Adaptive Energy Management for Self-Sustainable Wearables in Mobile Health

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Abstract

Wearable devices that integrate multiple sensors, processors, and communication technologies have the potential to transform mobile health for remote monitoring of health parameters. However, the small form factor of the wearable devices limits the battery size and operating lifetime. As a result, the devices require frequent recharging, which has limited their widespread adoption. Energy harvesting has emerged as an effective method towards sustainable operation of wearable devices. Unfortunately, energy harvesting alone is not sufficient to fulfill the energy requirements of wearable devices. This paper studies the novel problem of *adaptive energy management* towards the goal of self-sustainable wearables by using harvested energy to supplement the battery energy and to reduce manual recharging by users. To solve this problem, we propose a principled algorithm referred as *AdaEM*. There are two key ideas behind AdaEM. First, it uses machine learning (ML) methods to learn predictive models of user activity and energy usage patterns. These models allow us to estimate the potential of energy harvesting in a day as a function of the user activities. Second, it reasons about the uncertainty in predictions and estimations from the ML models to optimize the energy management decisions using a dynamic robust optimization (DyRO) formulation. We propose a light-weight solution for DyRO to meet the practical needs of deployment. We validate the AdaEM approach on a wearable device prototype consisting of solar and motion energy harvesting using real-world data of user activities. Experiments show that AdaEM achieves solutions that are within 5% of the optimal with less than 0.005% execution time and energy overhead.

Introduction

The increasing cost of healthcare (Dieleman et al. 2020) and its growing need due to chronic diseases and aging (Dorsey et al. 2016) motivates the need for remote health-monitoring (Espay et al. 2016). Towards this goal, wearable devices that integrate multiple physiological sensors, processors, and communication technologies to monitor the user's health have emerged as a promising technology (Daneault 2018). For example, in patients diagnosed with cardiac arrhythmia, we can use the measurements from sensors to predict the likelihood of a cardiac failure. The design of wearable devices is optimized for user comfort using

emerging technologies including flexible hybrid electronics (Khan et al. 2016), as they need to be worn for an extended duration. As a result, wearable devices are typically lightweight with a small form-factor which severely limits the size of the available battery. The small battery, in turn, limits the operating life, leading to the need for frequent recharging, reduced usability, and adoption (Johansson, Malmgren, and Murphy 2018). Therefore, there is a strong need for approaches that enable sustainable operation of wearable devices and minimize recharging requirements.

Energy harvesting (EH) (Kansal et al. 2007; Vigorito et al. 2007; Tuncel et al. 2021) from ambient sources has emerged as a promising solution to enable self-sustainable wearable devices. We can integrate various EH modalities including photovoltaic (PV) cells, piezoelectric sensors, and thermoelectric generators to harvest energy from ambient light, user motion, and body heat, respectively. The harvested energy from ambient sources can be used to supplement the battery of the device and prolong the interval between manual recharges. The overall goal of energy management (EM) is to maximize the utilization of harvested energy and to reduce the frequency of manual recharging. EM decisions include the timing and duration of manual recharging. Decision-making for EM is challenging for the following reasons: **1)** energy availability from ambient sources is highly stochastic. EM decision-making should account for this inherent uncertainty so that the battery is not exhausted completely; **2)** the wearable device must not miss any critical events, such as falls, during recharging periods; and **3)** recharging during intervals of abundant energy availability can lead to poor utilization of harvested energy. Therefore, EM algorithms must learn the usage patterns of the users and the EH potential to optimally schedule manual recharging.

This paper proposes a novel and principled AI-based approach referred to as *AdaEM* to solve the above-mentioned challenges of energy management. AdaEM relies on two key ideas. First, we use machine learning (ML) techniques to predict user activities, energy usage patterns, and EH availability in the future. These predictions are fed as input for EM decision-making. Second, to reason about the worst-case uncertainty in ML predictions and ambient energy harvest, we formulate a *dynamic robust optimization (DyRO)* problem to make EM decisions. Due to limited compute and energy resources in wearables, we cannot use expen-

sive methods to repeatedly solve DyRO problem instances for decision-making. Therefore, we propose a highly effective light-weight approach to solve DyRO instances for real-world deployment. We validate our AdaEM approach on a real wearable device prototype consisting of light and motion EH. We start by characterizing the potential of energy harvest on the prototype. The characterization data is then combined with the user activity data from publicly available datasets to determine the available energy in day-to-day activities of the users. Finally, we apply AdaEM on the user data to maximize the interval between recharging operations without missing critical activities. Our results show that AdaEM achieves solutions that are within 5% of the optimal solution with less than 0.005% execution time and energy overhead on real wearables. Moreover, comparison with a realistic baseline shows that AdaEM has significantly lower energy constraint violations while providing the required level of accuracy for the target application.

Contributions: The key contribution of this paper is the development and evaluation of the AdaEM algorithm for energy management in wearable devices for mobile health.

- Specifying the novel AI-based energy management problem for self-sustainable wearable devices via energy harvesting, which has the potential for high social impact.
- Development of a principled dynamic robust optimization formulation for decision-making to maximize the utilization of the harvested energy.
- A light-weight and highly effective algorithm for repeatedly solving DyRO instances for decision-making to meet the needs of real-world deployment.
- Experimental evaluation on a real wearable prototype with data from five users over five years to show the benefits of the AdaEM algorithm in achieving sustainable operation with negligible overhead. We also release the source code on GitHub at: https://github.com/gmbhat/adaEM

Related Work

Research and development of wearable devices has increased in recent years due to their applications in health and activity monitoring (LIVMOR 2021; Dempsey 2015). However, their adoption by the medical community is limited. One of the primary reasons for the limited adoption is the frequent recharging requirements of most, if not all, wearable devices (Ozanne et al. 2018). Therefore, recent research in wearable devices has focused on addressing the energy limitations of wearable devices (Chong et al. 2019).

Energy harvesting and management has emerged as the most promising technique to overcome the energy constraints in wearable devices. Common sources of energy include ambient light, user motion, and body heat. Out of these sources, ambient light has the highest power density and efficiency. For instance, prior studies have shown that ambient light can provide up to 0.1 mW/cm^2 and 100 mW/cm^2 in outdoor and indoor conditions, respectively (Valenzuela 2008). Motion EH has received increased attention recently due to its applicability in activity monitoring devices (Mitcheson et al. 2008).

Harvesting energy from ambient sources necessities development of algorithms that manage the harvested energy effectively. This is critical because the ambient energy is not available at all times during the day. As such, the device must have sufficient energy reserves to operate effectively when harvested energy is not available. To this end, Kansal et al. (2007) proposed the concept of energy neutral operation using linear programming, whereby the energy used in a given period (e.g. a day) is equal to the energy harvested in that period. Recent work has also used dynamic programming and control-theoretic methods to achieve energy neutral operation (Vigorito et al. 2007; Bhat et al. 2017; Geissdoerfer et al. 2019; Yamin, Bhat, and Doppa 2022).

ML methods have also been used for energy harvest prediction and allocation to achieve energy neutral operation. For instance, neural networks and other predictors have been used to estimate light energy available in the future (Barrera et al. 2020; Dhillon et al. 2020; Shresthamali, Kondo, and Nakamura 2017). The energy estimates are then used to decide the energy allocation and duty cycle in the future. These prior methods don't address our general adaptive EM problem. In contrast, we formulate a *dynamic robust optimization* to make EM decisions by accounting for uncertainty in the harvested energy. We propose a light-weight solution, AdaEM, to make EM decisions at runtime.

Background and Preliminaries

This section first provides a brief background on emerging technologies in form-factor and EH for wearable devices, with detailed explanations in the Appendix. Then, we describe challenges and opportunities for the widespread adoption of wearables using these technologies.

Flexible hybrid electronics: Flexible electronics can enable comfortable wearables through the use of materials that are fully bendable and rollable. However, the performance capabilities of fully flexible electronics are low compared to conventional CMOS devices. To address these limitations, recent research has proposed flexible hybrid electronics (FHE) (Khan et al. 2016). FHE uses rigid components on a flexible substrate to implement a device that conforms to the shape of the user's body. By using rigid components for processing and sensing, FHE devices are able to utilize the performance advantages provided by CMOS technology and form factor advantages of the substrate.

Light EH: Small form-factor flexible PV cells have shown potential for use in wearable devices (Park et al. 2009). These PV cells can be easily integrated into wearable devices including fabrics, hats, and jackets. Therefore, they are an important step towards sustainable operation and adoption of wearable devices.

Motion EH: Motion EH is another promising technology for wearable devices as motion energy harvesters can be easily integrated with human activities (Mitcheson et al. 2008). For example, piezoelectric harvesters can be used on knees and elbows to harvest energy whenever the user moves. Some studies have also used motion EH as a feature in performing activity classification (Khalifa et al. 2017). As a result, motion EH can act as a sensor and an energy source.
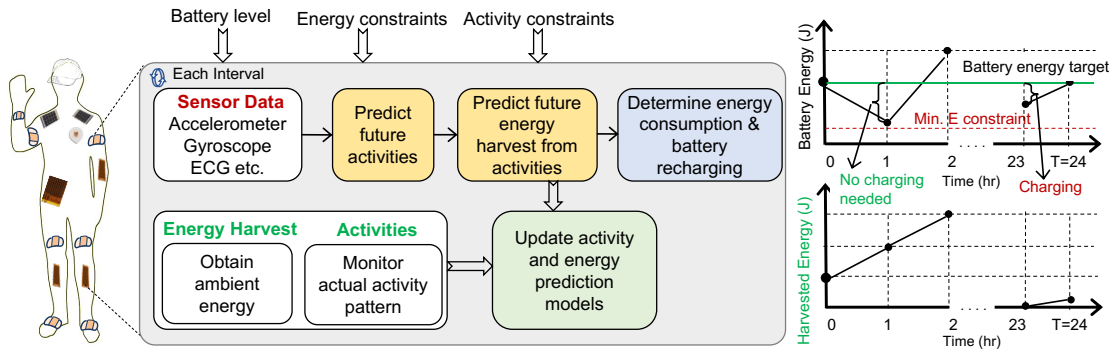
Figure 1: Overview of the system for sustainable wearable health monitoring via adaptive energy management.

Challenges & Opportunities for Wearables

Despite the development of the above technologies, the widespread adoption of wearable devices has been limited to laboratory studies and smartwatches. One of the primary reasons for the lack of adoption of wearable devices is frequent recharging requirements along with lack of comfort of rigid devices. To address these challenges, we take a holistic view of the problem. Specifically, our problem formulation considers the application requirements, user activity patterns, and EH together to enable optimal operation of wearable devices. The formulation also includes unique properties of FHE, such as bending, so that the changes in EH are accounted correctly (Park et al. 2017).

Figure 1 shows an overview of the system for sustainable wearable health monitoring. The left side shows an illustration of a user wearing number of sensors and EH modules. The data obtained from the sensors is used to identify the user's activities and health status. During each interval of operation, the system takes the current battery level, energy constraints, and activity constraints as the input. The energy constraints may specify that the battery must be maintained above a certain minimum level to ensure sufficient reserves in case of an emergency. Similarly, the activity constraints specify a set of activities that have the highest priority for the user. The first step in the EM is to predict future activities using the sensor data. The activities are then used to predict future energy requirements and harvest. Finally, the energy consumption of the device is allocated such that the battery life is maximized while satisfying the constraints. At the end of the interval, we use the actual energy and activities of the user to update the models. We also determine the optimal charging time for the device so that critical events are not missed and ambient energy is not wasted. For instance, the battery trajectory on the right shows that we do not need charging at hour one because there is sufficient ambient energy available, while hour 23 needs charging. The AdaEM approach accurately predicts this behavior and schedules charging only for hour 23.

Dynamic Robust Optimization Approach

The energy management (EM) problem is challenging due to the following reasons: 1) Energy harvesting from ambient sources is highly stochastic; 2) At the same time, the wear-

able device should have sufficient energy to fulfill the requirements of target application at all times; and 3) Recharging during periods of important activities (e.g., gait monitoring in a patient with Parkinson's disease) leads to a reduction in the quality of service to the user. Therefore, EM algorithms for wearable devices must account for the future *worst case* uncertainty in the ambient energy harvest and predictions about user activities and energy usage. To overcome these challenges, we formulate the EM decision-making as a *dynamic robust optimization (DyRO)* with constraints on the battery energy and activity accuracy. In what follows, we first describe the DyRO formulation and then provide a light-weight algorithm for real-world deployment.

DyRO Formulation

Setup for Decision-making: Without loss of generality, we consider a set of equal length intervals $\mathcal{T}$ (minutes, hours, etc.) in a given time horizon T. The EM decision-making is performed at each discrete interval $t \in \mathcal{T}$ over a fixed time horizon of T, such as a day, to account for the repetitive nature of human activities. At the beginning of each interval (decision epoch) t, the EM algorithm allocates the energy to be consumed in the interval based on the user activities, battery level, and energy harvest. Similarly, any manual charging is scheduled for one or more intervals depending on the energy required to replenish the battery. For example, the EM algorithm can decide to recharge the battery for three consecutive intervals.

Variables and Constraints: We define the following variables and constraints to describe the system dynamics.

1) Battery recharging indicator $B(t)$**:** This binary variable indicates whether recharging is scheduled in a given interval or not. At each decision epoch $t \in \mathcal{T}$, the EM algorithm assigns $B(t)$ to 1 (recharge) or 0 for maximizing the duration between recharges while satisfying the constraints.

2) Battery energy dynamics: In each interval $t \in \mathcal{T}$, the battery receives energy from the harvesting sources and a charging source, if the charging is enabled. The harvested energy in an interval ξ_t^H is a random variable with uncertainty because environmental conditions can affect the harvested energy. We have a random variable for the energy harvested for each interval in $\mathcal{T}$. Furthermore, the target ap-

plication will draw energy from the battery to execute the required tasks. The energy used by the application is a decision variable that is computed by the EM algorithm. These dynamics of the battery can be captured as follows:

$$E_{t+1}^B = E_t^B + \eta \xi_t^H + E_t^I B(t) - E_t^c, \quad t \in \mathcal{T} \quad (1)$$

where E_t^B and E_{t+1}^B are energy at the beginning of the current and next interval respectively, η is the EH efficiency, $\xi_t^H \in \Xi_t^H$ is the realization of harvested energy at interval $t \in \mathcal{T}$, $B(t)$ is the battery charging flag, E_t^I is the charging energy, and E_t^c is the energy consumed in the interval t.

3) Battery energy constraints: The battery must always maintain a minimum level of charge so that it has sufficient energy to take actions in case of an emergency. For example, if the device detects a patient fall, it must be able to notify a caretaker and call for help. We also ensure that the energy at the end of any horizon T is equal or greater than a target level E_{target} for the next horizon. Similarly, the energy in the battery cannot exceed the design capacity. Therefore, the battery energy constraints can be expressed as:

$$E_{min} \le E_t^B \le E_{max}, \quad t \in \mathcal{T}, \quad E_T^B \ge E_{target} \quad (2)$$

where E_{min} and E_{max} are the min. and max. energy values.

4) Accuracy constraint: Without loss of generality, we assume that the device is performing a prediction task for monitoring health of the user. It is critical to ensure that appropriate accuracy is provided to the user and their health providers. Therefore, we impose an accuracy constraint on the application using a threshold A_{min} as follows:

$$A_t >= A_{min}, \quad t \in \mathcal{T} \quad (3)$$

where A_t is the accuracy in interval t.

5) Critical activity constraint: In general, some activities performed by the user have a higher priority for health monitoring than others. For example, in a user with movement disorders, it is critical to monitor for falls or freezing of gait when they are walking. We designate a subset of the activities $\mathcal{A}_c \in \mathcal{A}$ as critical activities, during which recharging cannot be scheduled.

Optimization Problem: The primary objective of the EM algorithm is to maximize the utilization of harvested energy and maximize the duration between consecutive charging operations. Suppose the start times of the charging are given by the set $\mathcal{T}_c = \{c_1, c_2, \ldots, c_m\}$. The charging times are a function of the realizations of the harvested energy $\xi_t^H, t \in \mathcal{T}$. Therefore, the optimization objective is:

$$\text{maximize} \quad [\min \mathbb{E}\{\Delta \mathcal{T}_c(\xi_1^H, \cdots, \xi_T^H)\}] \quad (4)$$

The objective function first takes the first-order difference of the elements in the set $\mathcal{T}_c$. The minimum value of the first-order difference gives the shortest time interval between two charging sessions. Since our goal is to prolong the operation of the device, we maximize the minimum of the first-order difference of $\mathcal{T}_c$. In summary, we can write the overall optimization problem as follows:

$$\text{maximize} \quad \min \mathbb{E}\{\Delta \mathcal{T}_c(\xi_1^H, \cdots, \xi_T^H)\} \quad (5)$$

$$\text{s. t.} \quad E_{t+1}^B = E_t^B + \eta \xi_t^H + E_t^I B(t) - E_t^c, \quad t \in \mathcal{T} \quad (6)$$

$$E_{min} \le E_t^B \le E_{max}, \quad t \in \mathcal{T}, \quad E_T^B \ge E_{target} \quad (7)$$

$$A_t \ge A_{min}, \quad t \in \mathcal{T} \quad (8)$$

$$B(t) = 0 \quad \forall t : A_t \in \mathcal{A}_c \quad (9)$$

Optimization variables: Solving the above optimization problem involves determining the values of $B(t)$, E_t^c, and E_{t+1}^B. The battery charging indicator is the primary variable that directly relates to the objective function. The EM algorithm must assign a zero or one to each of the intervals in $\mathcal{T}$ while satisfying the constraints. E_t^c, and E_{t+1}^B are indirect variables which affect the battery dynamics and target application accuracy. Specifically, higher energy consumption E_t^c leads to a faster depletion of the battery, which in turn requires the user to recharge the device sooner. At the same time, higher energy consumption typically leads to higher accuracy. Therefore, the EM algorithm should minimize the energy consumption of the device while satisfying the accuracy constraints. Finally, E_{t+1}^B is a function of the energy consumption, harvest, and the charging availability. The goal of the optimization is to ensure that the battery level always stays between E_{min} and E_{max} constraints.

Problem complexity: The optimization problem in Equations 5–9 is an instance of *dynamic robust optimization (DyRO)* (Bertsekas 2012) with a discrete and non-linear objective. In particular, solution to the problem must consider the worst-case uncertainty in the energy harvest to ensure that battery constraints are not violated. Furthermore, as new information becomes available at runtime in the form of actual EH values, the optimization for adaptive EM should change future decisions as a function of the new information. The uncertainty in the problem, along with a mix of zero/one ($B(t)$) and continuous variables (E_t^c and E_{t+1}^B) make the problem computationally hard to solve. Specifically, obtaining the optimal solution to the general problem formulation requires an exhaustive search, which leads to a time-complexity of $\mathcal{O}(c^{|\mathcal{T}|})$, where $c > 1$. If we make the problem convex and use continuous variables for $B(t)$, the time-complexity will be at least $\mathcal{O}(|\mathcal{T}|^3)$ for iterative algorithms. The time-complexity is especially critical for wearable devices since they are energy constrained and repeated calls to computationally expensive algorithms can defeat the purpose of energy management. Therefore, in the next section, we develop a light-weight algorithm that achieves comparable results to the optimal solutions from a solver.

AdaEM: a Light-Weight Algorithm for DyRO

Key challenges: Solving the DyRO problem instance optimally at runtime is infeasible for two key reasons: **1)** the true values of the uncertain energy harvest for current and future intervals within the decision-making horizon; and **2)** wearable devices are constrained by both computing and energy resources needed for solving the DyRO problem. Therefore, we develop a two-stage approach to design an efficient and

practical algorithm referred to as AdaEM to solve the DyRO problem instances for making adaptive EM decisions.

Overview of the AdaEM algorithm: The first stage of AdaEM involves using supervised learning algorithms to learn the distribution and uncertainty of the energy harvest in both current and future intervals. We exploit the historical data and side information about energy harvest for this purpose. For example, the wearable device can record information about energy harvested in the past as features to predict future energy and uncertainty. Similarly, the side information available for wearable devices includes the location (e.g. outdoors vs. indoors), user activity, and current day (e.g., weekday vs. weekend). This side information can be used to further improve the ML models for energy harvest. The energy predictions and uncertainty from the ML models are then used to get a concrete instantiation of the DyRO problem to obtain EM decisions.

The second stage of AdaEM solves the concrete DyRO problem instance as follows. At the beginning of each decision-making horizon, the predicted energy harvest and uncertainty are used to obtain initial assignments of battery charging and energy consumption allocations, i.e., EM decisions. Subsequently, at runtime, the EM decisions are revised based on the actual values of the harvested energy. This approach ensures that the wearable device takes advantage of any excess harvested energy to extend the battery life or account for shortfall of energy so that the constraints are not violated. In what follows, we describe these two stages in more detail.

Energy Harvest Prediction: The quality of EM decisions depends critically on the accuracy of predicted future energy harvest. In addition to energy harvest prediction, we also need the uncertainty in predictions to reason about the worst-case behavior. Towards this goal, we use the historical energy harvest data to train a ML model using supervised ML algorithms. The input features of the system state s, $\phi(s)$, for making predictions include the energy harvest in the past days, hours, and the derivative of the energy harvest in the past hour (Yamin and Bhat 2021). We also include side information such as the current location, user activity, and day as part of the feature set $\phi(s)$. The ground-truth energy harvest values y^* are used as supervised data. We have a regression learning problem at hand and any off-the-shelf regression learner can be employed. However, due to the constraints on energy and compute resources in wearables, we need to select a light-weight ML model such as trees, since comparison operations are efficient.

To choose the energy harvest predictor, we compare the performance of neural networks, linear regression, and an ensemble of regression trees. All the learning approaches have a non-negativity constraint for the predictions since energy harvest is always non-negative. Neural networks and regression trees gave similar accuracy while linear regression showed relatively lower accuracy. In our specific implementation, we employ an ensemble of regression trees: prediction is the mean and uncertainty is the variance. We note that our final results are not dependent on any particular regression learner. In fact, both neural networks and regres-

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Algorithm 1: AdaEM for Charging Optimization

Input: EH prediction $\hat{\xi}_t^H$ and uncertainty U $\forall t \in \mathcal{T}$, Energy constraints, Accuracy constraints, Energy vs. Accuracy profile
Output: Battery recharging indicator $B(t), t \in \mathcal{T}$, Energy consumption, Battery levels

1: Set $B(t) = 0 \; \forall t : A_t \in \mathcal{A}_c$
2: Set $E_t^c, t \in \mathcal{T}$ such that accuracy is maximized
3: Calculate E_{min}^c that satisfies the accuracy constraint
4: Obtain $E_{t+1}^B, t \in \mathcal{T}$ using EH prediction and assigned E_t^c
5: **while** $\exists t | (E_{t+1}^B < E_{min})$ **do**
6:     **if** $\exists t | (E_t^c > E_{min}^c)$ **then**
7:        Reduce E_t^c for intervals with higher consumption
8:     **else**
9:        Calculate the energy deficit $\delta E = E_{target} - E_{T+1}^B$
10:       Calculate number of charging intervals: $\delta E / E^I$
11:       Set $B(t) = 1$ starting with the first violation
12:     **end if**
13:     Obtain $E_{t+1}^B, t \in \mathcal{T}$ using EH prediction, E_t^c, and $B(t)$
14: **end while**
15: **return** $B(t), E_t^c, E_{t+1}^B \forall t \in \mathcal{T}$

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sion trees for energy prediction lead to similar performance for the overall energy management.

Charging Optimization Algorithm: This algorithm takes the predicted energy harvest and uncertainty to determine the charging policy and energy consumption for all intervals in a given decision-making horizon, as shown in Algorithm 1. It is inspired from the water filling algorithm in communication systems (Cover and Thomas 2012) where the goal is to allocate a given power to multiple channels so that the throughput is maximized. At the beginning of each decision-making horizon, the predicted energy harvest, uncertainty, and the constraints for all intervals are taken as the input. Additionally, it also takes a profile of the energy and accuracy trade-off to ensure that the activity constraints are satisfied. The energy and accuracy trade-off are obtained by characterizing the target application on the wearable device. Specifically, we collect activity data with different sampling rates and design a classifier for each sampling rate. These datapoints are then used to obtain the relationship between sampling rate and accuracy (Mirzadeh and Ghasemzadeh 2020; Bhat et al. 2019).

After getting the above inputs, the algorithm first initializes the battery charging indicator to zero for intervals where the user performs critical activities. This assignment is based on the history of user's activities. For example, by monitoring a user's activities for a month, we can generate an expected pattern of their activities and use it to set the values of $B(t)$ at the beginning of each horizon. As new data becomes available, the algorithm adjusts the values of $B(t)$ so that any deviations from the expected activity pattern are taken into account. The algorithm also sets the energy consumption of all intervals to the highest value so that the accuracy is maximized. Next, using the worst-case EH predictions, we calculate the energy in the battery for each interval in the horizon (Line 4). If the algorithm detects any violations in the battery levels, it either reduces the energy consumption or enables charging (Lines 5–14). Since our goal is

to maximize the battery lifetime, we first reduce the energy consumption of the target application while maintaining the minimum accuracy. If the reduction in energy consumption does not resolve the battery violations, the algorithm calculates the potential deficit in the energy and the number of intervals required to complete the charging. Finally, it sets the battery charging indicators for the required number of intervals to one, starting with the first violation.

The initial values of the energy consumption and battery charging are based on the EH predictions. At runtime, the actual energy is typically different from the predicted values. Therefore, as data about the actual EH becomes available, we re-run Algorithm 1 with a shorter horizon to adjust the energy consumption and battery charging. For instance, if excess energy is harvested in an interval, we can either increase the energy consumption in the following intervals to improve the accuracy or reduce the time spent in charging. The time complexity of the algorithm is $\mathcal{O}(|\mathcal{T}|^2)$ in the worst-case when the while loop runs $|\mathcal{T}|$ times, where $|\mathcal{T}|$ stands for the number of decision-making steps.

Experiments and Results

In this section, we present the experimental results for the proposed AdaEM algorithm along different dimensions.

Experimental Setup

Wearable device: We employ a prototype based on the Texas Instruments (TI) CC2652R micro-controller (MCU) (Texas Instruments Inc. 2018) as the primary wearable device in our experimental validation. The TI-CC2652 integrates a low-power ARM Cortex M4 core and interfaces such as SPI and I2C for sensors. In addition to the MCU, we include a SP3-37 flexible PV cell (FlexSolarCells 2013) for harvesting energy from ambient light and a piezoelectric harvester for motion EH. The wearable device incorporates a GMB 031009 (GMB 2009) Lithium polymer battery with a capacity of 12 mAH (160 J) as the energy storage element.

Activity Dataset: We use the American Time Use Survey (ATUS) (US Department of Labor 2015) to obtain the user activity data. The ATUS, conducted by the U.S. Department of Labor, contains typical activity data for approximately 10,000 users. We pre-process the ATUS data to obtain five main activity categories: {*Sleep, work, exercise, leisure, and others*}. The wearable device is then used to identify these activities using the sensors available on the device. Of these activities, we choose 'exercise' as the critical activity. This means that battery recharging must not be scheduled in time intervals when the user is exercising.

Energy Harvesting Dataset: The potential energy available from the motion harvesters is a function of the user motion during the activity. To this end, we set the activity intensity for legs and hands for each activity. Starting with a baseline intensity of 1 for exercise, we set the intensity for the 'active' activity as 0.5, while the intensity for sleeping is zero. The activity intensities are then combined with a baseline power of 13 μW (Tuncel et al. 2020) available from the piezoelectric harvesters. Similarly, the energy available from light is a function of the location. To illustrate the performance of

AdaEM clearly, we use outdoor light intensity throughout the day. Specifically, we utilize five years (2016–2020) of solar irradiation measured by National Renewable Energy Laboratory (NREL) (Andreas and Stoffel 1981) in Golden, Colorado. The irradiance is combined with the time of the day to calculate the light energy using the area and I-V characteristics of the PV cell (FlexSolarCells 2013).

Experiment Parameters: We set the finite horizon to be 24 hours, since EH and user activities typically follow a daily pattern (Huynh, Fritz, and Schiele 2008). The length of each interval is set to one hour while noting that other intervals also work well with AdaEM. Finally, we set the minimum energy constraint to 10% of the battery capacity and the target energy constraint to 60% of the battery capacity.

Optimal Solution: We obtain the optimal solution using the CVX package (Grant and Boyd 2014) in Matlab. Specifically, we make the problem convex by minimizing the sum of $B(t)$. This is feasible since the optimization is done over a finite horizon. As a result, minimizing the sum of $B(t)$ maximizes the operating time of the device in each horizon. We make the problem convex to avoid the prohibitive cost of an exhaustive search. The CVX implementation is run on a server consisting of 32 Intel® Xeon® Gold 6226R cores with 192 GB of memory. As noted earlier, the optimal solution uses the actual energy harvest values with no uncertainty.

On-demand Baseline Algorithm: We also implement a baseline that aims for a fixed accuracy and begins charging whenever the battery drops below E_{min}. The charging continues until the battery reaches E_{target}. We refer to this charging policy as the on-demand baseline algorithm since it enables charging whenever the energy drops below E_{min} and more energy is needed. This policy reflects the behavior of most wearable and smartphone users. As a result, it provides a useful baseline to evaluate the efficacy of AdaEM.

Energy Management with Ideal Predictions

We start with an ablation study where we provide the actual EH values to the adaptive charging algorithm. Results obtained using the actual EH give us the upper bound on the performance of the proposed charging optimization algorithm. Figure 2 shows a distribution of the daily charging energy required for five distinct users over a period of five years. We see that the median values of the charging energy for AdaEM are within 1% to the optimal solution. Further-
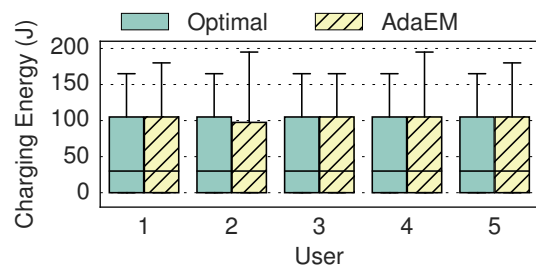
Figure 2: Energy used for recharging by the optimal and proposed approaches for each month of the year (2016–2020) under ideal EH predictions
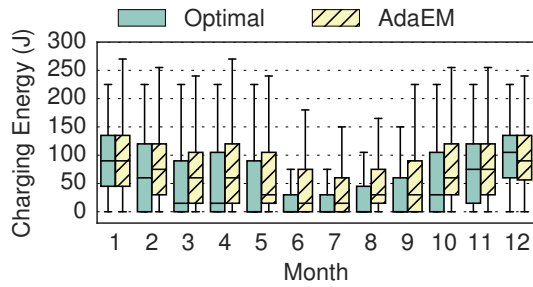
Figure 3: Energy used for recharging by the optimal and proposed approaches for each month of the year (2016–2020) under uncertain EH predictions
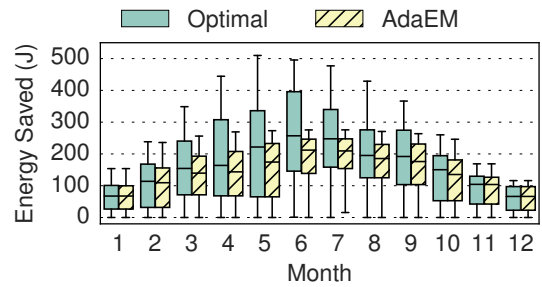

Figure 4: Energy saved by using energy harvesting and sustainable allocation by the optimal and proposed approaches for each month of the year (2016–2020)
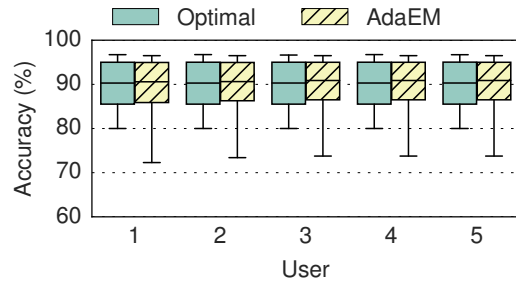

Figure 5: Average daily accuracy of activity recognition for five users over a period of five years

more, the range and distribution of the charging energies are close to the optimal solution. This shows that AdaEM is able to accurately determine the charging intervals with significantly lower computations than the optimal algorithm.

Energy Management with Uncertainty in EH

In this section, we analyze the performance of AdaEM with uncertain energy harvest predictions. To this end, we first predict the available energy harvest at the beginning of each day using the trained regression learner. This energy prediction is used by Algorithm 1 to assign the energy consumption and charging policy for each interval of the day while satisfying all the constraints. Since the actual energy can deviate from the predicted values, the algorithm is re-run at the beginning of each interval to account for these differences. Figure 3 shows the comparison of the charging energy used by the proposed approach and the optimal solution. The optimal solution is computed offline and it uses the actual values of harvested energy. We see that, in general, the energy used by the proposed approach is close to the optimal solution for most months. A higher variation is observed for summer months, where the distribution of AdaEM is wider than the optimal solution. This is because in summer months the algorithm generally expects a higher solar energy harvest. Therefore, when it encounters cloudy days with a lower solar energy harvest, the prediction error increases, which, in turn, causes the device to use more energy for charging.

Energy Savings: One of the primary advantages of sustainable operation and optimal charging is the savings in the total energy consumption through use of EH. Figure 4 shows the distribution of energy savings achieved by the proposed approach when compared to the optimal solution for each month of the year over a period of five years. The savings here represent the additional energy that would be needed if EH is not used. As expected, the energy savings are higher in summer months due to higher energy availability. The optimal solution is able to achieve higher savings than AdaEM because it has full information about the future energy harvest. At the same time, the proposed approach achieves median savings that are within 5% of the optimal values. We also see that both approaches achieve significant savings even in winter months when the harvested energy is lower.

Effect of the Activity Constraints: Next, we analyze the

impact of the critical activity constraint on the accuracy of the application. We choose five users with varying lengths of the critical activity constraint. Specifically, user 1 has the longest critical activity constraint with six intervals while user 5 has a critical activity constraint with two intervals. The distribution of average daily accuracy for the five users is shown in Figure 5. The minimum accuracy constraint in the figure is 90%. The optimal solution meets the minimum accuracy constraint for all the users. On the other hand, AdaEM has few outliers where the accuracy constraint is not met. This happens on days with limited energy harvest and the device is unable to recharge the battery in time. As a result, the energy consumption has to be reduced, which leads to a reduction in the accuracy. We observe that the number of outliers decreases as the length of the critical activity constraint decreases (user 1 to user 5). This is because a lower number of critical activity intervals gives more opportunity for the device to recharge. In summary, these experimental results show that AdaEM efficiently enables sustainable operation of wearable devices for health monitoring.

Comparison to the Baseline Algorithm

In this section we compare AdaEM with the baseline algorithm. Recall that the On-demand algorithm begins charging whenever the battery level drops below E_{min}. This approach is not suitable for sustainable health monitoring because of two key limitations: 1) the baseline does not account for critical activity constraints. Consequently, the device may have insufficient energy to provide high accuracy for critical activities, and 2) Unlike AdaEM, the On-demand algorithm is
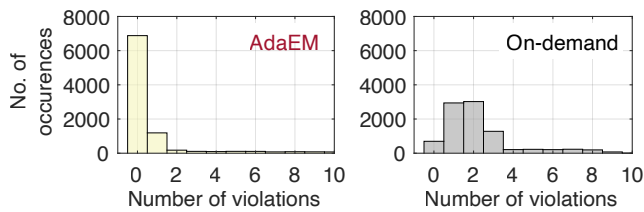
Figure 6: Constraint violations for AdaEM and the On-demand baseline algorithm

Figure 7: Average daily accuracy of activity recognition for five users over a period of five years

reactive in nature and does not plan for satisfying the minimum and target battery energy constraints. As a result, the quality of service to the application can suffer significantly.

To illustrate the above limitations, we compare the energy constraint violations for AdaEM and the On-demand algorithm in Figure 6. The optimal solution is not included in the figure because it does not have any constraint violations due to the knowledge of exact energy harvest and consumption. The figure shows that the On-demand algorithm suffers a significantly higher degree of constraint violations when compared to AdaEM. Specifically, it has more than 3000 occurrences of two or more violations over five years of evaluation data for five users. In contrast, AdaEM has negligible number of instances with two or more constraint violations. AdaEM is able reduce the number of violations and satisfy the critical activity constraints by leveraging future EH and user activity predictions in making EM decisions. In summary, the comparison with the baseline shows the effectiveness of the proposed AdaEM approach in achieving sustainable operation for wearable health monitoring devices.

Comparison to Energy Neutral Methods

Energy neutral methods that rely only on harvested energy have been popular for wearable devices (Kansal et al. 2007). However, as we noted before, energy neutral methods rely on duty cycling the device, which can lead to reduced performance. To illustrate this, we implemented an optimal energy neutral approach that uses the actual harvested energy from 2016 to 2020. The energy neutral approach allocates the device energy consumption such that the total energy consumed in a day is equal to the harvested energy. Figure 7 shows a histogram of the accuracies achieved over five years. As we can see, a significant number of days have close to zero accuracy. As a result, the user is unable to monitor their health parameters, which can lead to adverse effects. This shows the benefits of using AdaEM to balance the accuracy requirements of the user while utilizing harvested energy.

Implementation Overhead

We characterize the overhead of Algorithm 1 by implementing it on the TI-CC2652 MCU. We observe that the algorithm takes 3 ms to run at a power consumption of 11 mW. This amounts to 33 μJ of energy. Since the algorithm runs once every hour, the total energy consumption over a day is 792 μJ, which is less than 0.005% of the battery capacity. This shows that AdaEM achieves sustainable operation with negligible overhead.
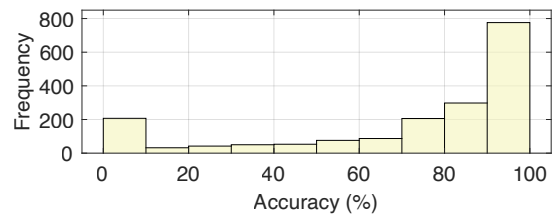
Social Impact

The social impact potential of the proposed AdaEM approach is two-fold. First, AdaEM can catalyze widespread adoption of wearable devices by enabling sustainable operation with high quality of service. Specifically, our holistic approach of combining energy harvesting and management with flexible hybrid electronics leads to sustainable operation with user comfort. This will, in turn, have significant advantages in public health and healthcare expenditure.

Second, it is projected that there will be billions of internet of things (IoT) devices by 2050. Integrating AdaEM into the IoT devices will help in reducing the overall energy footprint through sustainable operation. For instance, even savings of 100 J per day for each device represents a decrease of $3*10^7$ units of electricity per year. This energy is equivalent to the consumption of 20,000 U.S. households, as per the Energy Information Administration (2021).

Conclusion and Future Work

Wearable devices present a tremendous potential to change the landscape in health monitoring. However, their widespread adoption has been hindered by frequent recharging requirements. This paper presented the novel problem of *adaptive energy management* towards sustainable operation of wearable devices. Starting with a dynamic robust optimization, we presented a light-weight solution that uses ML predictions of energy harvest to optimize the charging of the wearable device. Using real-world data and a wearable prototype, we showed that AdaEM achieves solutions that are within 5% of the optimal with less than 0.005% overhead. Our immediate future work includes deploying the proposed solution in the field by performing user studies.

The dynamic robust optimization formulation presented in this paper has applications in a number of fields including agricultural monitoring, wide area sensing, and defense. Even in the area of mobile health, accounting for sudden changes in user activity remains a challenge. For instance, conditions such as freezing of gait, cardiac arrest, or falls are difficult to predict using the history of past activities. The challenge in the activity prediction further complicates the energy management problem since the algorithm must account for these sudden changes in an energy-efficient manner. We hope that this paper inspires the artificial intelligence community to develop new algorithms in this exciting area of self-sustainable wearable devices.

Acknowledgments

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