SAFER: An IoT-Based Perpetual Safe Community Awareness and Alerting Network

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***Abstract*—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 extracts activities-of-daily-living 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. Using initial measurements to drive larger simulations, we show that our Cost-Function-Gradient algorithm can achieve greater than 4X reductions in energy dissipation without loss of sensing accuracy.**

I. 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. Such IoT awareness systems are comprised of diverse heterogeneous IoT devices that interact and cooperate to deliver a service and trigger a crucial event.

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.

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 com-

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munication; 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.

II. 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.

Related Work: In recent years, novel techniques have been proposed to reduce energy consumption in sensor networks at the device, communication and network levels. At the *device level*, vendors and engineers look into circuit and hardware optimization to reduce power consumption through energy harvesting methods and improved duty-cycling methods [4, 5]. At the *communication layer*, standardization bodies and industry associations (IETF, IEEE, Bluetooth SIG, Zigbee Alliance, etc.) have specified and developed protocols to enable energy efficient IoT by reducing communication overheads. This research has 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.). Literature on wireless sensor networks (WSNs) for *network level* energy optimization can be classified into three main approaches *duty cycling*, *data-driven* and *mobility* [6].

Duty cycling approaches [7]–[10] focus on optimizing the networking subsystem by exploiting node redundancy. As sensor nodes perform a cooperative task, nodes alternate between active and sleep states. Early work in duty cycling generally assume that the sensor nodes in the wireless sensor networks are homogeneous, and connected via homogeneous transmission methods which are energy constrained (battery, energy harvesting). Techniques such as Low-Energy Adaptive Clustering Hierarchy (LEACH) [8], applied in homogeneous networks, aims to distribute energy dissipation evenly, so doubling the useful system lifetime. *Data-driven* approaches [11, 12] focus on reducing data sampling and transmission by exploiting data aggregation, compression, or prediction. *Mobility* [6] is focused in having mobile entities, which can be the sink or the whole network nodes.

In comparison, the IoT ecosystem is characterized by a larger level of heterogeneity. Clustering algorithms used in heterogeneous networks include techniques such as the Stable Election Protocol (SEP) [13], where nodes have two different energy levels, normal and advanced and the Energy efficient heterogeneous clustered (EEHC) technique [14] which assumes that a percentage of the population of static sensors are equipped with additional energy. Similarly, the Energy Efficient Clustering Scheme (EECS) [15], uses cluster heads, i.e. nodes with more residual energy as gathering points. Energy efficient cluster head election protocols [16] have been designed for heterogeneous networks. A distributed extension, Distributed Energy Efficient Clustering (DEEC) [17], assumes that all nodes in the sensor network are equipped with different levels of energy. In [18], they explore placing static nodes that have unlimited energy resources, so they have two levels, nodes that consume the most energy should be line powered and the leaf nodes that consume less power.

A. Problem Description

The energy efficiency problem is characterized in a assisted living context where heterogeneous IoT devices (wearable, ambient, and vision), Figure 5, 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. Knowledge of the activities of daily living (ADLs) of a resident can provide us with information about the location and activity type; this can

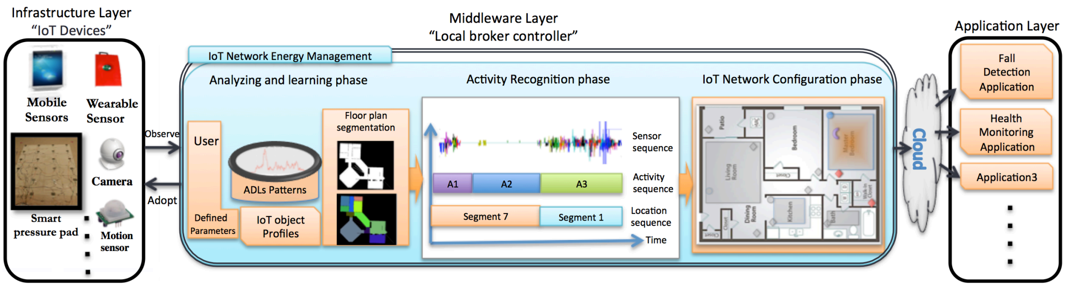


Fig. 1: The SAFER Architecture illustrating the Three Phase Approach

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.

B. SAFER: 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 (Figure 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 *activity 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.

III. 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.

A. Assumptions

We assume only *one resident* at home, because our approach targets independent assisted living systems; also, our dataset and recognition techniques are applied for one resident [19]. Moreover, 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.

B. Terms and Notations

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

C. 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, $i = 1, \cdots, n$. 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.

We have 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. 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, we have the following optimization problem:

$$\text{minimize} \quad \sum_{i=1}^{n} \sum_{k=1}^{l_i} x_{ik} \cdot c_{ik} \tag{3}$$

$$\text{subject to} \quad 1 - \prod_{i=1}^{n} \prod_{k=1}^{l_i} (1 - x_{ik} \cdot a_{ik}) \ge \tau \tag{4}$$

$$\sum_{k=1}^{l_i} x_{ik} = 1, \forall i \tag{5}$$

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

We can simplify constraint (4) as follows:

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

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

$$\sum_{i=1}^{n} \sum_{k=1}^{l_i} x_{ik} \cdot \ln(1 - a_{ik}) \le \ln(1 - \tau) \tag{6}$$

Consequently, we obtain:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{i=1}^{n} \sum_{k=1}^{l_i} x_{ik} \cdot c_{ik} \\
\text{subject to} \quad & \sum_{i=1}^{n} \sum_{k=1}^{l_i} x_{ik} \cdot \ln(1 - a_{ik}) \leq \ln(1 - \tau) \\
& \sum_{k=1}^{l_i} x_{ik} = 1, \forall i
\end{aligned} \tag{7}
$$

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 [20].

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 [21].

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.

IV. 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.

A. The Priority Algorithms

1) Based on location: In this approach, we activate the IoT devices that are present in the segment area where the user is currently in.

2) Based on power supply: 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.

B. Greedy Algorithms

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.

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 [22], 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 which stops short of the last selection that results in a fractional placement. The algorithm starts with an empty set with 0 overall benefit and 0 cost. 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 Algorithm 1.

Algorithm 1: IoTSelectionBasedonCFG(τ, s)

$CombinedAccuracy = 0$;
Initialize $list(i,k) \leftarrow$ all the available IoT devices with its configurations k in this segment;
Enable $selectedIoT(i,k) \leftarrow$ the lowest configuration k for all available IoT devices
while ($CombinedAccuracy \leq \tau$) **do**
    (**for all** list(i,k))$\leftarrow 1 + \beta \cdot \exp(-\frac{r_i}{r_i^0})$
    foreach $list(i,k)$ **do**
        $deltaA = accur(i, k_{next}) - accur(i, k_{cur})$
        $deltaC = cost(i, k_{next}) - cost(i, k_{cur})$
        Calculate slope$(i,k) \leftarrow deltaA/deltaC$
    end
    Select i_k with the largest slope;
    $selectedIoT(i,k) = 1$;
    $CalculateCombinedAccuracy$;
end

V. SAFER: A Prototype Platform and Testbed

SAFER is a low-cost elderly fall detection system, it was motivated by the SCALE smart community project [23]; 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.

A. 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 non-institutionalized 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 minutes 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 Figure 2, includes (a) a smart pressure pad which is a 4x6 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.

(a) Smart pad (b) Ti Tag (c) Accelerometer

Fig. 2: SAFER Prototype's IoT Devices

B. *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 I.

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 (5ms), GAME (20ms), UI (66ms), and Normal (200ms). 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 100ms. The tag uses KXT J9 accelerometer and a standard CR2032 coin battery, which has the typical capacity of 240mAh. Therefore, we do not expect the Ti Sensor Tag to work longer than 48 hours 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 sec.

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 Figure 5, we consider 39 occupancy sensors that have been used by CASAS dataset [19, 24] for daily activity recognition. 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.

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	∞	Fast sample rate	2.1 W	70%
4x6		Slow sample rate	1.85 W	50%
		Idle	1.1 W	0%
Camera	∞	High image resolution	3 W	84%
[25] [26]		Low image resolution	2 W	≃ 50%
		Idle	1 W	0%
Microsoft Kinect	∞	High resolution	12 W	91%
[27]		Low resolution	7 W	83%
		Idle	1 W	0%

TABLE I: SAFER IoT Devices' Configurations

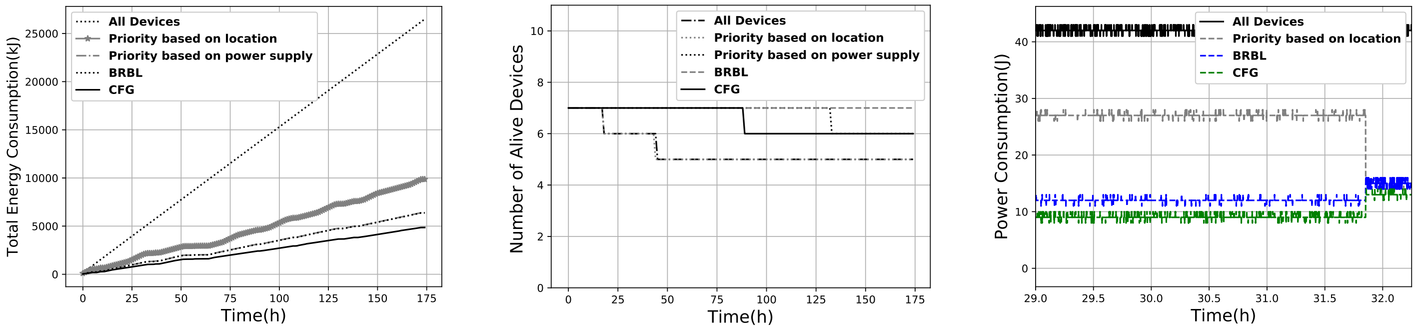
VI. Performance Evaluation and results

A. *Experimental Setup - Simulation Studies*

To conduct further experiments, we developed a discrete-event simulator and created two test cases at different scales based on real-world elderly living options. 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. Figure 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 floor-plan includes 2 bedrooms, a living room, kitchen, office and 2 bathrooms with an average space of 900 ft^2 (Figure 5). In the large scale setup, we considered 18 IoT devices: 15 static wall-powered devices and 3 mobile battery-powered devices. We execute our simulations on the CASAS trace dataset obtained from [19] 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.



(a) Energy consumption in 'medium setting' (b) Number of alive devices in 'medium scale' (c) Power consumption comparison

(d) Energy consumption in 'large setting' (e) Number of alive devices in 'large setting' (f) Accuracy comparison

Fig. 3: Simulation Results

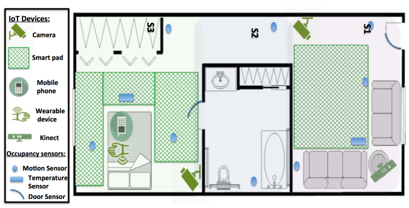


Fig. 4: Floor-plan of the "medium" scale setting

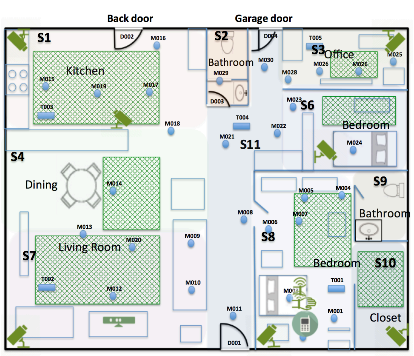


Fig. 5: Floor-plan of the "large" scale setting

- *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.

B. Experimental Results

1) Cumulative energy consumption comparison: Figure 3a 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.

2) Battery lifetime of IoT devices: In our experiments, we used at least two battery-powered devices: the mobile phone, and wearable devices. Figure 3b shows power drain patterns of the battery-powered 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 hours, 20 hours 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 hours, while the second IoT battery capacity extends to more than 175 hours. The BRBL algorithm extends the battery capacity of the constrained IoT devices up to 175 hours 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.

3) Power consumption and accuracy comparison: Figure 3c and Figure 3f show the comparison among different algorithms in terms of power consumption and accuracy respectively. Specifically, we zoomed a 4-hour window after 29 hours 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.

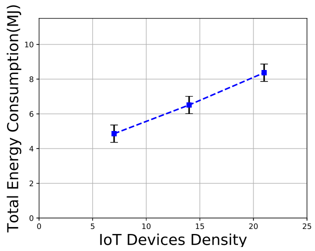


Fig. 6: Density of IoT devices and energy consumption using the CFG algorithm in the medium scale setting

4) 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 Figure 6 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.

VII. 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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