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Context-aware energy optimization for perpetual IoT-based safe communities

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ABSTRACT

The IoT revolution has provided a promising opportunity to build powerful perpetual awareness systems. Perpetual awareness systems are sensing systems characterized by continuous monitoring and ubiquitous sensing; they are essential to many safety and mission-critical applications, e.g. assisted living, healthcare and public safety. In this paper, we present SAFER, a perpetual heterogeneous IoT system; deployed in homes to detect critical events (injury, hazardous-environment) that must trigger immediate action and response. A key challenge here is the energy consumption associated with perpetual operations. We propose a novel energy-aware perpetual home IoT system where battery-operated and wall-powered IoT devices co-execute to ensure safety of occupants. We use a semantic approach that utilizes context of extracted activities of daily living (ADLs) from device data to drive energy optimized sensor activations. To validate our approach, we developed an elderly fall detection system using multi-personal and in-situ sensing devices derived from real world deployments in SCALE project which has been deployed in Montgomery county, MD. Using initial measurements to drive larger simulations, we show that proposed Cost-Function-Gradient algorithm can achieve greater than 4X reductions in energy dissipation and doubling system of battery powered devices lifetime without loss of sensing accuracy.

1. Motivation

Recent advances in device, communication and processing technologies have created the internet of things (IoT) revolution; this is considered to be a key technological enabler that can embed intelligence into various aspects of our daily lives by creating smart homes, communities, and city level infrastructures worldwide. For instance, smart buildings, today, contain heterogeneous IoT devices, that manage control systems to improve the safety and comfort of building occupants by enabling a range of applications such as surveillance/security and fire protection while reducing energy footprints to lower operational cost.

Similarly, in the past decade, smart home sensing systems have created the capability to automatically and unobtrusively collect information about a resident's everyday behavior and provide value-added services derived from this information. Such efforts have used sensing technology to monitor the resident's activities in their home environment [1]. The new generation of personal sensing devices has also created the ability to sense personal health factors (e.g. heart rate, activity) and is making possible always connected health-care IoT solutions for elder care and care for individuals with disabilities.

One relevant use case of an IoT-based perpetual awareness application is that of elderly fall detection. Fall detection is a major challenge in the public health care domain – the Center for Disease Control reports over 2 million falls annually in the United States. The design of reliable systems to quickly detect and mitigate the effects of falls will help improve outcomes significantly. Similarly, a smart home security system can assist those with disabilities (with vision impairments, deaf and hard of hearing) by capturing anomalous events and intrusions and providing alerts in the event of suspicious movement.

While IoT deployments hold significant promises to improve the quality of life of citizens, several limitations arise in operating IoT deployments in a scalable, resilient manner over time. First, mission-critical awareness systems are expected to operate 24/7, i.e. perpetually, to monitor and detect any critical event. This raises issues of the cost of operation and continuous energy consumption. Second, IoT devices typically are small in size with restricted resources including limited compute power, battery and storage capability. Third, the need for low cost and mass-scale production further enhances the likelihood of component variability and structural failures. Lastly, the diversity of settings and deployments play an important role in both the accuracy and cost of the applications deployed.

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In this paper, we aim to handle the energy limitations caused by perpetual operation. Execution lifetimes of IoT devices rely heavily on limited on-board battery capacity; this has an impact on service availability and in turn affects the quality of service delivered by these solutions. Our key idea is to exploit heterogeneity of IoT devices and knowledge of the activities of daily living to create an energy-efficient perpetual IoT system without loss of service quality. Using a multistage approach that models the behavior of humans in a space, we develop intelligent device activation techniques that can enhance the effectiveness of the IoT awareness system, in terms of energy consumption and accuracy.

Our IoT setting is dynamic – it includes devices with varying capabilities in terms of computation, sensing, energy source, energy consumption, mobility and communication; these devices use diverse communication protocols and direct connections to cloud platforms. Perpetual IoT applications incur high communication and energy costs; managing the number of active devices to reduce network overhead is critical. We aim to design a system model that alters the state of IoT devices and communication by utilizing real time semantic knowledge on user activities. We also exploit the heterogeneity of IoT devices, multiple communication networks, current environment conditions and the *activity patterns* being inferred to enable energy efficiency. To lend focus, we develop our techniques in a target application domain – our IoT-based assisted living system aims to provide occupant safety while ensuring energy efficiency. Note that accuracy of event detection is a primary goal - missing a critical event (i.e. injury or fall) as a result of energy optimizations is not acceptable.

Key contributions of this paper include:

- Formalizing energy efficiency of perpetual Iot-based awareness systems as a constrained optimization problem, which we show to be NP-hard.
- Design a three-phase framework and associated algorithms for smart homes that combines a floor-plan segmentation algorithm [2], an activity recognition technique [3], and energy optimization algorithms with heterogeneous IoT devices.
- Development and validation of a prototype heterogeneous IoT system, "SAFER: an elderly fall detection IoT system" in a real world testbed.
- Extensive evaluations to study the scalability and effectiveness of our algorithms and approach using simulation studies.

2. Related work

In the last years, internet of things and energy efficiency have gained increasing attention from research communities. Many researchers focus on how IoT-enabled energy efficiency of home, building, etc. using IoT intelligent systems [4,5]. On the other side, novel techniques have been proposed to reduce energy consumption in the internet of things (IoT) platforms and Wireless sensor networks at the device, network and middleware/system levels.

In comparison, the IoT ecosystem is characterized by a larger level of heterogeneity, horizontal scalability, which mean that you can plug and play devices on the fly, and the node computation load can be higher than the transmission load. Despite the term IoT is relatively new, the idea of monitoring and controlling devices through computers and networks has been around for decades. IoT is a new paradigm that integrates several technologies that already existed, such as WSN. The number of scientific publications related to WSN has been declining in recent years, and this is not due to WSN is losing importance in nowadays, but researchers are beginning to treat WSN as a technology integrated into the IoT ecosystem.

2.1. *Energy optimization at the* device level

Vendors and engineers look into circuit, hardware, and software hardware optimization to reduce power consumption through dynamic voltage and frequency scaling, power-aware scheduling, power mode management, micro architectural techniques and energy harvesting methods. Dynamic voltage and frequency scaling (DVFS) is adopted to reduce power consumption by configuring the processor based on the requirements of the executing applications [6]. Moreover, power-aware scheduling aims at maximally exploiting the benefit of power manageable resources through switching among multiple power saving modes as different modes consume different amount of power [7]. Also, micro-architectural techniques leverage application properties to dynamically reconfigure a specific component of the system to save energy, such as main memory,cache [8–11]. In addition, energy harvesting methods where energy is derived from external sources, such as vibration, light, thermal, human motion and wireless energy harvesting to prolong battery longevity [12–14].

2.2. *Network layer energy efficiency approaches*

Standardization bodies and industry associations (IETF, IEEE, Bluetooth SIG, Zigbee Alliance, etc.) have developed protocols to enable energy efficient IoT by reducing communication overheads. Also, researchers have focused on the optimization of access technologies (802.15.4 radio, BLE, Wi-Fi low power, etc.), on adaptation of IP protocols (6LoWPAN, RPL, and CoAP) to extend the web architecture to the most constrained sensors, and on developing lightweight protocols enabling the connection of almost everything to the cloud (MQTT, etc.) [15–17]. Literature can be classified into three approaches *scheduling*, *routing* and *data-driven* [18].

Scheduling approaches [19–22] focus on optimizing the networking subsystem by exploiting node redundancy by employing adaptive duty cycling. Early work in duty cycling [23–26] assume that the sensor nodes and connections are homogeneous that are energy constrained (battery, energy harvesting). Techniques such as Low-Energy Adaptive Clustering Hierarchy (LEACH)[24], in homogeneous networks, aims to distribute energy dissipation evenly. Clustering algorithms [27–32] used in heterogeneous Wireless sensor networks such as the Stable Election Protocol (SEP) and the Energy efficient heterogeneous clustered (EEHC) assumes that a percentage of the population of static sensors are equipped with additional energy or have unlimited energy resources.

Routing approaches, such as [33–37] play an important role in the overall architecture of the internet of things. As routing techniques propose energy efficient routing, forwarding, topology strategies to controls the transmission of the packets with in the IoT by selecting the optimal route to save energy and ensure a longer network lifetime. Routing protocols fall into three categories: *reactive*, which establishes a route on demand, *proactive*, which maintains the topology and updates the routing tables periodically, and *hybrid* protocols.

Data-driven approaches [38–42]focus on reducing data sampling and transmission by exploiting data aggregation, compression, or prediction.

2.3. *Optimize energy at the* middleware level

There has been several research efforts to modify IoT behavior based on the application requirements which can be classified into two approaches. *Quality driven* approaches [43–46] that modify IoT behavior dynamically to conserve energy with meeting threshold such as QoS, in response to system changes. Secondly, *Event driven* approaches [47,48] that achieve energy efficiency by selectively allowing the minimum IoT resources and triggers more IoT resources as needed based on the application demand.

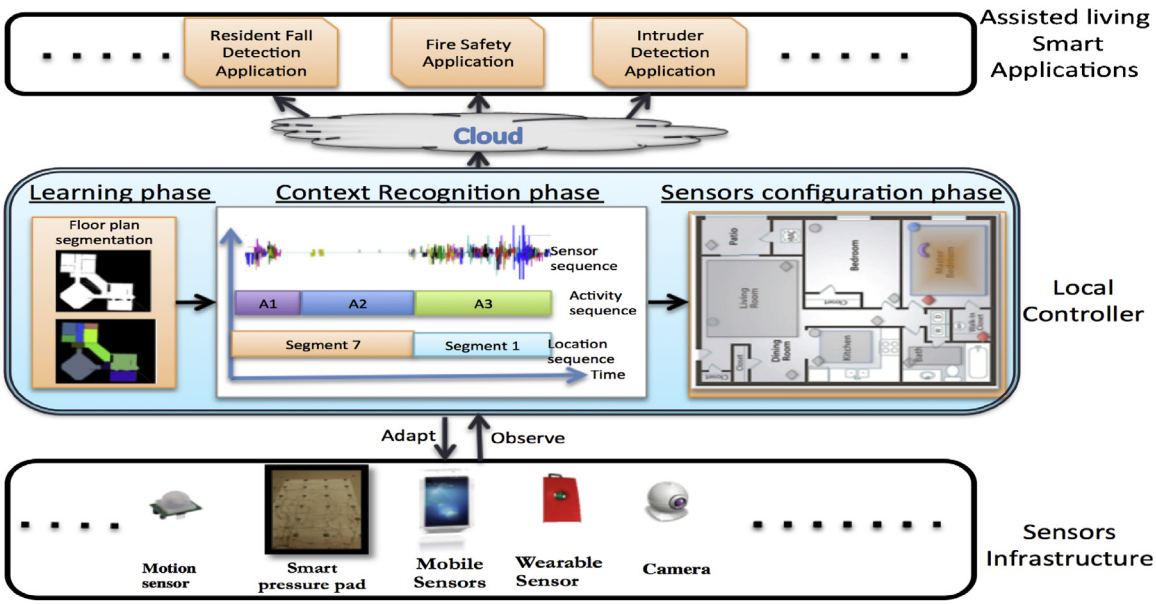


Fig. 1. The SAFER architecture illustrating the three phase approach.

3. Context-aware energy efficiency and perpetual IoT

In this section, we describe the unique aspects of energy optimization in the perpetual IoT setting and design a phased approach to address this concern.

3.1. Problem description

The energy efficiency problem is characterized in an assisted living context where heterogeneous IoT devices (wearable, ambient, and vision) are scattered in a home. These IoT devices have varying capabilities (power source, battery lifetime, connectivity, reliability and accuracy) are used as a part of an elderly fall detection system (SAFER). In general, they can be used for any critical event detection task. Through the elderly fall detection system, we recognized and identified problems and opportunities for improved operations. Battery-powered devices such as mobile and wearable sensors dissipate power quickly and need to be recharged.

Furthermore, one can designate areas in the floor plan that are used in patterns; i.e. not all wall-powered IoT devices are utilized all the time. In addition, context-aware activities of daily living (ADLs) knowledge of a resident can provide us with information about the location and activity type; this can be utilized intelligently to minimize energy dissipation in the integrated system. Knowledge of device capabilities can be also used to activate an adequate subset of IoT devices to meet the accuracy demand levels.

Given the above observations, our goal is to minimize energy consumption of the integrated IoT deployment (battery and wall-powered) to enable long-term operation while meeting accuracy threshold demands. We formalize the energy efficiency problem for heterogeneous IoT devices as a constrained optimization problem (proven to be NP-hard). Note that this optimization problem can be applied to any heterogeneous IoT deployment setting (independent of layout and instrumentation) and can be configured to preserve the desired accuracy thresholds.

3.2. The three phase approach

Developing an optimal energy efficient system for perpetual and heterogeneous IoT operation needs comprehensive knowledge about the floor-plan architecture, individual's activity patterns and IoT device status. To handle this complexity that arises due to dynamic nature and diversity of the underlying ADLs and IoT devices, we propose a three-phase system framework (Fig. 1).

In the first phase, i.e. the *learning phase*, we aim to capture the deployment setting. Specifically, we compute a floor-plan segmentation [2] of the space being instrumented and monitored, the IoT device profiles, including status and different configurations given infrastructure information; we also leverage an elementary activity pattern that is provided by the user. In the second *context recognition phase*, we utilize the infrastructure knowledge to develop a sliding window based approach [3] to perform activity recognition in a streaming fashion; recognizing activities as and when new occupancy sensor events are recorded, such as motion sensors. In the third phase, *the configuration phase*, the status of participating IoT devices is adjusted at run-time based on the current activity location and type. We design a dynamic configuration algorithm that is executed on the local controller to control the IoT network and to compute and realize the optimal overall energy configuration.

4. The energy optimization problem for perpetual IoT systems

In this section, we discuss our assumptions and define frequently used terms and notations. With the assumptions, we formulate the heterogeneous IoT devices energy problem as an NP-hard optimization problem.

4.1. Assumptions

We assume that in each home there is a *local controller*, which is a fixed device that has the ability to connect with all IoT devices through different protocols, such as Wi-Fi, Bluetooth, Ethernet, and ZigBee, to track and manage the IoT devices' status. Also, we assumed that all IoT devices are operating independently in terms of detecting the critical event they are monitoring.

4.2. Terms and notations

The *Activities of daily living (ADLs)* are routine activities that people tend to do every day without needing assistance, such as

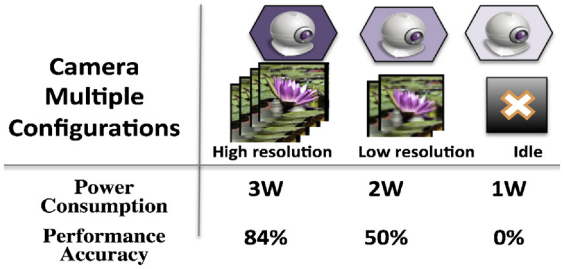


Fig. 2. Multiple configurations for each IoT device, camera as an example.

cooking. Additionally, we define a *critical event* to be an incident that has a high consequence such as fall of an elderly person in an assisted living home. All IoT devices deployed in the scene are intended to monitor the person and detect the critical event if it's ever happened. In addition, the floor-plan is divided into several *segments*, where each segment is a sub area of the home, such as the living room, that consists of a set of IoT devices.

We classify IoT devices in two groups in terms of their source of energy/power: unconstrained *wall-powered devices* that are connected to the energy grid all the time; constrained *battery-powered devices* that rely on their own limited battery or energy harvesting throughout their lifetime. Each IoT device can operate in different *configurations* in terms of choosing values for their different operating parameters, such as communication intervals, sampling rate and computation frequency. The variation of these values results in different amount of energy consumption rate and varying degree of accuracy level across the different configurations of a particular IoT device. For example, the camera (Fig. 2) can operate in multiple configuration, which affects its power consumption and the image quality.

We define *accuracy* of an IoT device for a given configuration to be the probability of detecting the critical event when the device operates in that configuration for a certain amount of time (referred to as the operation cycle). Obviously, there is a trade-off between the energy consumed by a device at its different configurations and their accuracy levels. Higher accuracy is desired but only at the cost of higher energy consumption, which leads to shorter system lifetime (it drains out the battery-powered devices). We are required to choose configurations for the devices so that system lasts long.

4.3. Problem formulation

We formulate ENERGY OPTIMIZATION FOR HETEROGENEOUS IOT DEVICES PROBLEM as a constrained optimization problem as follows. We have a set of n heterogeneous IoT devices in a certain segment, $i = 1, \ldots, n$. Each device can be described by a *profile*, which consists of different configurations the device can operate. Let device i have l_i configurations, and e_{ik} and a_{ik} denote the rate of energy consumption and accuracy level respectively for configuration k of device i ($1 \le k \le l_i$). Each device has a remaining battery capacity, denoted by r_i, at a certain time. Note that for wall-powered devices r_i is not defined or assumed to be ∞. Once a configuration is chosen for a device, it operates for a certain amount of time before the next configuration is chosen. This duration, the operation cycle, is denoted by T.

The recognized context such as a set of predefined ADLs each of which has its own *demand accuracy*, denoted by τ. The demand accuracy is the level of accuracy that all *active* devices should at least produce.

The second phase should recognize the performed activity with a level of uncertainty which is a challenge.To overcome this challenge we obtain the formulation as follow by considering the combined demanded accuracy which is the probability that at least one among the set of the expected recognized activities is performing by the monitored patient.

We argue that when multiple devices monitor the critical event, the combined accuracy increases. For example, if two devices independently detect the critical event with accuracy, which is the probability of detecting the critical event, equals to a_1 and a_2, then the combined accuracy will be the probability that at least one of them is detecting the event. That is:

$$\text{combined accuracy} = 1 - (1 - a_1)(1 - a_2)$$

The demand accuracy is a variable that changes depending on the daily activity performed. For example, the demand accuracy will be higher if the individual is cooking versus if he is sleeping. The more the activity is crucial, the higher the demand accuracy should be. Therefore, the demanded accuracy τ for each ADL can be defined in many ways. It can be defined based on labeled activity pre-training phase model. Another way is to increase the demand accuracy when the intensity of occupancy sensors' readings are increased. In addition, it can be prescribed by the supervising physician which we considered in this paper. We want to select the optimal IoT devices subset with their appropriate configurations, so that the total energy expenditure remains as low as possible, while keeping the expected level of accuracy from the selected configurations above the demanded activity's accuracy level τ.

This subset selection minimizes the overall energy consumption and maximizes the battery-powered devices lifetime. In order to minimize the overall energy consumption, we should consider the device's energy consumption rate at its different configurations and the number of active devices (depending on the demand accuracy). We also need to extend the lifetime of battery-powered devices, so we should consider the remaining battery capacity of those devices. Considering all these issues, we define a *cost function*, denoted by c_{ik}, for each configuration of an IoT device as follows:

$$c_{ik} = \eta_i \cdot e_{ik} \cdot T \tag{1}$$

The cost function captures the "cost" of operating device i in configuration k. The cost is directly proportional to the amount of energy consumed during the cycle, which is e_{ik}. T. 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. This is because battery-powered device runs on battery and their life depends on the remaining battery capacity. 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:

$$\eta_i = 1 + \beta \cdot \exp\left(-\frac{r_i}{r_i^0}\right) \tag{2}$$

where r_i^0 denotes the initial battery capacity of the device and β is a tunable parameter to adjust the effect. Obviously, for wall-powered device, we have $r_i^0 = \infty$, hence $\eta_i = 1$. For battery-operated devices, $\eta_i > 1$. Particularly, at the beginning (when r_i and r_i^0 are equal), $\eta_i = 1 + \beta.\frac{1}{e}$, and then η_i progressively takes higher value (as the r_i declines) until it reaches to $1 + \beta$ when there is no battery power left (i.e. $r_i = 0$).

We obtain an optimization formulation that chooses the configurations minimizing the overall cost of operation subject to the constraint that the combined accuracy level remains equal or above the demand accuracy. For the ease of exposition, we introduce an *idle* configuration (configuration 1) for each device that has zero accuracy at zero or low cost. This allows all devices to be operating exactly one configuration. By denoting x_{ik} to be the binary variable indicating whether we choose configuration k of device i. As we assumed that all IoT devices are independent, the combination

probability that all IoT devices detect the critical event can be wrote as follow.

$$1 - \prod_{i=1}^{n}\prod_{k=1}^{l_i}(1 - x_{ik} \cdot a_{ik}) \geq \tau \tag{3}$$

Therefore, we have the following optimization problem:

$$\text{minimize} \quad \sum_{i=1}^{n}\sum_{k=1}^{l_i} x_{ik} \cdot c_{ik} \tag{4}$$

$$\text{subject to} \quad 1 - \prod_{i=1}^{n}\prod_{k=1}^{l_i}(1 - x_{ik} \cdot a_{ik}) \geq \tau \tag{5}$$

$$\sum_{k=1}^{l_i} x_{ik} = 1, \quad \forall i \tag{6}$$

$$\forall x_{ik} \in \{0, 1\}, \quad \forall i = 1, \ldots n, \quad \forall k = 1, \ldots l_i$$

We can simplify constraint (5) as follows:

$$1 - \prod_{i=1}^{n}\prod_{k=1}^{l_i}(1 - x_{ik} \cdot a_{ik}) \geq \tau$$

$$\ln \prod_{i=1}^{n}\prod_{k=1}^{l_i}(1 - x_{ik} \cdot a_{ik}) \leq \ln(1 - \tau) \tag{7}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{l_i} x_{ik} \cdot \ln(1 - a_{ik}) \leq \ln(1 - \tau)$$

Consequently, we obtain:

$$\begin{aligned} &\text{minimize} && \sum_{i=1}^{n}\sum_{k=1}^{l_i} x_{ik} \cdot c_{ik} \\ &\text{subject to} && \sum_{i=1}^{n}\sum_{k=1}^{l_i} x_{ik} \cdot \ln(1 - a_{ik}) \leq \ln(1 - \tau) \\ & && \sum_{k=1}^{l_i} x_{ik} = 1, \quad \forall i \end{aligned} \tag{8}$$

The ENERGY OPTIMIZATION FOR HETEROGENEOUS IOT DEVICES PROBLEM is an NP-hard problem that can be reduced from the Minimum Multiple Choice Knapsack Problem. The knapsack problem is known to be a well-studied NP-hard problem and a special case of the multiple choice knapsack problem with the feature that each item is in a group of its own [49].

In the MINIMUM MULTIPLE CHOICE KNAPSACK PROBLEM there is a set of items which are partitioned into groups and each item has a benefit and a weight. The objective of the MMKP is to find the least profitable set of items such that the total weight of the selected items is at least the weight limit [50].

Similarly, in the HETEROGENEOUS IOT DEVICES ENERGY OPTIMIZATION PROBLEM, the goal is to select a set of IoT devices that minimize the total cost with exceeding the activity's accuracy threshold. Each IoT device has a set of configurations, including the option of not selecting it. Therefore, each IoT device defines a class from which we are selecting at most one option.

5. Proof on computational complexity

We prove the computational complexity (NP-hardness) of the energy optimization for heterogeneous IoT devices problem, by showing that the minimum multiple-choice knapsack problem, which is known to be NP-complete, can be reduced to it. Knapsack problem has been widely studied in computer science for years. It is one of the problems on Karp's original list of 21 NP-complete problems [51]. There exist several variants of the problem, in this proof we use the minimum multiple-choice version of the problem.

The formulation of the energy optimization for heterogeneous IoT devices problem is:

According to our settings,we have a set of n heterogeneous IoT devices in a certain segment, $i = 1, \ldots, n$. Each device i can be described by a *profile*, which consists of multiple configurations k.

e_{ik} and a_{ik} denote the rate of energy consumption and accuracy level respectively for configuration k of device i ($1 \leq k \leq l_i$). Each device has a remaining battery capacity, denoted by r_i, at a certain time. Note that for wall-powered devices r_i is not defined or assumed to be ∞.

We prove this constraint optimization problem, formulated as equation (8). with all information available, is an NP-hard by showing that the minimum multiple-choice knapsack problem which is known to be NP-complete, can be reduced to it.

In order to define the minimum multiple-choice knapsack problem formally, consider m mutually disjoint classes$N_1 \ldots N_m$, $i = 1, \ldots, m$ of items to be packed into a knapsack to be at least the capacity C. Each item j in i class has a cost c_{ij} and a size s_{ij}, and the problem is to find a subset of exactly one item from each class such that least profitable set of items such that the total size of the selected items is at least the capacity C. If we introduce the binary variables x_{ij}, which take on value 1 if and only if item j is chosen in class i, the MMCKP is formulated as:

$$\begin{aligned} &\text{minimize} && \sum_{i=1}^{m}\sum_{j \in N_i} x_{ij} \cdot c_{ij} \\ &\text{subject to} && \sum_{i=1}^{m}\sum_{j \in N_i} x_{ij} \cdot s_{ij} \geq C \\ & && \sum_{j \in N_i} x_{ij} = 1, \quad \forall i \end{aligned} \tag{9}$$

The energy optimization for heterogeneous IoT devices problem belongs to NP as there is a subset of IoT devices with selecting at most one configuration from each of n IoTs,device i has l_i different configurations, that has the least total cost, and the total combined-accuracy is more than or equal to the activity's accuracy demand τ. Thus, if we have a proposed correct 'yes' solution, we can verify this solution in polynomial time $O(n)$ by checking that energy optimization for heterogeneous IoT devices problem has a satisfying subset.

Reduction from minimum multiple choice knapsack problem $<_P$ energy optimization for heterogeneous IoT devices problem. In other words, minimum multiple-choice knapsack problem is polynomial reducible to the energy optimization for heterogeneous IoT devices problem. We consider an instance of minimum multiple-choice knapsack problem, and we will construct an equivalent instance of the energy optimization for heterogeneous IoT devices problem.

- m mutually disjoint classes in minimum multiple-choice knapsack problem $\rightarrow$ n IoT devices each with multiple configurations in energy optimization for heterogeneous IoT devices problem.
- Class N_i has multiple j items $\rightarrow$ Device i has l_i different configurations.
- c_{ij} cost for each item j in class N_i $\rightarrow$ c_{ik} cost for each IoT device i in its configuration k

Table 1
SAFER IoT devices' configurations.

IoT device	Battery capacity	Configurations	Power consumption	Performance accuracy
Mobile phone	**8** Wh	Fastest	421 mW	70%
		Game	392 mW	65%
		UI	334 mW	50%
		Normal	287 mW	40%
		Idle	28 mW	0%
Wearable device	**0.72** Wh	100 ms sample rate	16.5 mW	63%
		500 ms sample rate	12.48 mW	41%
		Idle	1.32 mW	0%
Smart pad 4 × 6	∞	Fast sample rate	2.1 W	70%
	18 Wh	Slow sample rate	1.85 W	50%
		Idle	1.1 W	0%
Camera [55,56]	∞	High image resolution	3 W	84%
	23 Wh	Low image resolution	2 W	≃ 50%
		Idle	1 W	0%
Microsoft Kinect [57]	∞	High resolution	12 W	91%
		Low resolution	7 W	83%
		Idle	1 W	0%

- s_{ij} size of each item → (-ln$(1 - a_{ik})$) accuracy delivered by each IoT device i in its configuration k, note that this is $(-\ln(1 - a_{ik}))$ a positive value as $0 \le a_{ik} \le 1$
- C the least capacity limit → (-ln$(1 - \tau)$) demanded accuracy

Therefore, the Minimum multiple-choice knapsack problem can be reduced to energy optimization for heterogeneous IoT devices problem, which means energy optimization for heterogeneous IoT devices problem is at least as hard as the Minimum multiple-choice knapsack problem. Therefore, the energy optimization for heterogeneous IoT devices problem is NP-hard.

6. Algorithms and heuristics for energy optimization in perpetual IoT systems

One naive approach we can consider is to *activate all the IoT devices* all the time. Obviously, that would deplete energy from all devices without raising system accuracy much. In this section, we propose a set of feasible techniques to energy efficient perpetual IoT operation.

6.1. Greedy algorithms

6.1.1. Balanced Remaining Battery Lifetime (BRBL)

In this approach, we activate the wall-powered devices first and then choose the battery-operated devices in descending order of their remaining battery capacity until we exceed the current activity's accuracy threshold. This algorithm inspired from some related work which schedule sensors activation based on its residual energy, such as [52]

6.1.2. Cost Function Gradient (CFG)

This solution is the greedy heuristic solution to our formulated MCKP problem. It is known that linear relaxation of MCKP [53], in which the indicator variables x_{ik} can be assigned real values instead of binary 0, 1, that can be optimally solved by the greedy algorithm. As we cannot add a fractional IoT device, we will use the greedy integral algorithm with multiple configurations selections for each device as fractional placement. The algorithm starts with an empty set with 0 overall benefit (delivered accuracy) and 0 cost (energy consumption). It then makes a sequence of changes in which the selected IoT devices' configurations are upgraded to more accurate option and more overall benefits. The process continues until the demanded accuracy is achieved.

The pseudo-code for CFG is given in the following algorithm.

Algorithm 1. IoTSelectionBasedonCFG(τ, s)

Algorithm 1: IoTSelectionBasedonCFG(τ, s)

```
Initialize CombinedAccuracy = 0;
Initialize list(i, k) ← all the available IoT
  devices with its configurations k in this
  segment;
Enable selectedIoT(i, k) ← the lowest
  configuration k for all available IoT devices;
forall list(i, k) do
    cost(i,k)= e_ik.(1 + β · exp(−r_i / r_i^0))
end
foreach list(i, k) do
    deltaA =
      accuracy(i, k_next) − accuracy(i, k_cur)
    deltaC = cost(i, k_next) − cost(i, k_cur)
    Calculate slope(i, k) = deltaA/deltaC
end
while (CombinedAccuracy ≤ τ) do
    Select i_k with the largest slope;
    selectedIoT(i, k) =1 ;
    forall selectedIoT(i, k) do
        PiAccuracy* = (1 − accuracy(i, k));
    end
    CombinedAccuracy = (1 − PiAccuracy);
end
```

6.2. The dynamic priority scheduling algorithms

Dynamic priority scheduling is a scheduling algorithm in which the priorities are calculated during the execution of the system. The goal of this dynamic priority scheduling is to adapt IoT devices' configuration dynamically. The priority policy can be based on the location of the monitored user. In this approach, we activate the IoT devices that are present in the segment area where the user is currently in.

Furthermore, the second approach is to activate a subset of IoT devices based on power supply policy. Since our goal is to keep the battery-powered devices alive for longer time, we implement a second approach that gives priority to the wall-powered devices and activates them first until the combined accuracy exceeds the demand accuracy for the current activity.

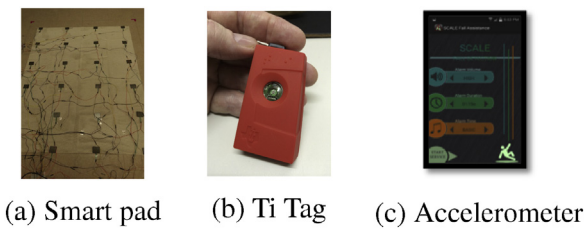


Fig. 3. SAFER prototype's IoT devices.

7. SAFER: a prototype platform and testbed

SAFER is a low-cost elderly fall detection system, it was motivated by the SCALE smart community project [54]; an initial version was deployed at a senior living facility in Montgomery County, MD. SAFER is implemented to validate our approach and explore challenges that arise in real world deployments.

7.1. Elderly fall detection system

According to the U.S. Department of Health and Human Services, the senior population (65+) represented 13.3% of the U.S. population in 2011 with an increase from 35 million in 2000 to 41.4 million in 2011. About 28% (11.8 million) of all noninstitutionalized seniors in 2012 lived alone. In addition, according to the Centers for Disease Control and Prevention, one out of three older people fall each year and 2.5 million elderly people are treated in emergency departments for fall injuries. For the elderly who experience serious fall injuries, the amount of time spent immobile often affects their health outcome. Muscle cell breakdown starts within 30–60 min of compression due to falling. Consequently, one of the most important personal sensing systems in the safe communities for elderly people is the fall detection system. The testbed for SAFER, as shown in Fig. 3, includes (a) a smart pressure pad which is a 4×6 matrix consisting of 24 Square Force-Sensitive Resistor sensors; (b) wearable sensor (CC2541 Ti SensorTag); (c) mobile sensor (accelerometer); (d) a camera (INSTEON). A local broker (Raspberry Pi B) supports the interconnections of multiple networks and sensors, and publishes data to the back-end SCALE server using the MQTT protocol.

7.2. Initial measurements on real testbeds

We measure the energy consumption and accuracy of fall detection for each participating IoT device in different configurations. The values are shown in Table 1.

For the mobile phone experiments, we used an Android Nexus 4 mobile with BLE support and an Invensense MPU-6050 accelerometer, which functions as an accelerometer and a gyroscope. The Nexus 4 system provides four default sampling rates: Fastest (5 ms), Game (20 ms), UI (66 ms), and Normal (200 ms). The sampling rate affects the sensor's ability to send information to the application layer.

A higher sampling rate delivers more frequent updates leading to more accurate results but also consumes more energy. The wearable device we used in the experiments is Ti Sensor Tag, a BLE (Bluetooth Low Energy) dongle that transmits its sensor data to the local controller at fixed intervals, the fastest interval being 100 ms. The tag uses KXT J9 accelerometer and a standard CR2032 coin battery, which has the typical capacity of 240 mAh. Therefore, we do not expect the Ti Sensor Tag to work longer than 48 h in its maximum mode. The smart pad consists of 24 FSR pressure sensors with the fast sampling rate of 5 system snapshots at every 2.4 s.

We also measure the energy consumption of occupancy sensors as we use them in the activity recognition phase. For many years, occupancy sensors, such as motion, door and temperature sensors, have been used in smart buildings, often for lighting and HVAC control. Studies have shown that adding occupancy sensors to control lighting consumption can reduce lighting energy use from 10% to 90% or more depending on the use of the space. One study conducted on a university campus found that installing occupancy sensors to control lighting in more than 200 rooms in 10 buildings provided an annual cost savings of about $14,000 with a simple payback of 4.2 years.

In our large setup, as shown in Fig. 5, we consider 39 occupancy sensors that have been used by CASAS dataset [58,59] for daily activity recognition. Our dataset and recognition techniques are applied for one resident [59]. It comprises of 31 motion, 4 door, and 4 temperature sensors. These sensors consume power at a rate less than 8 watts and can be wired or wireless with a slow-battery-drain. In contrast, in-home fall detection systems use IoT devices, such as cameras, Microsoft Kinect, and mobile phones that consume considerably higher amount of energy. The system also contains mobile and wearable sensors that are power restricted and are fast-battery-drain devices.

7.3. Additional use cases

Our approach can be replicated with diverse safety, healthcare and mission-critical scenarios such as assisted living applications, intruder detection application, fire safety application, etc. Theses applications aim to increase the quality of life of people such as elderly people and to help them have an independent lifestyle. As

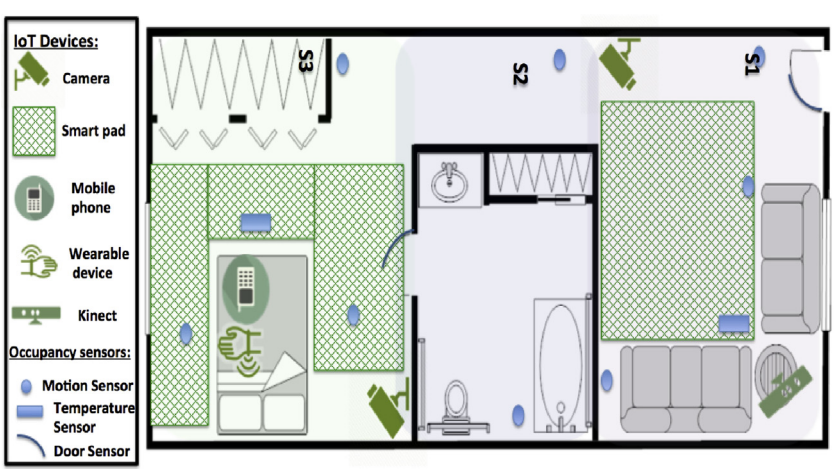


Fig. 4. Floor-plan of the "medium" scale setting 350 ft^2, 7 IoT devices.

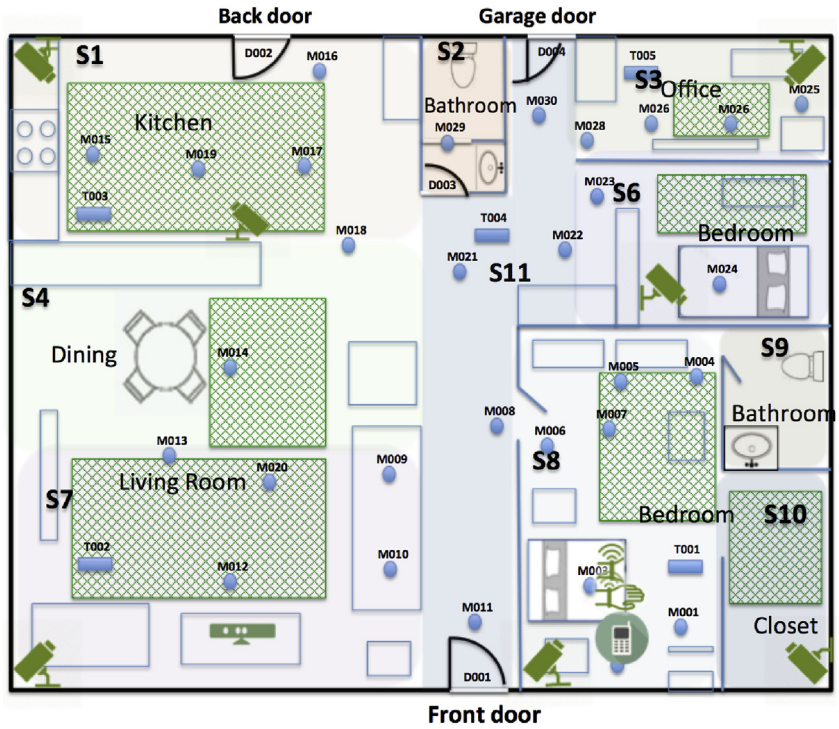


Fig. 5. Floor-plan of the "large" scale setting 900 ft^2, 18 IoT devices.

elderly people's population increases year after year, around 28% (11.8 million) of all elderly people in 2012 lived alone. If we apply our approach on another application scenario e.g. 'Intruder detection system' which is a network of integrated IoT devices working together with a central controller to protect against burglars and other potential home intruders. Our three-phase approach starts with a learning phase that captures the deployment setting by computing a floor-plan segmentation of the space, the participated IoT device profiles, including status and different configurations given infrastructure information. Then, in the second phase we perform activity recognition using our sliding window activity recognition based on sort of sensors such as smartphones, wearable sensors, cameras, and occupancy sensors. After that, based on the recognized location and activities' patterns the dynamic configuration phase adjusted the status of participating IoT devices in entry points, like doors and easily accessible windows, as well as interior spaces containing valuables like art, computers, etc. Then, compute the optimal overall energy configuration by reducing the energy consumption on the attended areas, for example.

8. Performance evaluation and results

We have implemented five different IoT devices activation scheduling algorithms and compared their performances: all Devices, Priority based on location scheduling, Priority based on power supply scheduling, BRBL (Balanced Remaining Battery Lifetime), and CFG (Cost Function Gradient).

8.1. Experimental setup – simulation studies

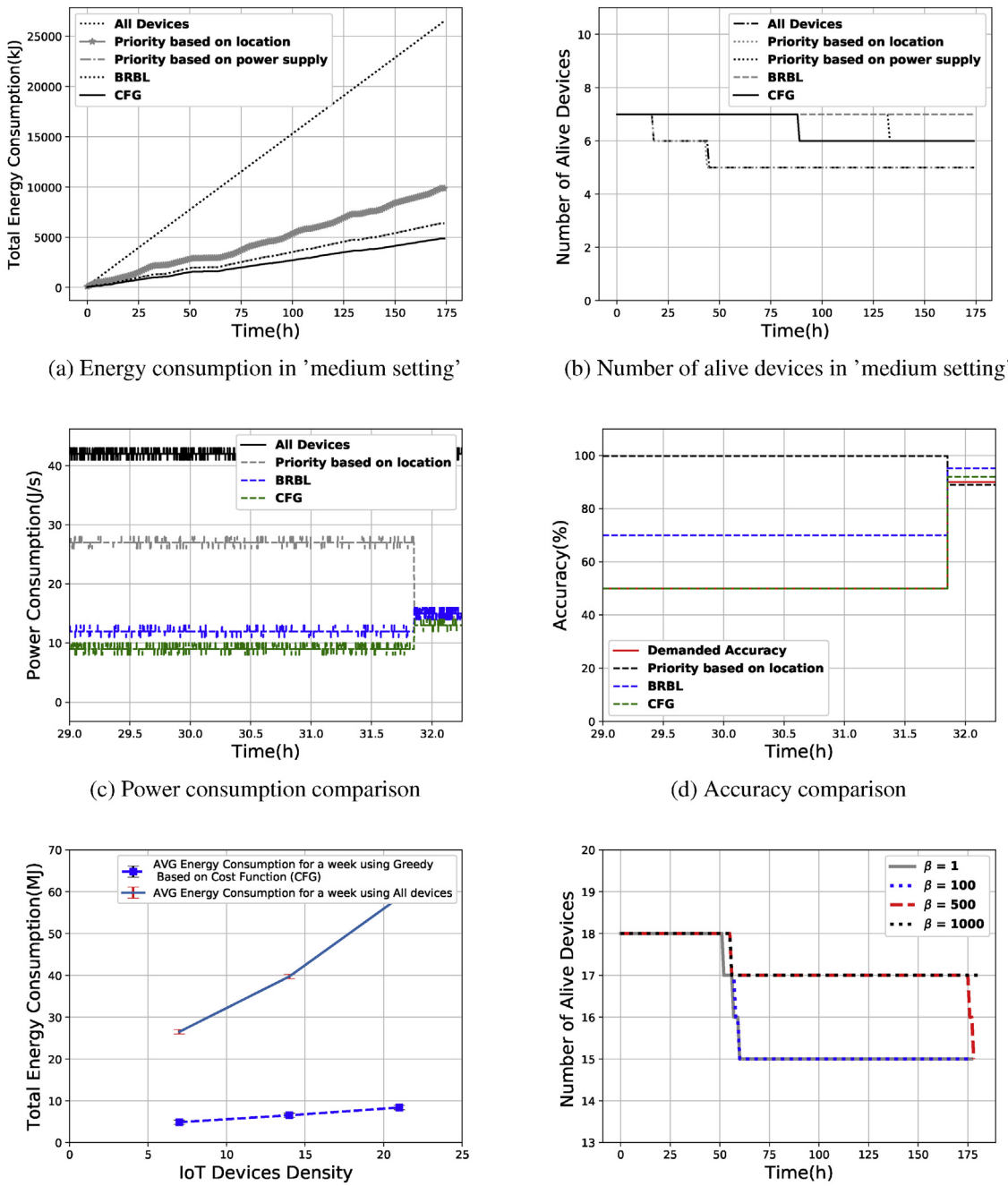
To conduct further experiments, we developed a discrete-event simulator and created based on real-world elderly living options four test cases at different scales in terms of size and battery devices ratio. The first case is of medium scale and corresponds to an assisted living community. The average floor-plan includes a bedroom, living room and a bathroom with an average space of 350 ft^2. (Fig. 4) shows the floor-plan with the associated IoT devices. We assume an instrumentation density of 1 IoT device for every 50 ft^2 – the medium scale, therefore, has 7 IoT devices: 5 static wall-powered devices and 2 mobile battery-powered devices.

The second test case is an independent living community, which is a large scale deployment. Here, the average CASAS floor-plan, includes 2 bedrooms, a living room, kitchen, office and 2 bathrooms with an average space of 900 ft^2 (Fig. 5). In the large scale setup, we considered 18 IoT devices: 15 static wall-powered devices and 3 mobile battery-powered devices in the standard setup. In addition, we considered a semi-portable setting in which battery powered devices form about 50% of the IoT platform, (8 wall-powered devices and 10 battery-powered). Also, we considered a portable setup that relies on approximately 95% battery-powered devices, (17 battery powered and 1 wall-powered).

We execute our simulations on the CASAS trace dataset obtained from [59] that contains the activities of daily living of an individual in an assisted living setting for a week.

Performance Evaluation Metrics:

- *Cumulative Energy Consumption*:
  The total energy consumption can be used as a benchmark to evaluate the energy optimization algorithms.
- *Number of alive battery-powered devices*:
  Intuitively, an optimized algorithm should maximize the lifetime of battery-powered devices by increasing their idle time and utilizing the wall-powered devices. As well as adjusting the effect of β which increases the priority of wall-powered over battery-operated devices.
- *Half-system lifetime*:
  In addition, the algorithm increases the system lifetime by adding a time extension in proportion to the original system lifetime. Therefore, we defined the half system lifetime as the period time where at least fifty-percent of the battery devices are alive.
- *Accuracy*:
  Moreover, increasing the accuracy is preferable which is the probability of detecting the event when the device operates in a configuration.



(a) Energy consumption in 'medium setting'

(b) Number of alive devices in 'medium setting'

(c) Power consumption comparison

(d) Accuracy comparison

(e) Density of IoT devices and energy consumption using the CFG algorithm in 'medium setting'

(f) β and battery lifetime of IoT devices using the CFG algorithm in 'large semi-portable setting'

Fig. 6. Simulation results.

- *Power Consumption*:
  Therefore, raising the accuracy, increase the power consumption cost in any device. An optimized algorithm should balance between these two parameters based on the application requirements.

8.2. Experimental results

8.2.1. Basic comparisons and effect of energy optimization algorithms

(a) Cumulative energy consumption comparison:
Fig. 6(a) shows the total energy consumption in different algorithms. As we can observe, activating sensors based on locations reduces energy consumption by half compared to the case when all IoT devices are running. The CFG algorithm saves nearly 80% to 90% energy. On the other hand, the BRBL algorithm consumes little more energy than CFG because of its high reliance on the wall-powered devices, which consume more energy than their battery counterpart. In addition, Fig. 8 shows the gained benefit from applying CFG (Cost Function Gradient) algorithm in two settings' scale, which illustrated that the effectiveness of CFG (Cost Function Gradient) increases as the scale grows.

(b) Battery lifetime of IoT devices:
In our standard medium experiments, we used two battery-powered devices: the mobile phone, and wearable devices. Fig. 6(b) shows power drain patterns of the battery-powered

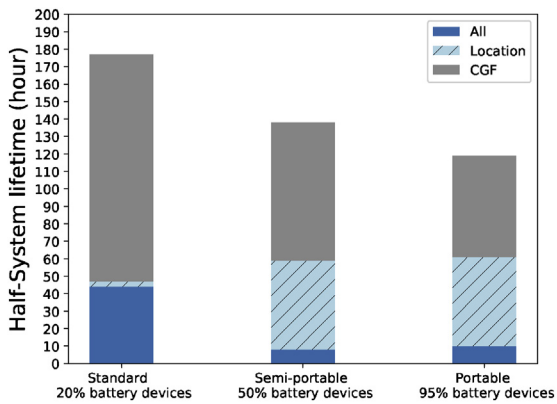


Fig. 7. Half-System lifetime in multiple setting with different ratios of battery-operated to wall-powered devices.

IoT devices. As such, we do not expect any wearable IoT device, such as the Ti Sensor Tag, and the mobile phone to work longer then 48 h, 20 h respectively. Note that battery-powered devices may be occasionally recharged, but for consistent comparison we show the results for only one full cycle (from a fully charged battery to zero-power).

The CFG algorithm extends the battery capacity 2–4 times by reducing the energy consumption of the IoT devices by choosing the best configurations for the devices. As we can see, the first IoT device in the CFG algorithm drains out after 80 h, while the second IoT battery capacity extends to more than 175 h.

The BRBL algorithm extends the battery capacity of the constrained IoT devices up to 175 h because it keeps them on the lowest configurations at all time, except in locations where wall-powered devices are not available, such as in the bathroom in the medium scale deployment.

(c) Power consumption and accuracy comparison:

Fig. 6(c) and (d) show the comparison among different algorithms in terms of power consumption and accuracy respectively. Specifically, we zoomed a 4-hour window after 29 h to observe the difference among the different algorithms. We notice that CFG has the lowest power consumption and it remains closest to the demanded accuracy. This is because of its utilization of different configurations in different devices.

8.2.2. Scalability comparisons and effect of tuning CFG algorithm

(a) Scalability:

We examine the effect of device density in energy consumption using the CFG algorithm. In our setting, we deploy one IoT device per 50 ft^2. We double and triple this number to see the effect on energy consumption. Results in Fig. 6(e) show that CFG works well when we increase the device density. As the density grows, the energy consumption also slightly rises, which is due to the energy consumption of the added IoT devices in their idle configurations.

(b) Half-System Lifetime:

We examine the effect of different ratios of battery-operated to wall-powered devices in our large settings (standard, semi-portable, and portable) using the CFG algorithm. Results in Fig. 7 show that CFG works well and increase the system lifetime in all our settings. However, as the percentage of battery devices grows, starting from standard setting to portable settings the time extension in proportion to original system lifetime slightly decrease, which is due to the increase relaying on battery-powered devices.

(c) β and Battery lifetime of IoT devices:

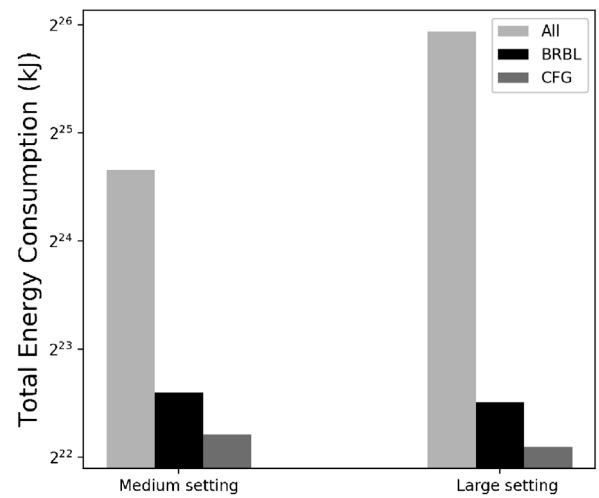


Fig. 8. Algorithms' total energy consumption for one week in two setting using BRBL and CFG algorithms.

We examine the effect of adjusting β in our large settings semi-portable, 50% battery-operated devices, using the CFG algorithm. Results in Fig. 6(f) show that as the value of β grows, the battery-powered devices' lifetime extended. This is because when we increase β value, it increases the priority of wall-powered over battery-operated devices.

9. Conclusion

In our approach we uniquely leveraged the concept of activities of daily living (ADLs) for energy-optimized sensor activations to create SAFER, a perpetual IoT awareness platform. We developed and deployed an elderly fall detection system; testbed measurements were used to drive larger scale simulation studies. Experimental studies with real world trace datasets indicated that the proposed Cost-Function-Gradient algorithm was able to achieve more than 80% reductions in energy consumption, doubling the system-lifetime. We believe that such techniques are essential to creating deployable IoT for mission-critical societal applications that require perpetual operations such as healthcare and assisted living. More broadly, we aim to enable and ensure the multiple functional and non-functional needs of societal scale applications by leveraging new emerging technologies - this will require an in-depth understanding of how these requirements interact.

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