Evolution of Computing from Mobile Systems to Self-Powered Wearable Devices

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Google exploreCSR Workshop

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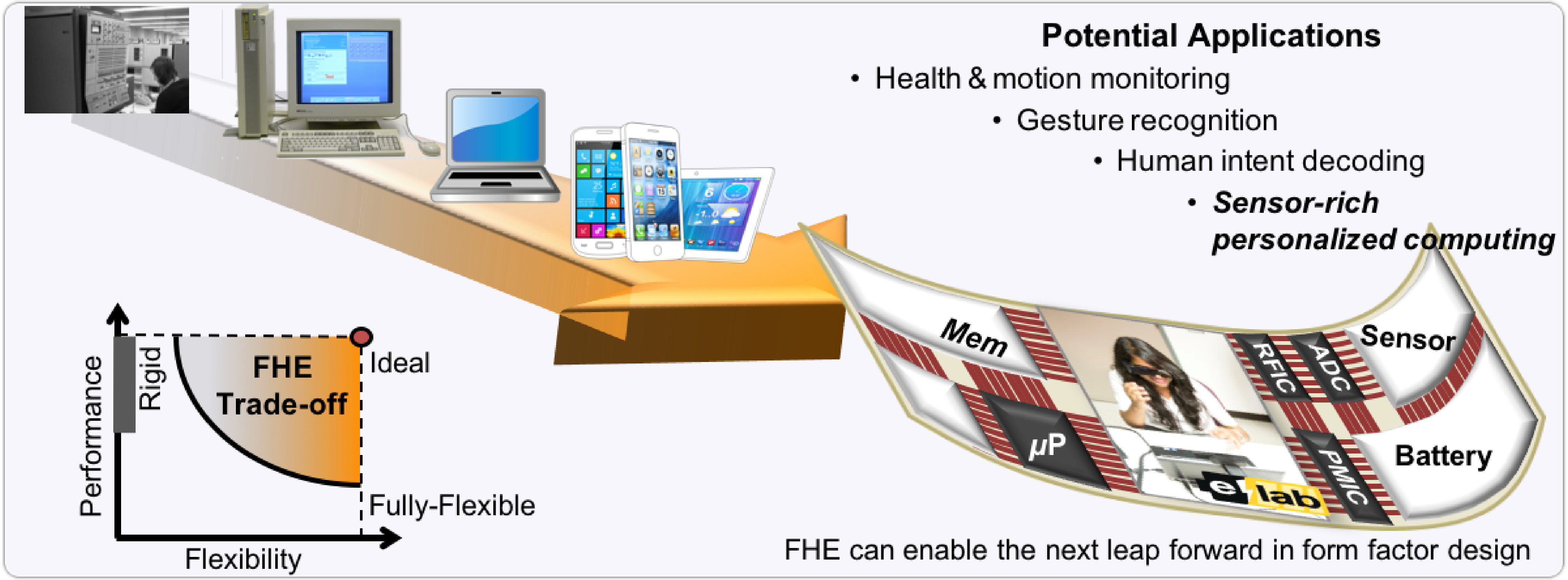
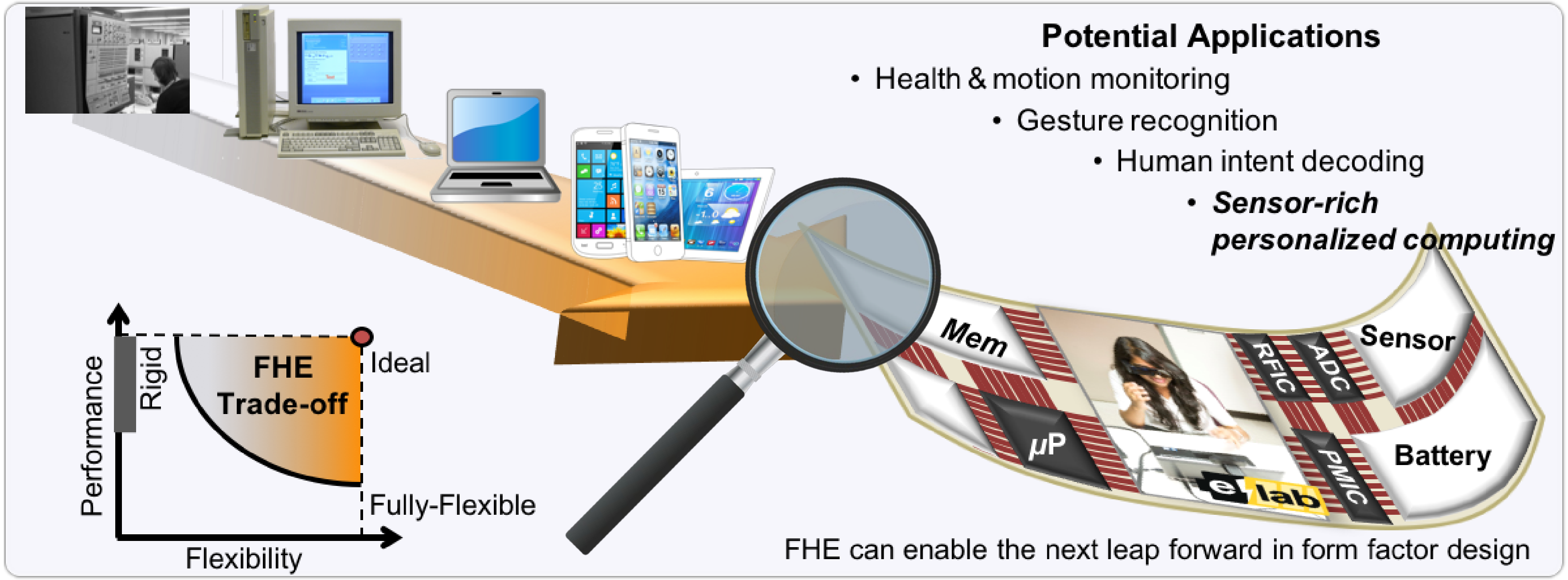
WASHINGTON STATE UNIVERSITY

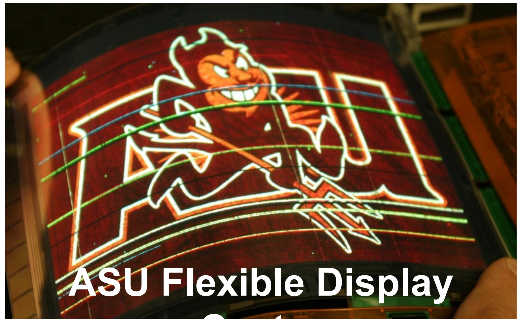
Mobile Devices to *Wearable Devices*



- **Impressive progress, but we still need to**
  – Carry a bulky device, re-charge everyday, rely on primitive interaction, …
- **Towards self-powered wearable systems** that can **understand the user**

Mobile Devices to *Wearable Devices*

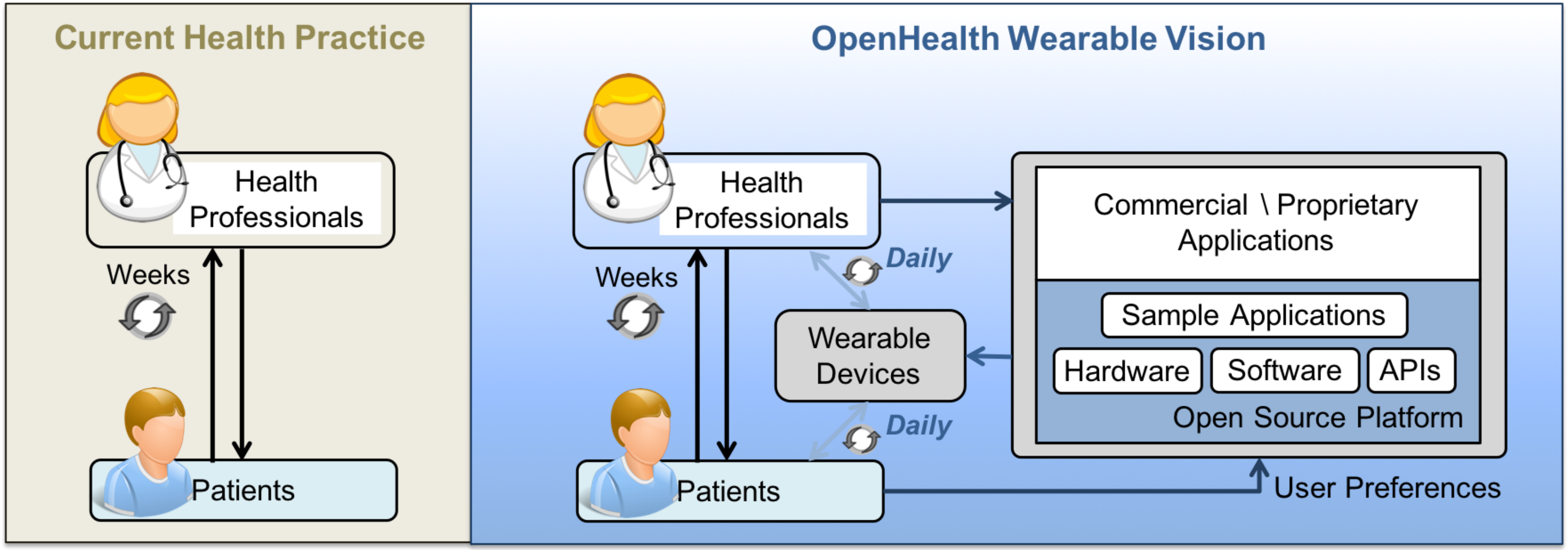




- **Flexible and wearable can enable the next leap in form factor design**
- **Flexible electronics refer to circuits on bendable, rollable, or elastic substrates**
  - Despite impressive potential, they are significantly larger and slower
  - Successful applications to displays, sensors, and solar cells
- **We will focus on wearable devices that use flexible and rigid components**
  - Combine the capabilities of silicon ICs with the physical benefits of flexible electronics

Health Monitoring using Wearable Devices

- **15% of the world's population lives with a disability***
- **110-190 million people face significant difficulties in functioning***
- ***Intl. Parkinson and Movement Disorders Society Task Force on Technology:***
  - Low-cost and small form-factor wearable devices offer great potential
  - Enabled by advances in low power sensors, processors, communications



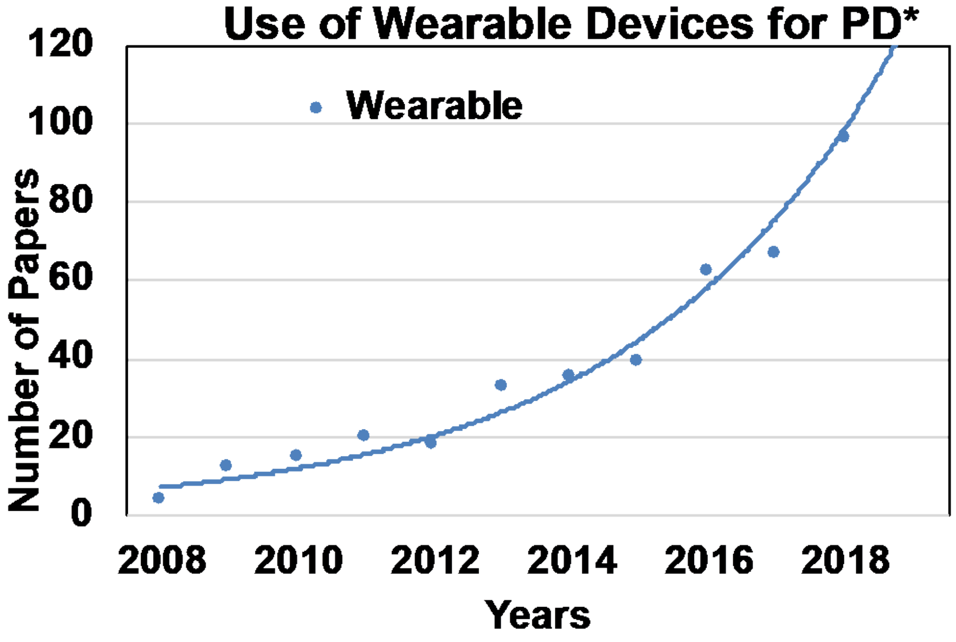
*World Report on Disability: http://www.who.int/disabilities/world report/2011/report/en/.

Challenges of Wearable Health Technology

- **Widespread adoption hindered by *adaptation* & *technology* challenges**
  - **Comfort:** Awkward to wear or carry a device
  - **Compliance:** Stop using technology due to maintanance
  - **Applications:** No killer applications

- **Is there an evidence for the need?**

- **Smartphones used in PD Dream Challenge**
- **But, they are not appropriate**
  - *Some patients cannot even carry them*
  - Cannot provide real-time guarantees (e.g., sampling rate)
  - Large power consumption & charging requirements



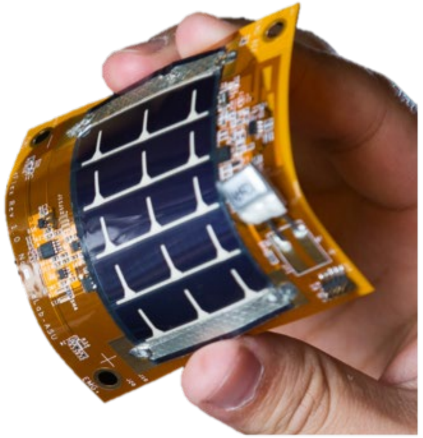
*Ranadeep Deb, MS Thesis, 2019

Solutions to Wearable Health Monitoring

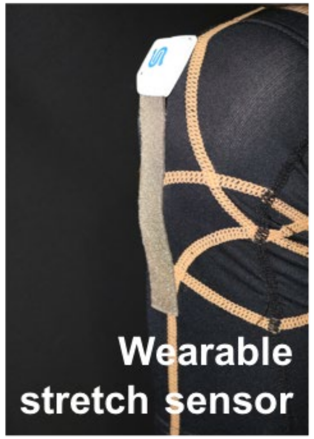
- **We address *adaptation* & *technology* challenges**
  1. **Comfort** → Flexible Hybrid Electronics (FHE)
  2. **Compliance** → Energy Neutral Operation
  3. **Applications** → Movement Disorders

- **Human Activity Recognition (HAR)**
  - Patient rehabilitation
  - Fall detection
  - Physical activity promotion

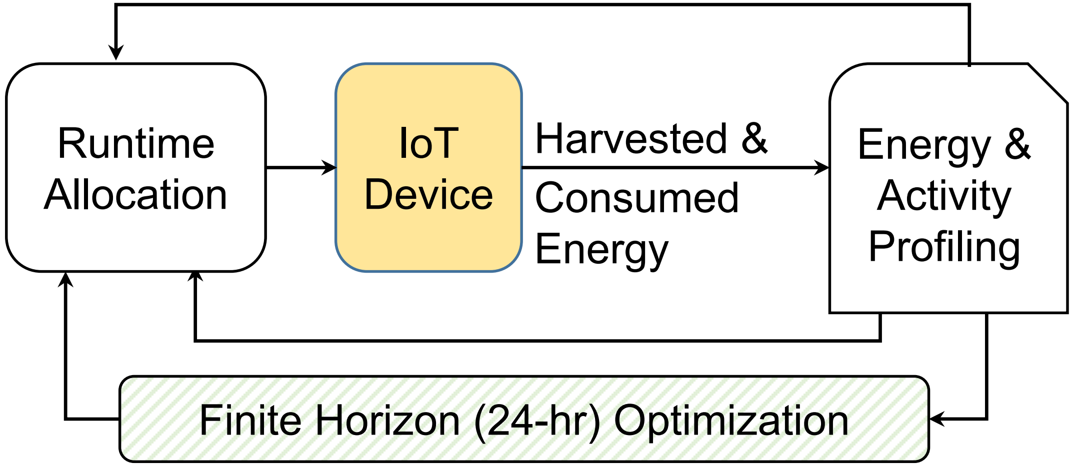
Flexible and Stretchable Devices



Optimal energy harvesting & management



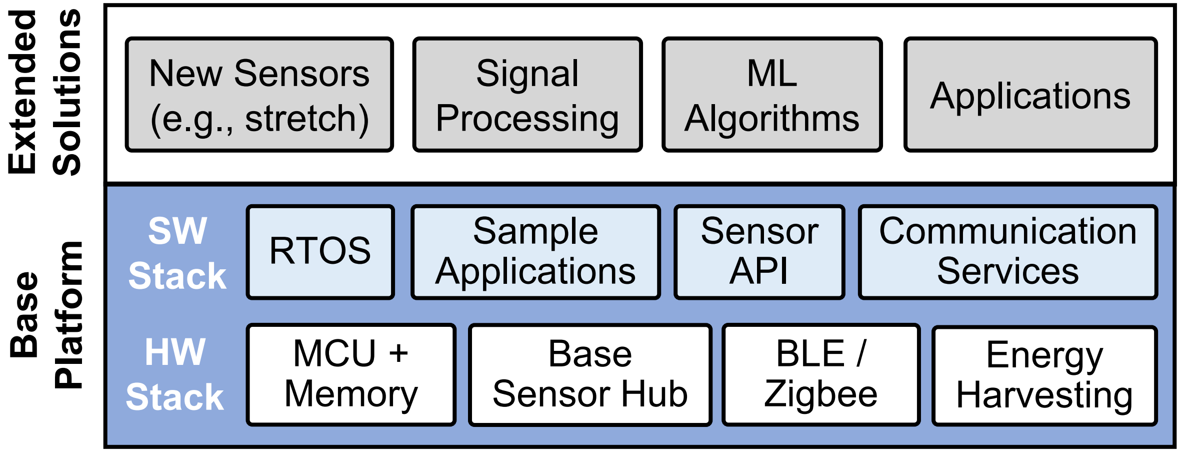
Closed-Loop Optimal Energy Allocation

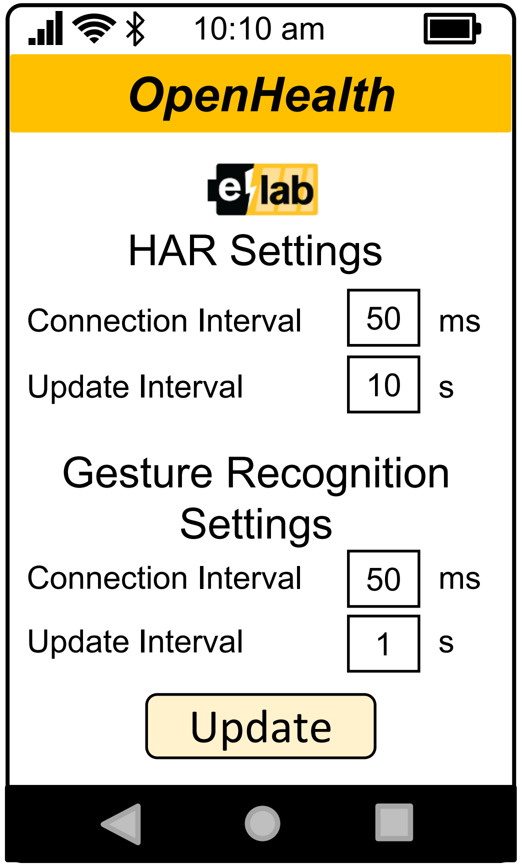


OpenHealth

An open-source HW-SW platform released to public

- **Aim to provide a common compatible HW/SW platform**
  - Address adaptation and technology challenges
  - Monitor clinically relevant technology-based objective measures (TOM)
  - Current release:

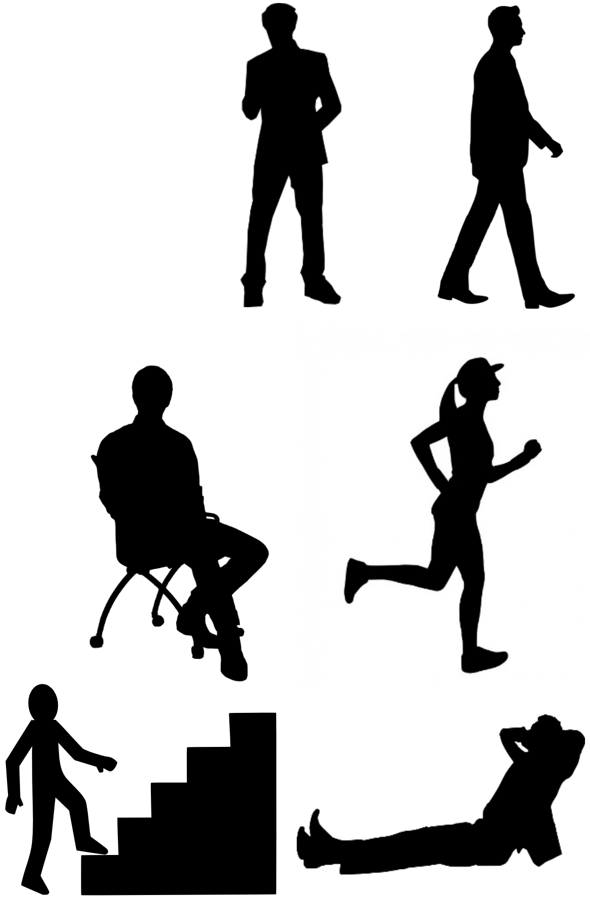




*IEEE D&T'19

Outline

- **Wearable IoT Devices for Health Monitoring**
  - *OpenHealth*: Open-Source Hardware/Software Platform
- **Optimal Energy Harvesting and Management**
- **Human Activity Recognition (HAR)**
  - Online Learning for Activity Recognition
  - Human Activity Recognition Accelerator
- **Conclusion**



Wearable IoT Devices: Limitations

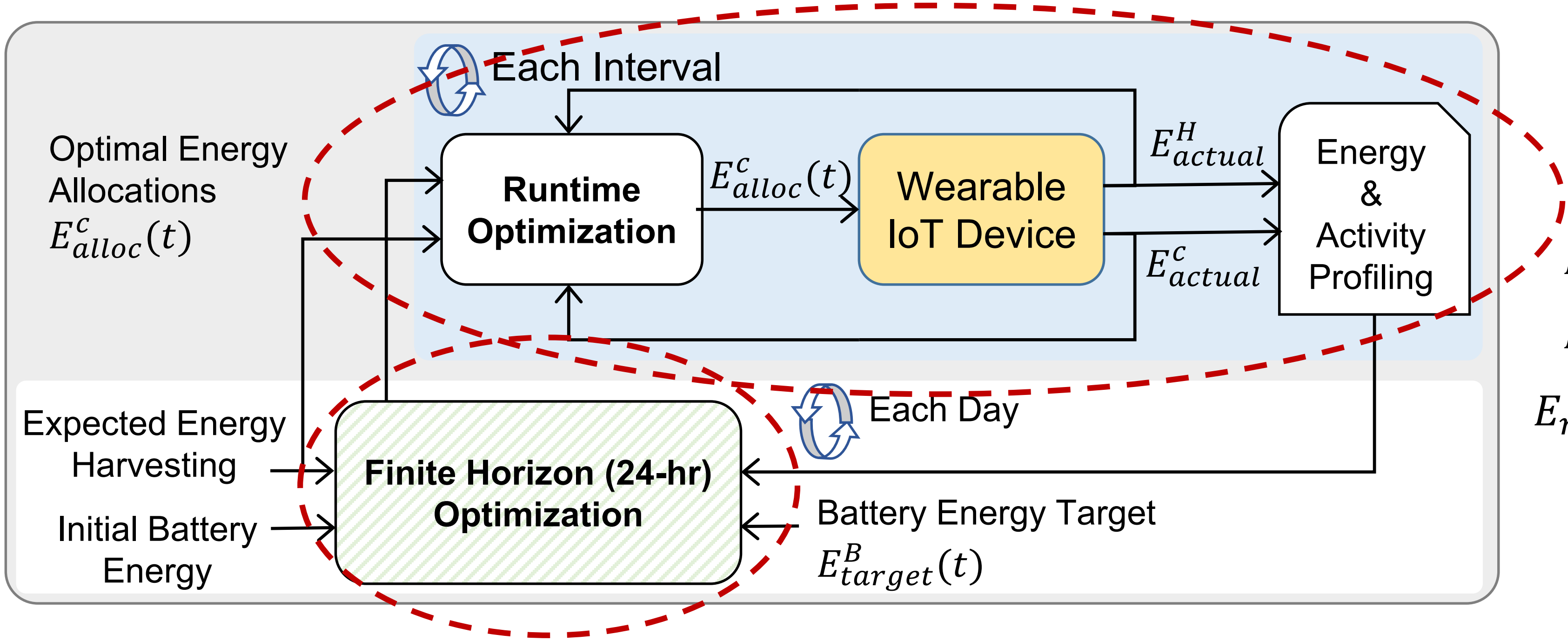
- **Wearable IoT Devices have limited battery life**
  - Bulky batteries are inflexible,
    while flexible batteries have low capacity
  - Small form factor limits the battery capacity

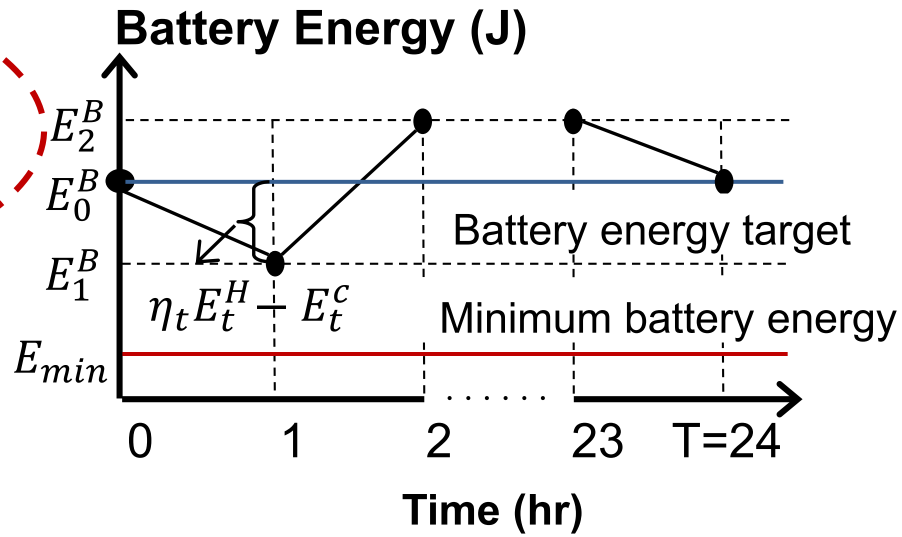
- **Critical need for**
  - Harvesting ambient energy sources
  - Energy harvesting necessitates effective management and allocation of the harvested energy

Flexible PV-cell

We developed a framework that can overcome these challenges and enable *recharge-free* operation

Energy Allocation Framework





- **One day is divided in 24 uniform intervals**
- **Finite horizon optimization determines energy allocation for each interval**
  - Allocation is optimal if expected energy harvesting pattern matches the actual
- **At runtime, we profile the actual harvested and consumed energy**
  - Use the actual values in each interval to correct the future energy allocations

Ganapati Bhat, Jaehyun Park, and Umit Y. Ogras. "Near Optimal Energy Allocation for Self-Powered Wearable Systems," *in Proc. of Intl. Conf. on Computer-Aided Design (ICCAD)*, November 2017

Problem Formulation

- **Our goal is to maximize the utility over one-day horizon**
- **Formulate the optimization problem as,**

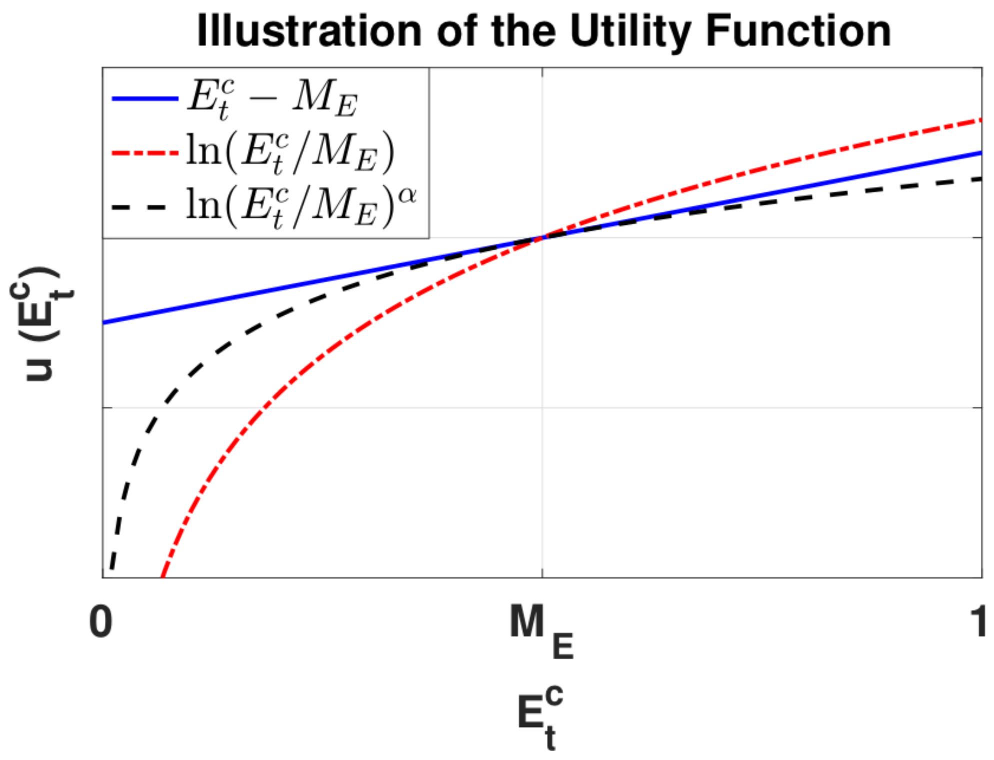
$$maximize \quad U(E_0^c, E_1^c, \dots, E_T^c) = \sum_{t=0}^{T-1} \beta^t \ln\left(\frac{E_t^c}{M_E}\right)^{\alpha}$$

where β is a discount factor

$$subject\ to \quad E_{t+1}^B = E_t^B + \eta_t E_t^H - E_t^c \qquad 0 \le t \le T-1$$

$$E_{t+1}^B \ge E_{min} \qquad 0 \le t \le T$$

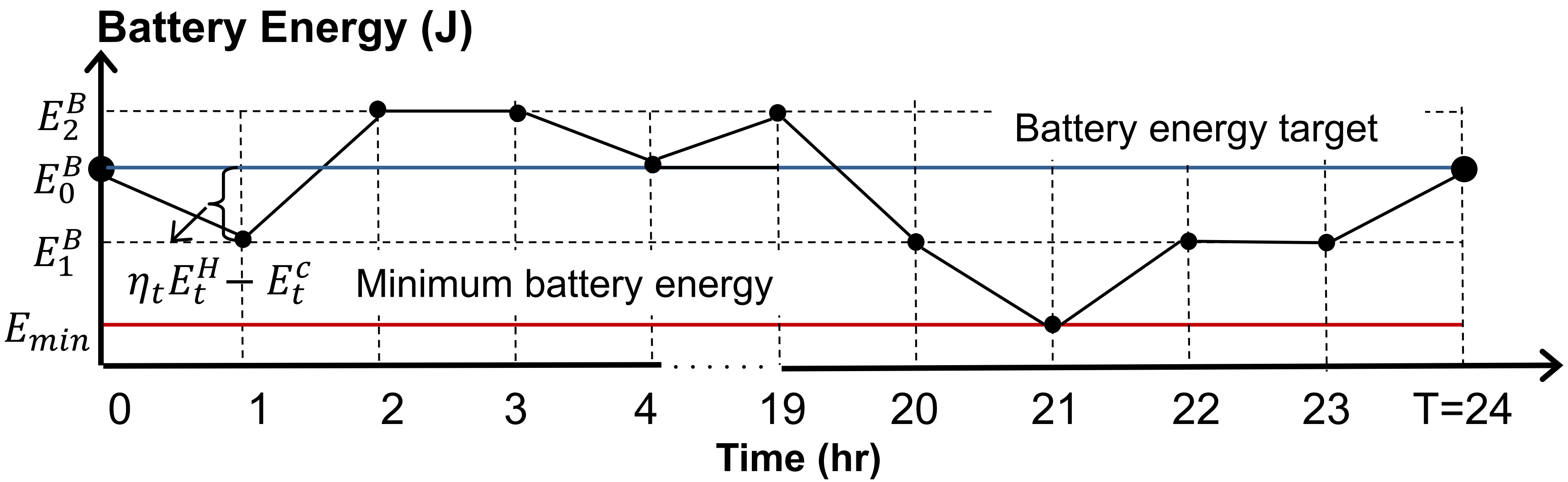
$$E_T^B \ge E_{target}$$



We use a two-step solution to overcome these challenges

Optimal Solution with Relaxed Constraints

- **Key insight 1**
  – Derive a closed form optimal solution by relaxing ***the min. energy constraint***
  – ***Enforce the minimum energy constraint at runtime***



- **Key insight 2**
  – Learn and use the expected harvested energy ***to derive a closed-form solution***
  – ***Account for deviations from the expected values at runtime***

Closed Form Solution

- **With relaxed minimum energy constraints, optimal solution:**

$$First\ interval: \qquad E_0^c = \frac{E_0^B - E_{target} + \sum_{t=0}^{T-1} \eta_t E_t^H}{1 + \beta + \beta^2 + \cdots + \beta^{T-1}}$$

$$Subsequent\ intervals: \qquad E_{t+1}^c = \beta E_t^c \qquad 0 \le t \le T-1$$

- **Use closed form solution for the first interval**
- **Harvested and consumed energy may deviate from expected values**
  - Δ_t^H is the deviation in harvested energy
  - Δ_t^c is the deviation in the consumed energy
- **Account for this difference in subsequent intervals to maintain optimality**

Correcting the Future Allocations

- **At the beginning of each interval, deviations from the expected values**
- **Use this to correct the allocation of future intervals**

$$E_t^c = \beta\left(E_{t-1}^c + \frac{\beta^{t-1}\Delta_{t-1}}{\sum_{k=0}^{T-1}\beta^k}\right)$$

- **But, the correction term** ***cannot change the past allocations!***

- **Add correction term to the revised allocation**

$$E_t^c = \beta\left(E_{t-1}^c + \frac{\beta^{t-1}\Delta_{t-1}}{\sum_{k=0}^{T-1}\beta^k}\right) + a_t\Delta_{t-1}$$

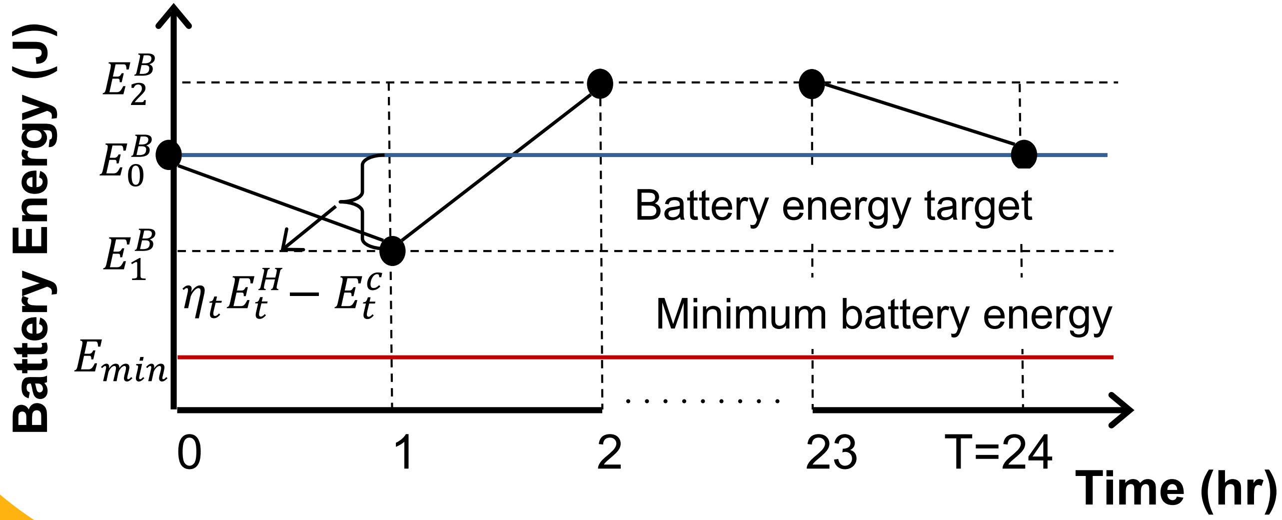
- a_t **is a normalization coefficient to ensure proper allocation**

$$a_t = \begin{cases} \dfrac{1-\beta}{1-\beta^{T-t}} - \dfrac{\beta^t}{\sum_{k=0}^{T-1}\beta^k} & 0 < \beta < 1 \\ \dfrac{1}{T-t} - \dfrac{1}{T} & \beta = 1 \end{cases}$$

Enforcing the Minimum Energy Constraint

- **In each interval, project the remaining battery energy E_{t+1}^{B}**
- **If violation is detected, allocate E_t^c such that constraint is met**

$$E_t^c = \begin{cases} \beta E_{t-1}^c + \left(\frac{\beta^t}{\sum_{k=0}^{T-1}\beta^k} + a_t\right)\Delta_{t-1} & E_{t+1}^B \geq E_{min} \\ E_t^B + \eta_t E_t^H - E_{min} & otherwise \end{cases}$$

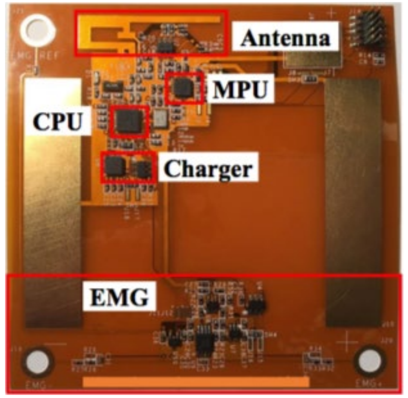


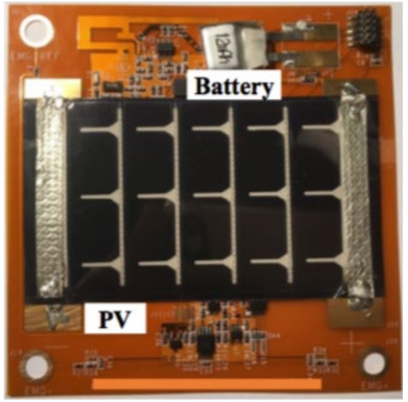
Summary

1. **Closed-form optimal solution using the expected values**
2. **Account for the deviations in harvested and consumed energy**
3. **Account for mis-allocations in the past**
4. **Enforce the min energy constraint**

Experimental Setup

- **Flexible hybrid electronics prototype**
  - TI CC2650 MCU, InvenSense MPU
  - 12 mAh Li-Po battery





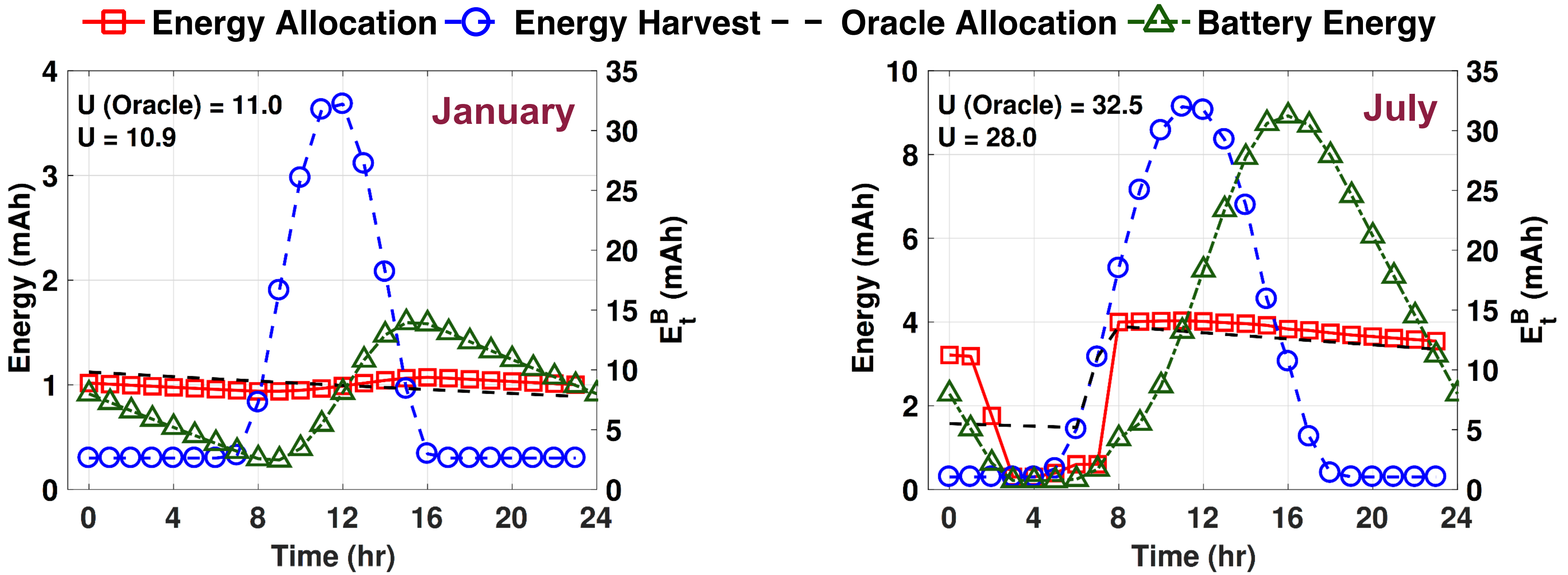
- **Energy harvesting model**
  - Sandia Ephemeris model
  - Get expected values of E_H

Parameter	Value
E_{min}	0.75 mAh
P_{idle}	2.2 mW
T	24

Parameter	Value
E_{target}	8 mAh
M_E	0.6 mAh
α	1

- **Oracle**
  - Global optimal solution found using the CVX package
  - The actual (*not expected*) harvested and consumed energies are known by the oracle

Energy Allocation Comparison



- Algorithm behaves aggressive during early hours in July
- We compared the allocation against Oracle over different months in a year
- On average, our solution is within 3% of the optimal solution

Outline

- **Wearable IoT Devices for Health Monitoring**
  - *OpenHealth*: Open-Source Hardware/Software Platform
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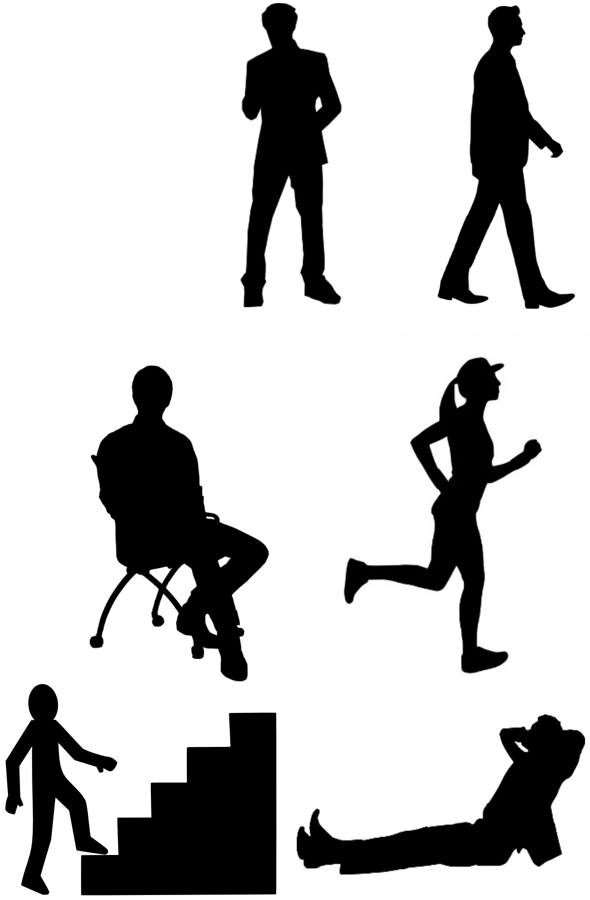


Why Human Activity Recognition (HAR)?

- **Recognize *six activities* and *transitions***
  - Applications in rehabilitation, fall detection, physical activity promotion
  - ***Must know what the patient is doing to reach a conclusion***
  - Provide valuable insight to health specialists

Walk Stand Sit

- **Aim day-long operation using flexible batteries**

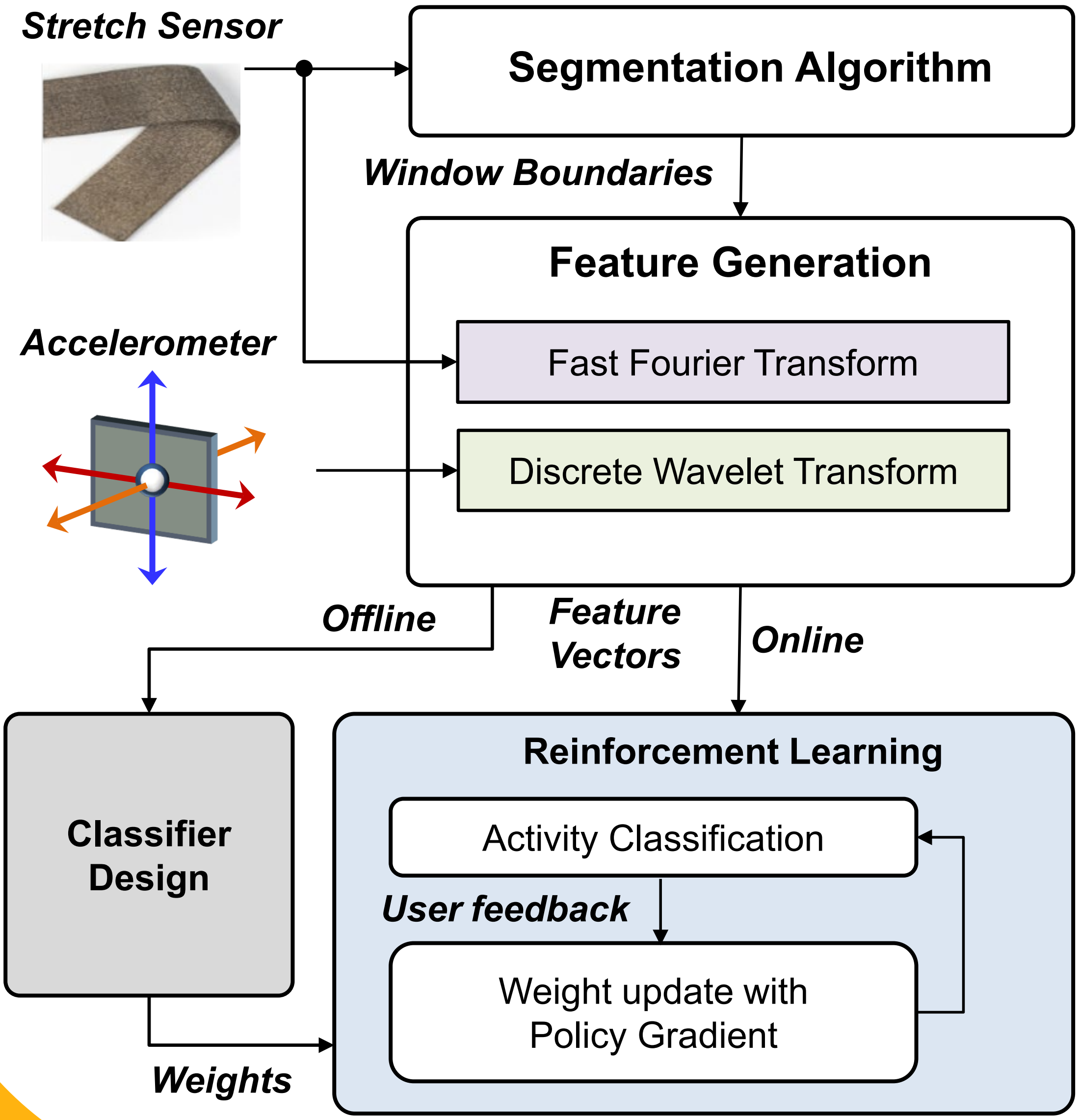
Jump Lie Down Drive

- **Existing work on wearables and smartphones**

	Offline	Online
Data Collection	✓	✗ → ✓
Learning	✓	✗ → ✓
Inference	✓	✓

- **Our solution**
  - Tailored to the problem
  - Low power & Energy-harvesting
  - Adapt to new users and changing user conditions

Overview of the HAR Framework



- **Segmentation**
  - Each activity has different length
  - Streaming stretch sensor data is processed to generate variable length segments
- **Feature Generation**
  - Accelerometer and stretch sensor data are processed to extract the features
- **Classifier Design**
  - Offline training of neural network using labeled segments
- **Reinforcement Learning**
  - Neural network weight updates using user feedback and policy gradient algorithm

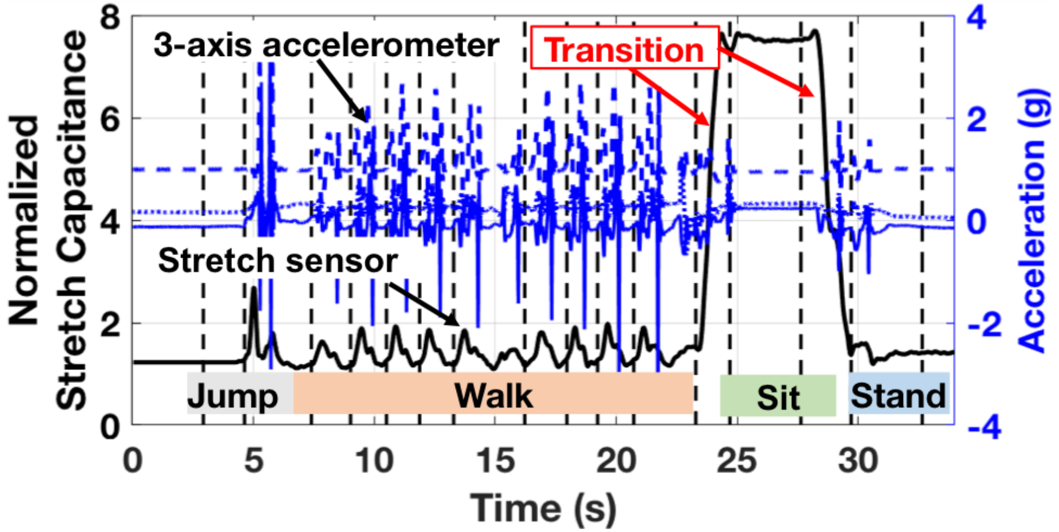
Ganapati Bhat et al. "Online Human Activity Recognition Using Low-Power Wearable Devices," *in Proc. of Intl. Conf. on Computer-Aided Design (ICCAD)*, November 2018

Segmentation Algorithm

- **Need for variable length segmentation**
  - Fixed length segments may contain multiple activities
  - Makes it harder to label and classify
- **We use stretch sensor data to segment the activities**
  - Accelerometer is more noisy
  - In contrast, stretch sensor provides a clean data for segmentation

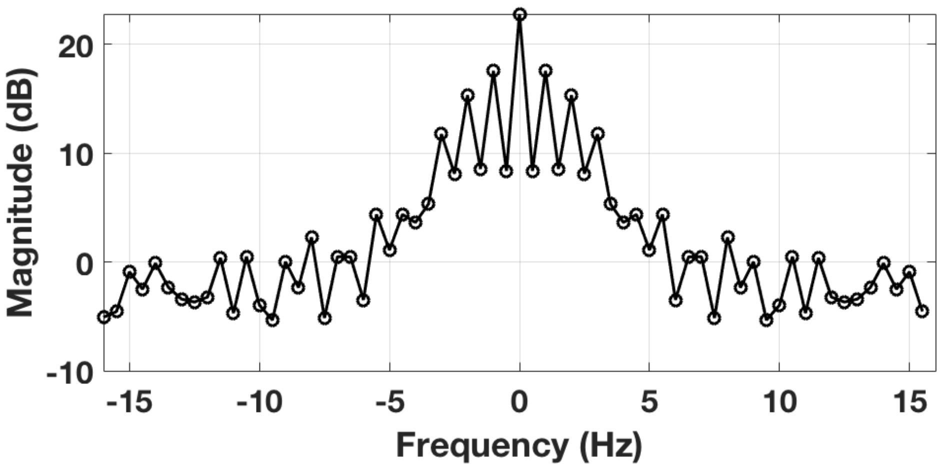
Stretch Sensor

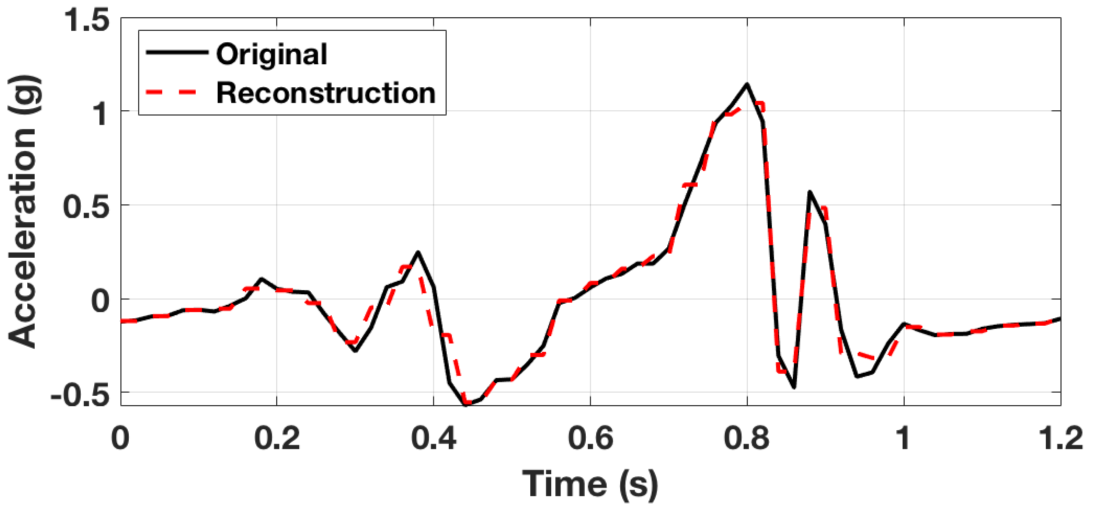
Result: Non-uniform activity segments



Feature Generation

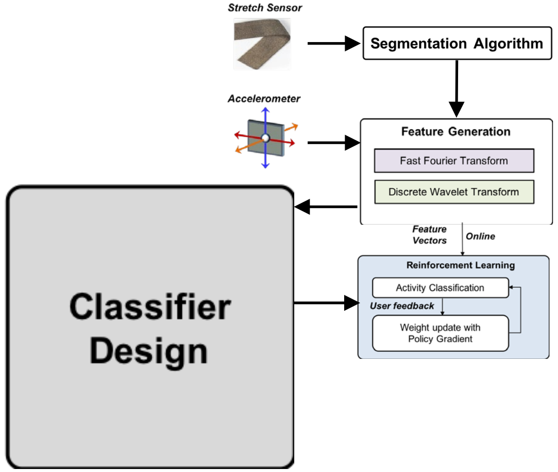
- **Most of the prior work on HAR uses statistical features for activity classification**
  - *However, statistical features do not provide insight into the actual shape of data*
- **In contrast, we use DWT and FFT to get better insight**
  - Stretch Sensor : **16 FFT coefficients**, minimum and maximum values in the segment
  - Accelerometer : **32 DWT coefficients** for a_x, a_z and body acceleration, mean of a_y
  - General features : Length of the segment and previous activity label





Supervised Learning for Activity Classification

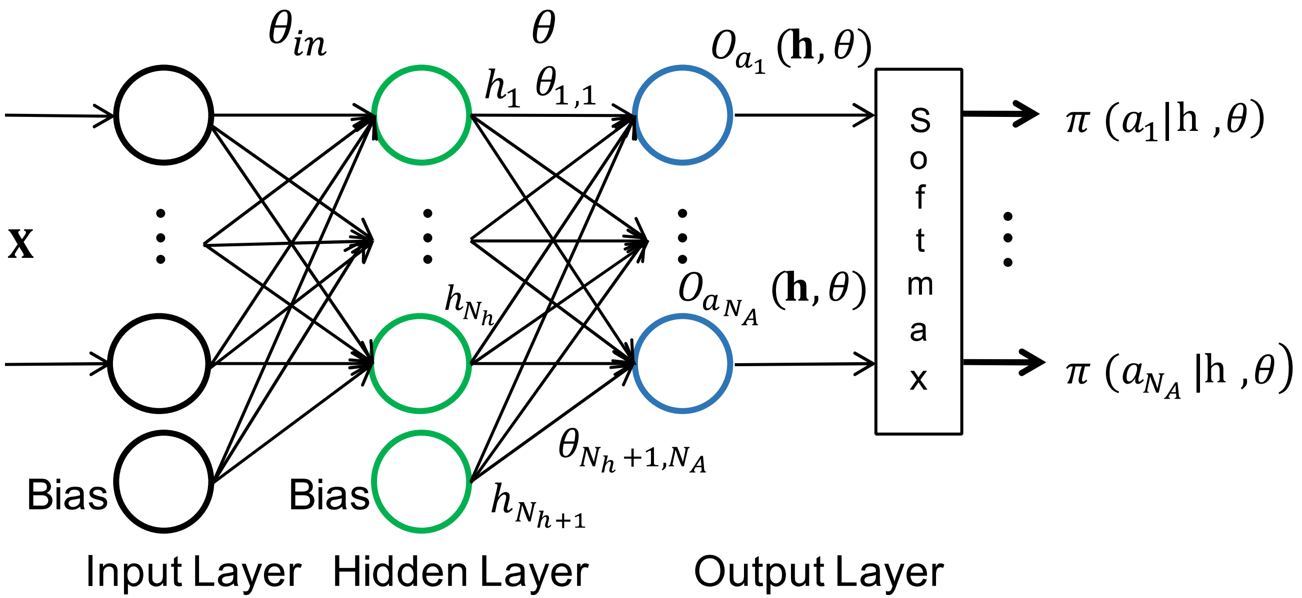
- **Designed a variety of classifiers**
  - SVM, Decision Tree, Random Forest, k-NN, and Neural Networks
  - Neural networks can be easily used for online learning



- **Neural network configuration**
  - One fully connected hidden layer
    - ReLU activation
  - Fully connected output layer
    - Softmax activation

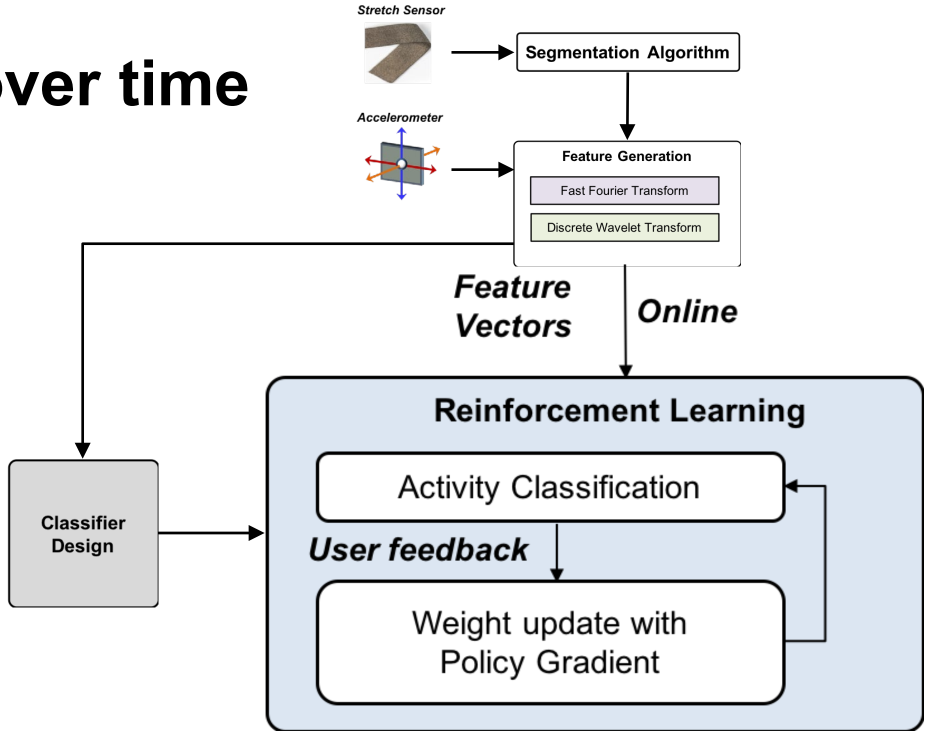
- **Probability of each activity is**

$$\pi(a_i|\mathbf{h},\theta) = \frac{e^{O_{a_i}(\mathrm{h},\theta)}}{\sum_{j=1}^{N_A} e^{O_{a_j}(\mathrm{h},\theta)}}$$



Why Online Learning?

- **Classifiers shipped with the device can be trained using *known user data sets***
- **User patterns can change with**
  - Physical condition, age, gender, and demographics
- **Even, condition of a given user may change over time**
- **Classifiers learned offline must adapt to**
  - New users
  - Varying conditions of its user
- ***Challenges***
  - Online training can be computationally intensive
  - Wearable devices do not have large storage area



Policy Gradient Weight Update

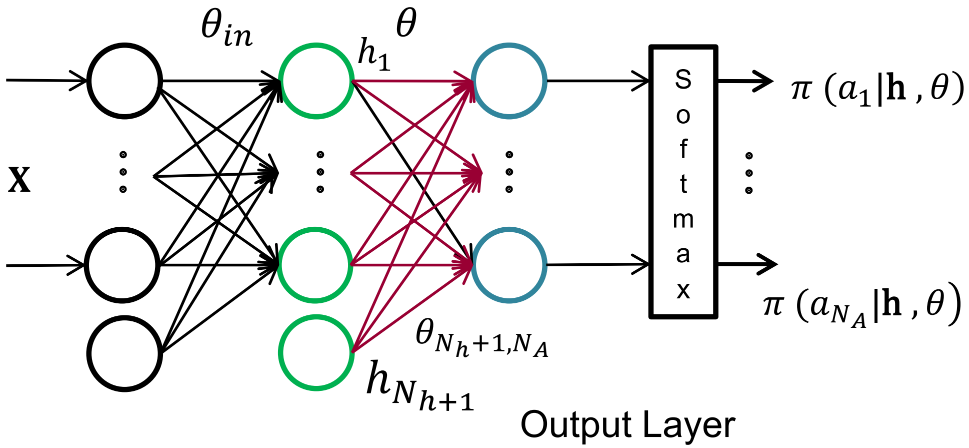
- **State ($\mathbf{X}$):** Accelerometer and stretch sensor readings within a segment define the continuous state space
- **Policy model (π):** The activity probabilities
- **Action:** Activity performed in each segment
- **Reward:** User provides the reward as a function of the classified action:
  – ***If correct***: **+1** ***Else***: **-1**

Objective: Maximize the total reward with respect to the classifier weights

- **We start with a trained policy network**
  – First few layers provide broadly applicable features
  – Hence, we update only the output layer weighs
- **Found the weight update equation as**

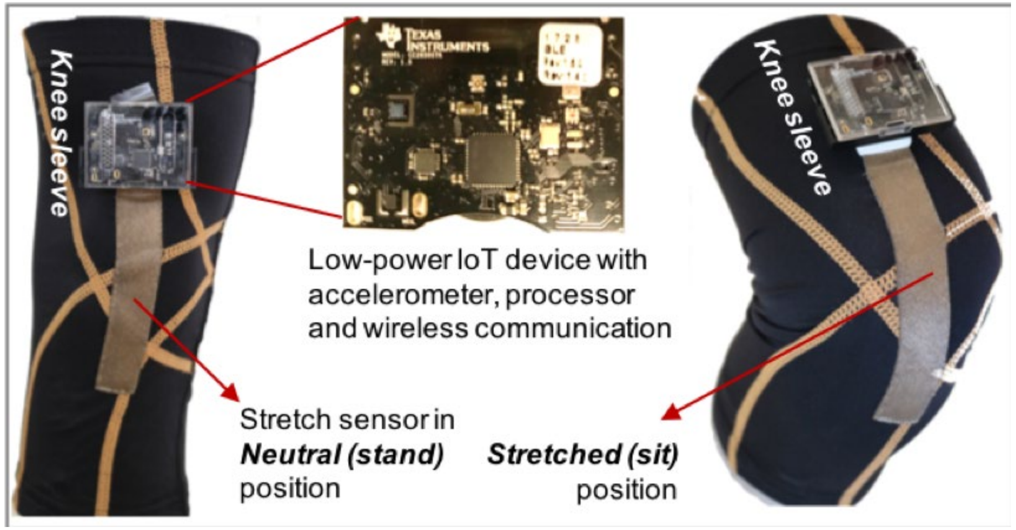
$$\boldsymbol{\theta}_{t+1} \equiv \boldsymbol{\theta}_t + \alpha r_t \frac{\nabla_{\theta}\pi(a_t|\mathbf{h}, \boldsymbol{\theta}_t)}{\pi(a_t|\mathbf{h}, \boldsymbol{\theta}_t)}$$

where α: *Learning rate*, r_t: *Reward*



Experimental Setup

- **Wearable Device**
  - TI CC2650 MCU, InvenSense MPU
  - Stretchsense Stretch Sensor
  - MPU is sampled at 250 Hz
  - Stretch sensor at 100 Hz
- **User studies**
  - Data from 22 users
  - Total of 4740 segments
- **Training data split**
  - 4 users for test
  - 18 users for training
  - 37% test data from unseen users

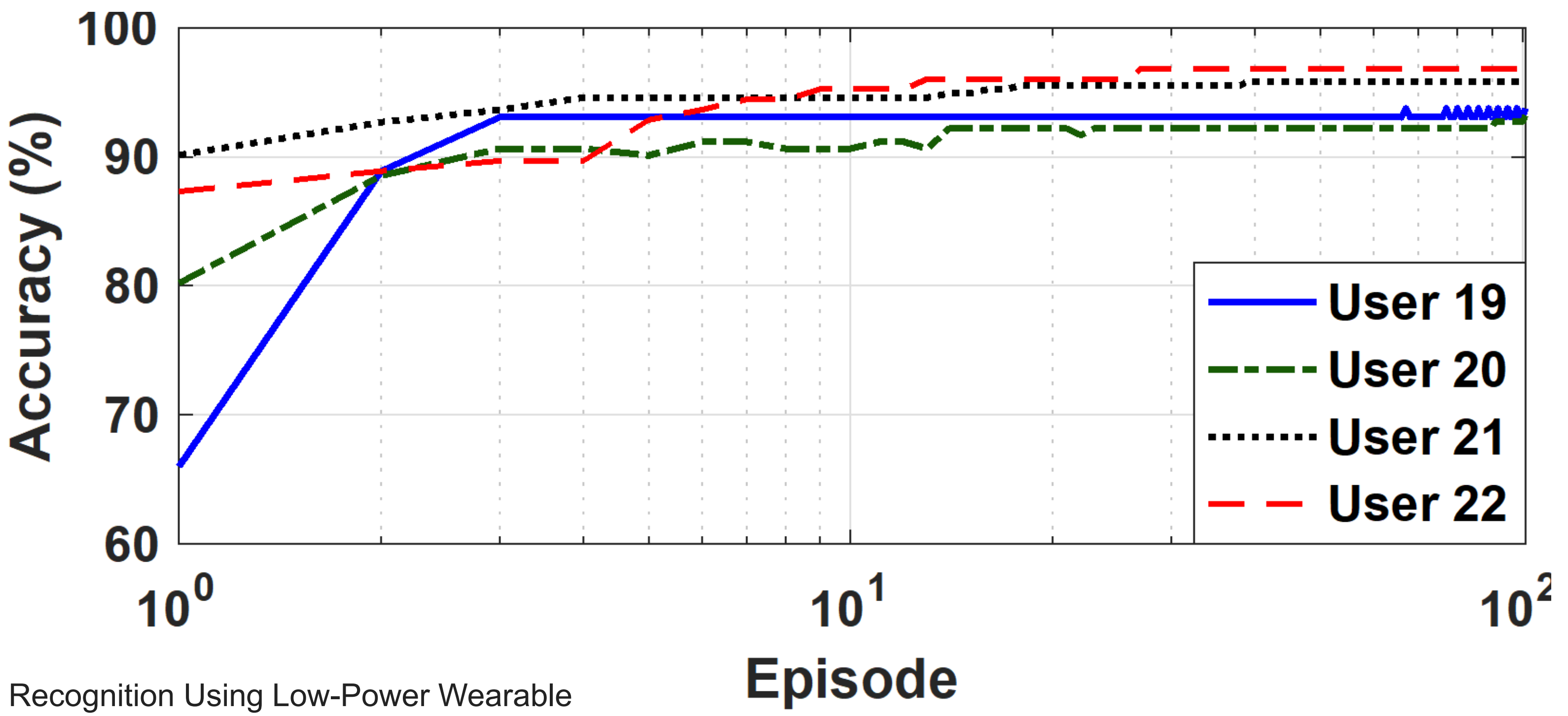


- **Data available open source**

Accuracy Analysis of Our Approach

- **Offline classifier achieves greater than 94% accuracy for all activities**
- **Apply reinforcement learning for four new users**
  - Run the policy gradient update for a total of 100 epochs
- **Accuracy improvement with reinforcement learning:**
  - ***User 19: 66% → 94%***
  - ***User 20: 80% → 93%***
  - ***User 21: 90% → 96%***
  - ***User 22: 87% → 97%***

HAR algorithm adapts to new users



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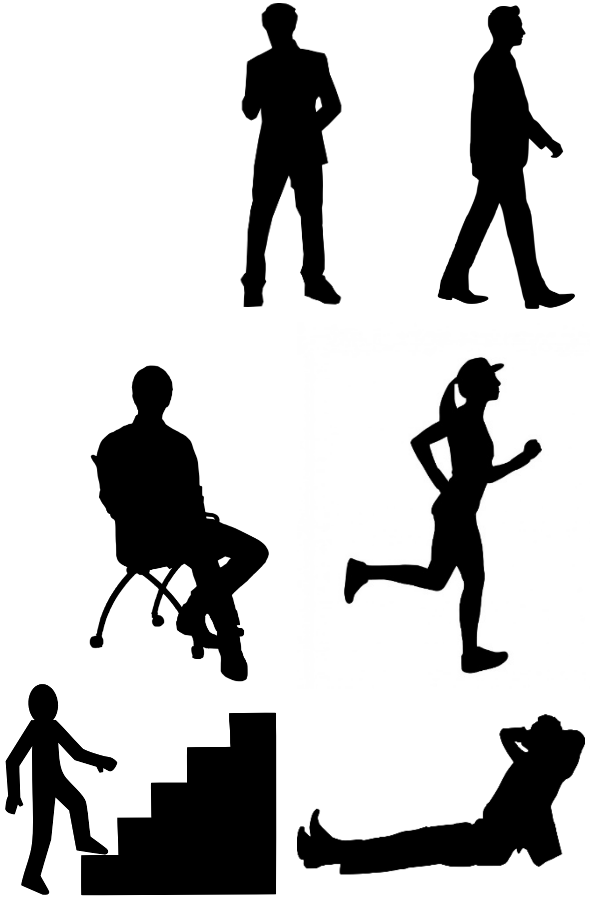

Challenges of Wearable Health Technology

- *Adaptation* & *technology* **challenges hinder widespread adoption**
  - **Comfort:** Awkward to wear or carry a device
  - **Compliance:** Stop using technology due to maintenance
  - **Applications:** No killer applications
- **27% users give up due to charging reqs [1]**
  - Practica

Low-power accelerators needed to meet energy budget

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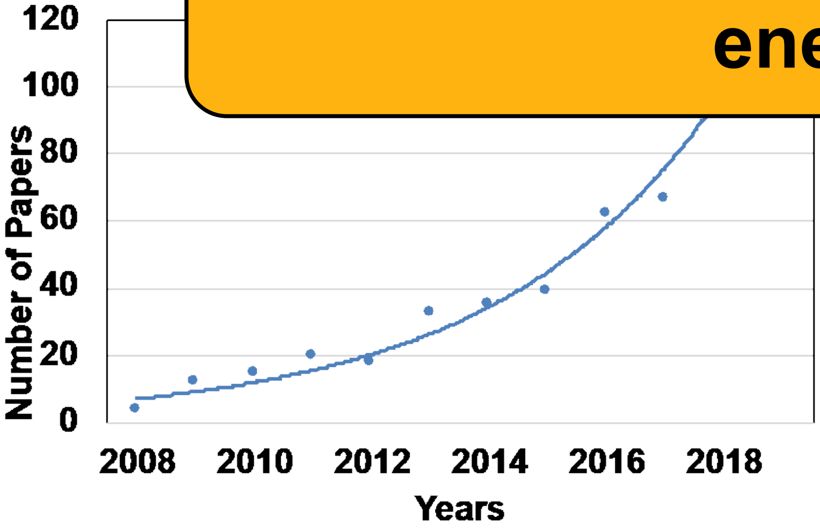


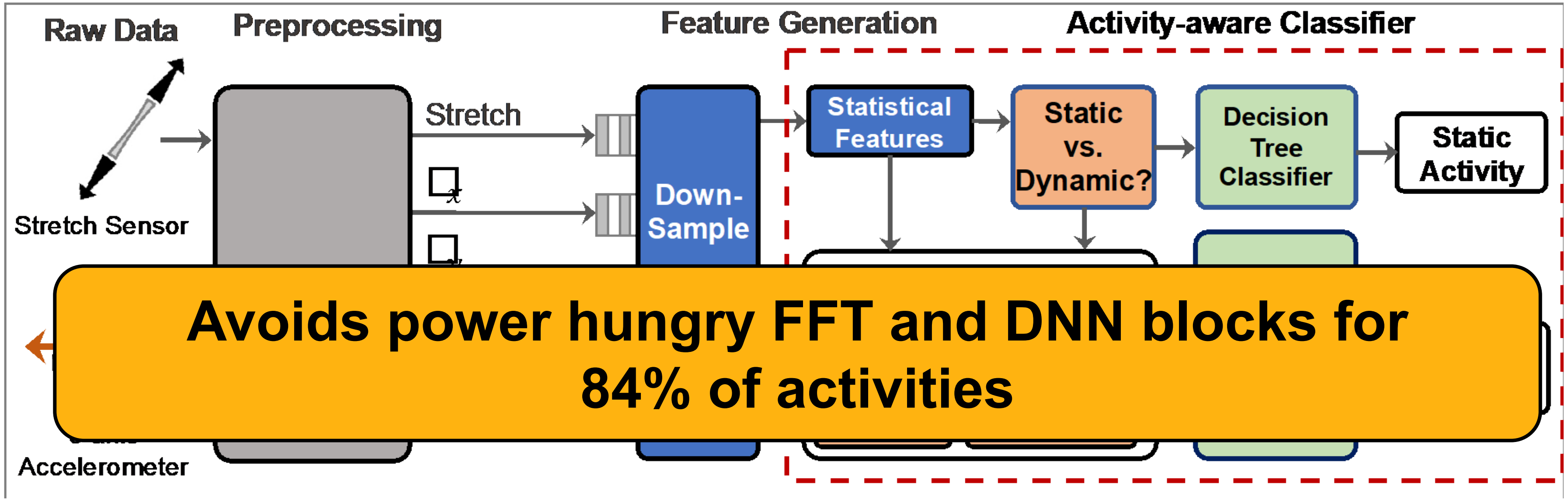
*Ranadeep Deb, MS Thesis, 2019

- **However,**
  - Ambient power is still lower than 10 to 30 mW requirement
  - Mere 40 hrs with 130 mAh battery

Flexible PV-cell

[1] Ana Lígia Silva de Lima et al.. *Feasibility of Large-Scale Deployment of Multiple Wearable Sensors in Parkinson's Disease*. PLOS One 12, 12 (2017), e0189161

Activity-Aware 2-Level Engine



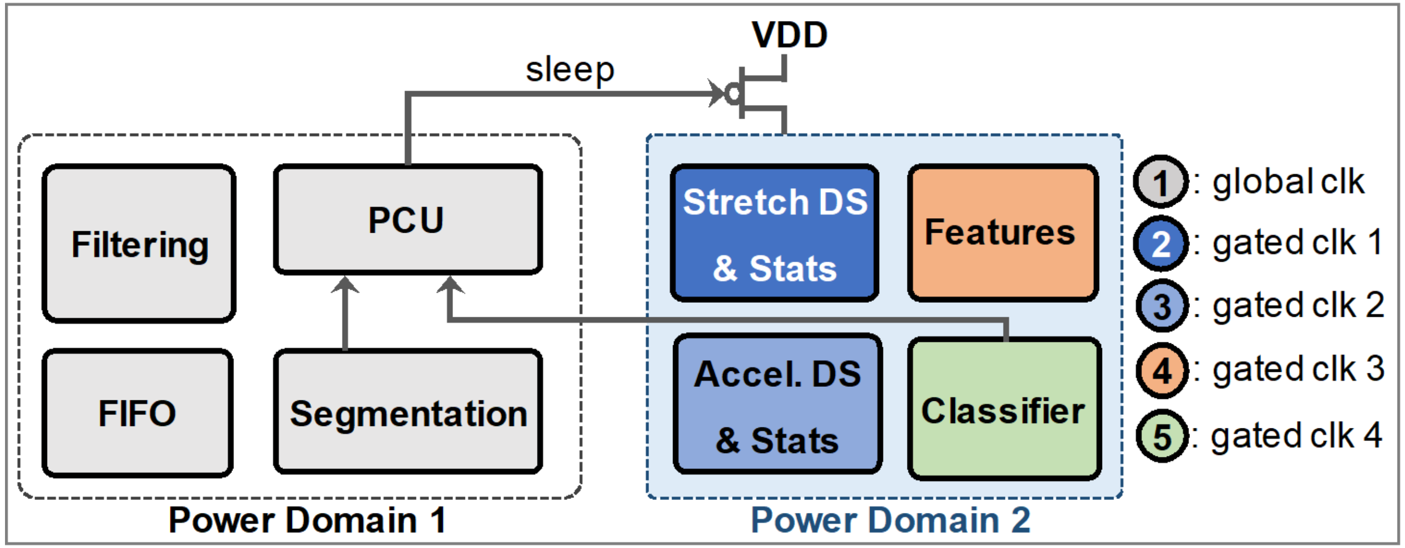
Avoids power hungry FFT and DNN blocks for 84% of activities

- **84% of human activities are static (e.g. sit, stand, lie down)**
  - We do not need a DNN to classify them
  - At the same time, more complex dynamic activities must be classified accurately
- **Divide the activities into two classes**
  - A simple support vector machine (SVM) to identify static vs dynamic
  - A 2-Layer NN classifier for dynamic activities

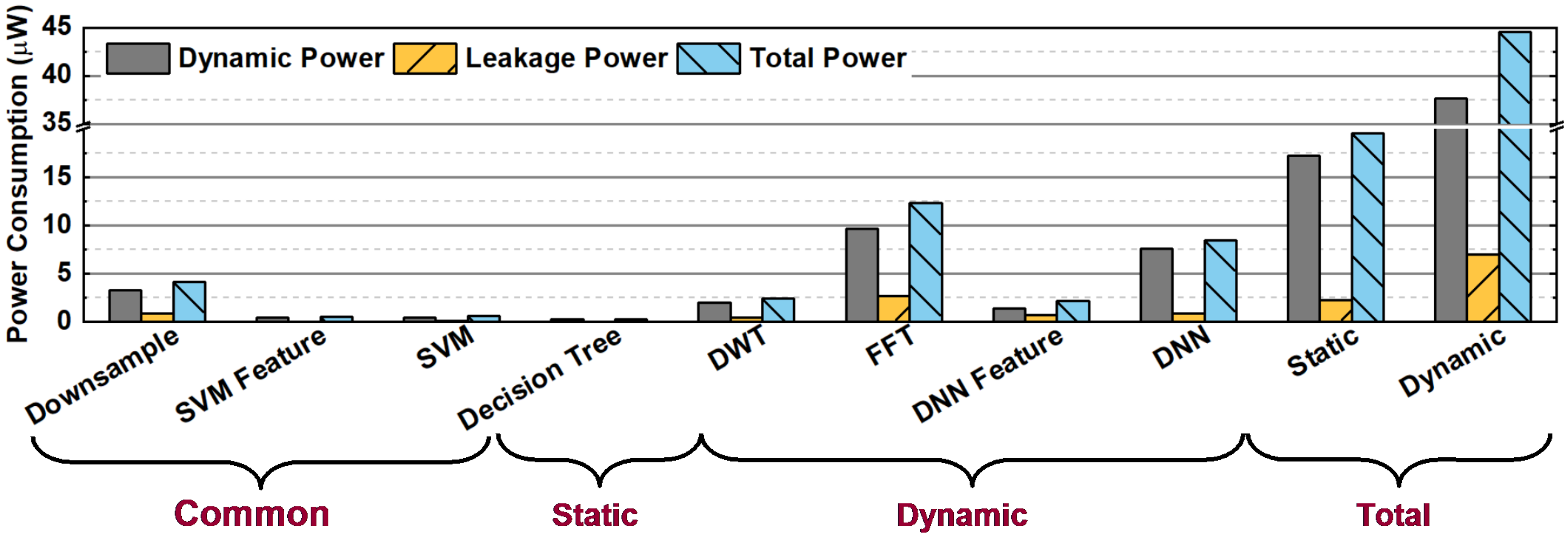
US Department of Labor. 2017. American Time Use Survey. [Online] https://www.bls.gov/tus/

Clock and Power Gating

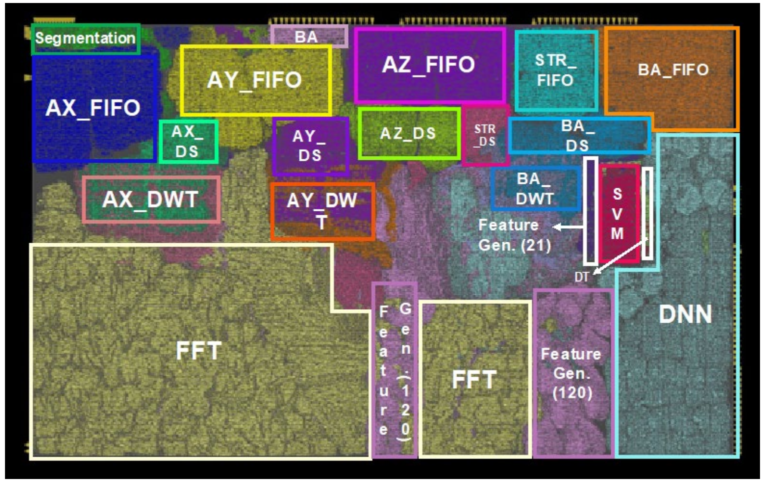
- **Human activities are in the order of few Hz**
  – Use this information to clock gate unused blocks
- **Insight from wearable applications domain**
  – Data collection and preprocessing have to be always ON
  – Processing blocks can be activated after the data is available
- **Major power savings potential by turning off processing pipeline**



Power Consumption of 2-Level Engine



- Static activities consume 19.5 µW (2.6× reduction)
- Dynamic activities consume 44.6 µW (1.14× reduction)
- 10× improvement compared to embedded solutions
  - Including sensor and communication energy
- 17 day operation using a 130 mAh flexible battery



Summary

- **Mobile and wearable devices offer great potential**
  - Health monitoring, activity tracking, gesture-based control
- **Exciting research directions**
  - Design of wearable devices using new technologies like flexible hybrid electronics and textile-based circuits
  - Energy harvesting and management
  - Health applications
  - Low-power hardware design

Thank you!