, Guihai Chen, and J. Wu, "Eecs: an energy efficient clustering scheme in wireless sensor networks," in *PCCC 2005. 24th IEEE International Performance, Computing, and Communications Conference, 2005.*, 2005, pp. 535–540.

[25] C. Tang and C. S. Raghavendra, "Wireless sensor networks." Kluwer Academic Publishers, 2004, ch. Compression Techniques for Wireless Sensor Networks, pp. 207–231.

[26] E. Fasolo *et al.*, "In-network aggregation techniques for wireless sensor networks: a survey," *IEEE Wireless Communications*, vol. 14, no. 2, pp. 70–87, April 2007.

[27] D. Zeng *et al.*, "Energy minimization in multi-task software-defined sensor networks," *IEEE Transactions on Computers*, vol. 64, no. 11, pp. 3128–3139, Nov 2015.

[28] X. Tan, H. Zhao, G. Han, W. Zhang, and T. Zhu, "Qsdn-wise: A new qos-based routing protocol for software-defined wireless sensor networks," *IEEE Access*, vol. 7, pp. 61 070–61 082, 2019.

[29] S. Li and J. Huang, "Energy efficient resource management and task scheduling for iot services in edge computing paradigm," in *ISPA/IUCC*, Dec 2017, pp. 846–851.

[30] K. Suresh *et al.*, "Eeiot: Energy efficient mechanism to leverage the internet of things (iot)," in *ICETT*, 2016, pp. 1–4.

[31] Z. T. Al-Azez *et al.*, "Virtualization framework for energy efficient iot networks," in *CloudNet*, 2015, pp. 74–77.

[32] P. Sarwesh, N. S. V. Shet, and K. Chandrasekaran, "Energy efficient and reliable network design to improve lifetime of low power iot networks," in *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 2017, pp. 117–122.

[33] H. Kellerer *et al.*, *Knapsack problems.* Springer, 2004.

[34] D. Cook, "Learning setting-generalized activity mdoels for smart spaces," *IEEE Intelligent Systems*, 2011.

[35] P. Sinha and A. A. Zoltners, "The Multiple-Choice Knapsack Problem," *Operations Research*, vol. 27, no. 3, 1979.

[36] S. Chiaravalloti, F. Idzikowski, and Ł. Budzisz, "Power consumption of WLAN network elements," 2011.

[37] " Product data sheet. Cisco Aironet 802.11a/b/g Wireless PCI Adapter," Cisco Aironet, Tech. Rep., January 2010.

[38] R. Balani, " Energy consumption analysis for bluetooth, wifi and cellular networks ," Tech. Rep.

[39] O. Kazeem, O. Akintade, and L. Kehinde, "Comparative Study of Communication Interfaces for Sensors and Actuators in the Cloud of Internet of Things," *International Journal of Internet of Things*, vol. 6, pp. 9–13, 2017.