Movers and Shakers: Kinetic Energy Harvesting for the Internet of Things

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EnHANTs

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Department of Electrical Engineering
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EnHANTs for the Internet of Things

- Small and flexible: can be attached to almost anything
- Harvest energy, form a wireless network and exchange basic information
  - Tag IDs, Partial location
- Can communicate with other EnHANT friendly devices
  - Laptops, mobile phones, access points
- Internet of Things

ALLSEEN ALLIANCE

industrial internet CONSORTIUM

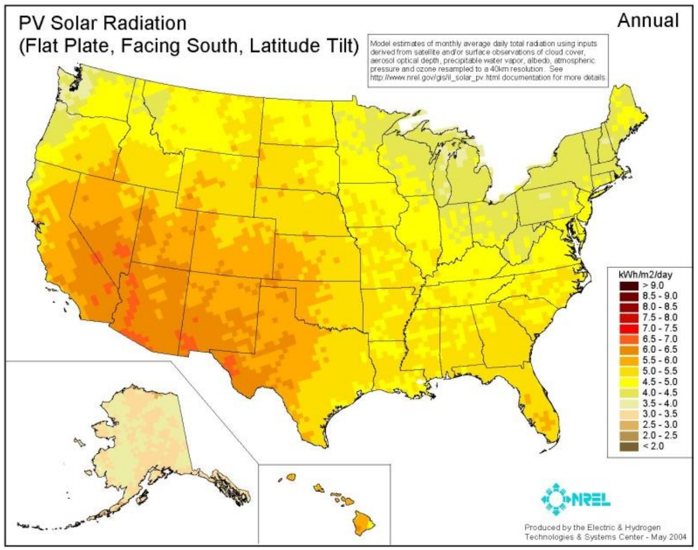
Smart Buildings

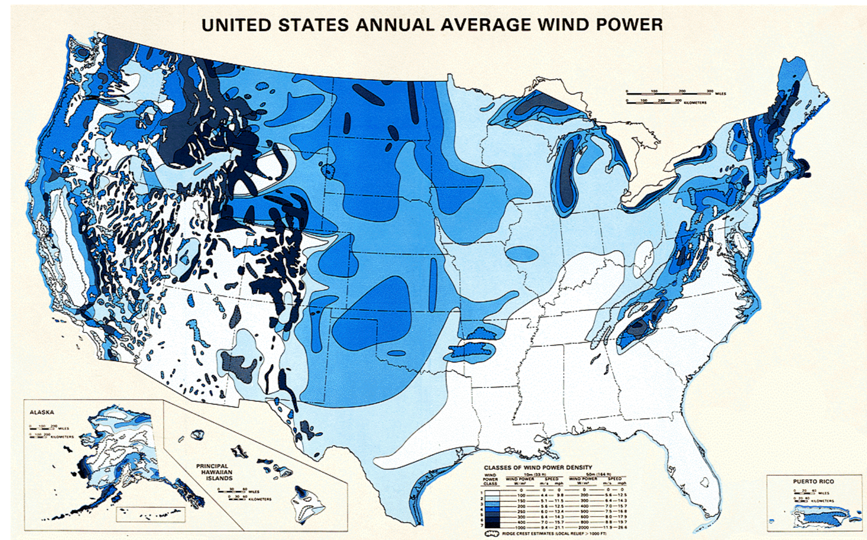
Monitoring of Objects

Searching Objects:
Where are my keys?

What are the properties of environmental energy sources for ultra-low-power energy harvesting nodes?

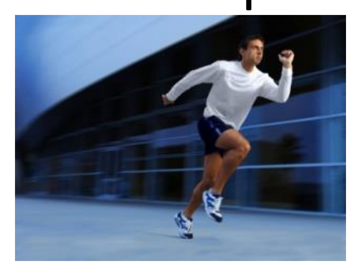
- Large-scale energy harvesting installations: energy availability - very well known





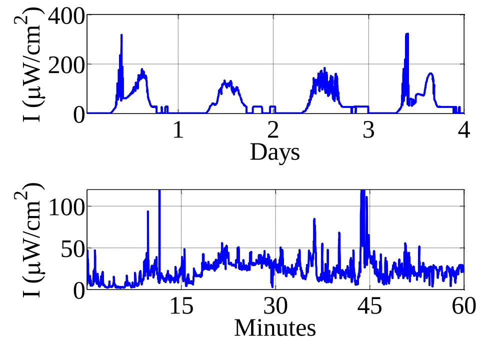
Maps source: NREL

- Energy in commonplace environments: much less explored
  - Indoor light
  - Object and human motion



Our Previous Work: Indoor Light Energy Study

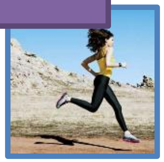
- First of its kind long-term indoor light energy measurement campaign
  - ➢ *Radiometric* TAOS TLS230rd sensor + LabJack U3 DAQ + custom monitoring system
  - ➢ Long-term (1.5 years) indoor measurements
  - ➢ Mobile device experiments
- Established energy budgets
- Obtained insights into energy predictability, variability, correlations
- Traces as energy feeds for simulators and emulators
  - ➢ Used to evaluate algorithm performance
  - ➢ On **enhants.ee.columbia.edu** and on CRAWDAD



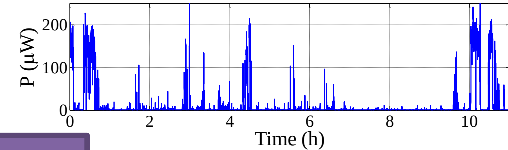
- ❑ M. Gorlatova, A. Wallwater, G. Zussman, Networking Low-Power Energy Harvesting Devices: Measurements and Algorithms, **Proc. IEEE INFOCOM’11**, Apr. 2011. **IEEE Transactions on Mobile Computing**, Sept. 2013.
- ❑ J. Sarik, K. Kim, M. Gorlatova, I. Kymissis, G. Zussman, More than Meets the Eye - a Portable Measurement Unit for Characterizing Light Energy Availability, in **Proc. IEEE GlobalSIP’13**, Dec. 2013
- ❑ M. Gorlatova, M. Zapas, E. Xu, M. Bahlke, I. Kymissis, G. Zussman, Dataset: Light Energy Measurements **CRAWDAD dataset**, Apr. 2011.

Kinetic Energy Study: Summary

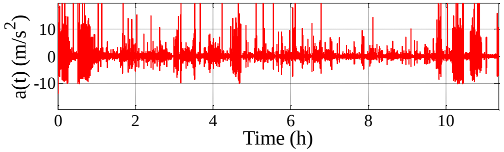
Motion → **Harvester** → **POWER**



Mitcheson'04, Aktakka'11, …



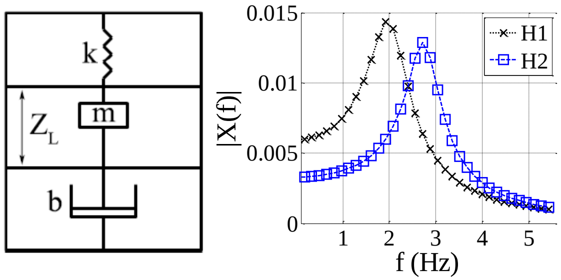
Motion → **Acceleration Traces** → **Harvester Model** → **POWER**



Yun'11, Zhu'11

- Goal: insights into node and algorithms design for Internet of Things (IoT) applications
- Object and human motion energy availability
  - Record acceleration, convert it to power
  - Particular human motions
  - Day-long human routines
- Develop and evaluate energy harvesting adaptive algorithms

CRAWDAD



2nd order mass-spring model

m: proof mass

Z_L: displacement limit

k: spring constant

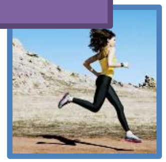
b: damping coefficient

Related Work

- Particular human motions:
  - ➢ Existing work: small number of participants, **walking** on a treadmill
    - 10 participants in *Huang'11*, 8 participants in *Buren'06*
  - ➢ We examine free-motion 40-participant dataset *Xue'10*
    - 7 motions, 3 sensing unit placements
    - Not examined from energy harvesting point of view before
- Day-scale human motion acceleration traces:
  - ➢ Previous work: *Yun'11* - Traces not available; only first-order statistics under different assumptions
  - ➢ We collect data, characterize process variability and properties not considered before
- Energy harvesting adaptive algorithms
  - ➢ Previous work: continuous energy spending rates, concave utility functions, battery for energy storage - *Chen'12, Devillers'12*
  - ➢ We consider an ultra-low-power node model: discrete energy spending rates, general utility functions, battery and capacitor models

Methodology: Inertial Harvester Model

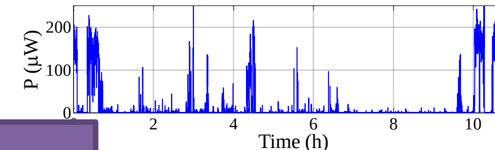
Motion



Harvester

Mitcheson'04, Aktakka'11, …

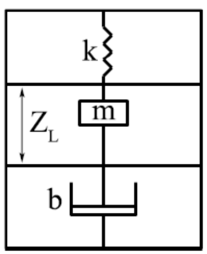
POWER

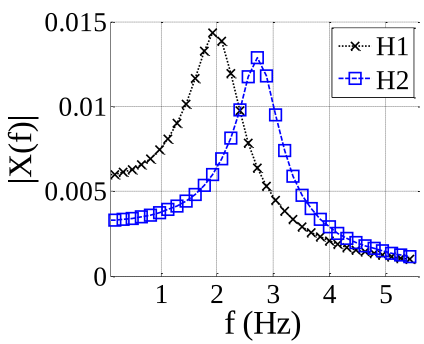


Acceleration Traces

Harvester Model

Yun'11, Zhu'11





2nd order mass-spring model

m: proof mass

Z_L: displacement limit

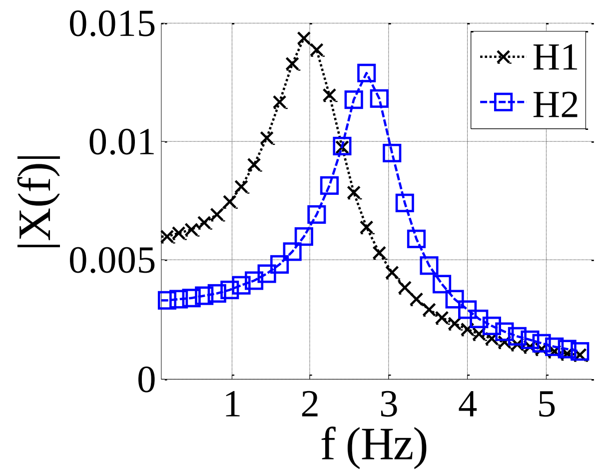
k: spring constant

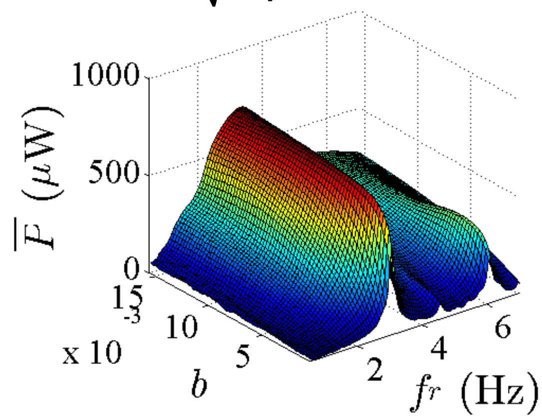
b: damping coefficient

- Key design parameters: m, Z_L
  - Application weight and size considerations
  - **1 gram** harvester proof mass, **10 mm** harvester size – *Von Buren'06*

Optimizing Inertial Harvester Parameters

- Tunable: k, b. Control harvester response:
  - Harvester resonant frequency, $f_r = 2\pi\sqrt{k/m}$
    - Key parameter
    - Should be reasonably close to f_m
  - Harvester quality factor, $Q = \sqrt{k/m}/b$

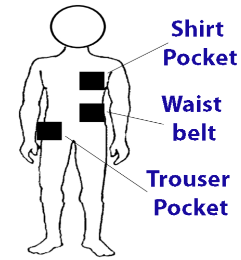




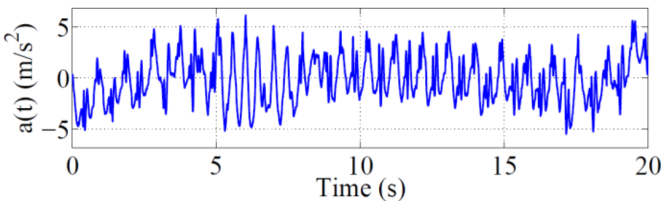
- Optimizing parameters: optimizing over a multi-dimensional surface of unknown geometry
  - Short motion samples: exhaustive search over k, b
  - Longer samples: select k such that f_r matches f_m, exhaustive search over b

Collecting and Processing Motion Information

- Tri-axial accelerometers, sampling frequency 100 Hz
  - Our measurements: ADXL345
  - 40-person dataset Xue'11: ADXL330
- Different accelerometer placements



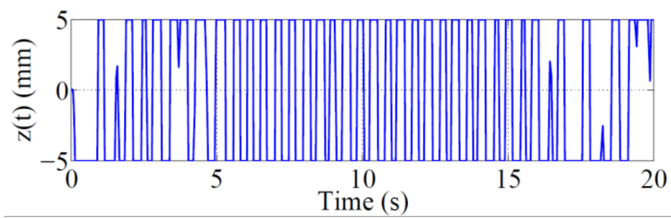
- Collect acceleration, obtain its magnitude



$$a(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2}$$

MATLAB

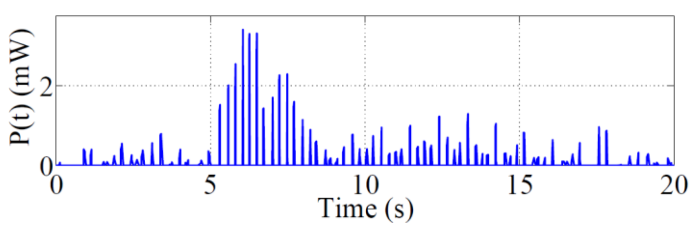
- Convert to proof mass displacement



$$z(t) = L^{-1}\{z(s)\} = \frac{a(s)}{s^2 + s\frac{2\pi f_r}{Q} + (2\pi f_r)^2}$$

- Apply limiter Z_L

- Obtain power



$$P(t) = b \bullet \left(\frac{dz(t)}{dt}\right)^2$$

- Average: $\overline{P}$

- Efficiency η= 20%, c_{tx} = 1nJ/bit (IoT-suitable ultra low power transceiver) → data rate r

Energy Availability: Object Motion

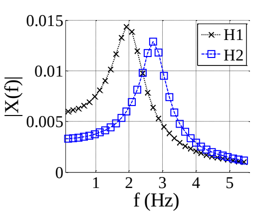
- Experiments: planes, trains, and automobiles

UNITED AMTRAK FedEx

System parameters: 1 gram harvester proof mass, **10 mm** harvester size, **20%** efficiency

Scenario	P, µW	Scenario	P, µW
Taking a book off a shelf	<10	Spinning in a swivel chair	< 10
Putting on reading glasses	<10	Opening a building door	<1
Reading a book	<10	Opening a drawer	10 - 30
Writing with a pencil	10 - 15	Shaking an object	>3,000

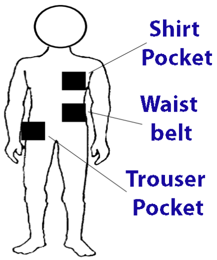
For comparison, human walking: 120 - 280 µW



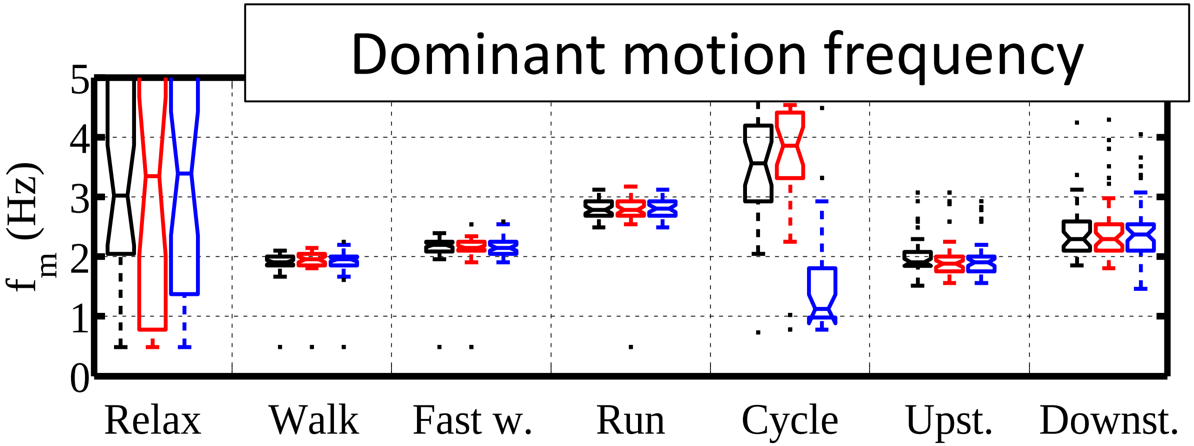
- Low for non-periodic motions
- Low for some periodic motions: drawer, door, swivel chair
  - ➢ Motions *damped (softened)*
    - **Possibility: Combining harvesters with mechanical dampers**
- Shaking: 12 - 29 times more power than walking
  - ➢ Can quickly recharge depleted nodes

Energy Availability: Human Motion, Short Samples

- Examined free-motion 40-participant dataset *Xue'10*
  - Collected and used for pattern recognition
  - 7 motions, 3 sensing unit placements, indexed with human physical parameters



Boxplots: left box: shirt pocket, **middle box**: waist belt, **right box**: trouser pocket



- f_m values consistent with human physiology
  - E.g., f_m increases from walking to fast walking to running

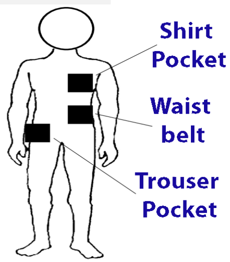
Energy Availability: Human Motion, Short Samples

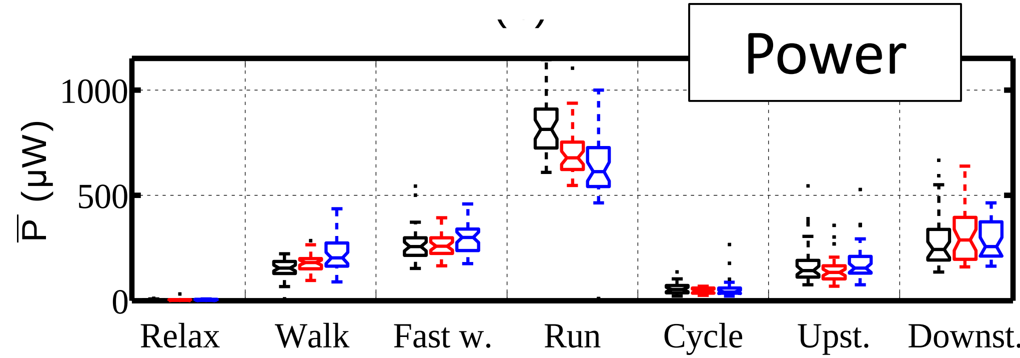
- Harvester optimized for each motion

1 gram harvester proof mass

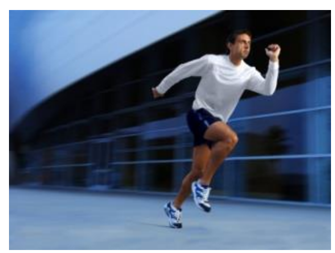
10 mm harvester size

20% efficiency





- Relaxing: almost no energy



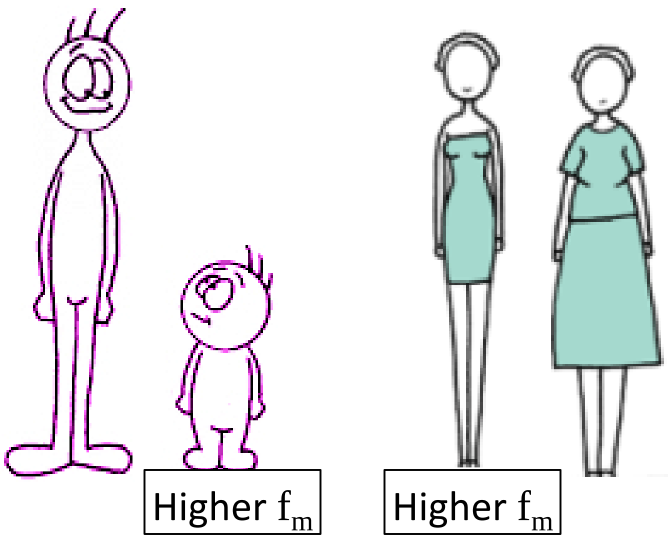
- Walking: 120 - 280 µW
  - ➢ In comparison, indoor light: 50-100 µW/cm^2
- Running: 610 – 810 µW

- Cycling: 40 – 50 µW
  - ➢ High cadence, low displacement
  - ➢ For cycling-specific IoT applications, harvester placements on lower legs should be considered

- Exertion ≠ power harvested
  - ➢ P is 1.6 – 2.1 times higher for going downstairs than upstairs

Energy Availability: Human Physical Parameters

- Dataset indexed with height and weight



- f_m *negatively correlated* with participants' height and weight
  - Different harvesters integrated in clothing of different sizes

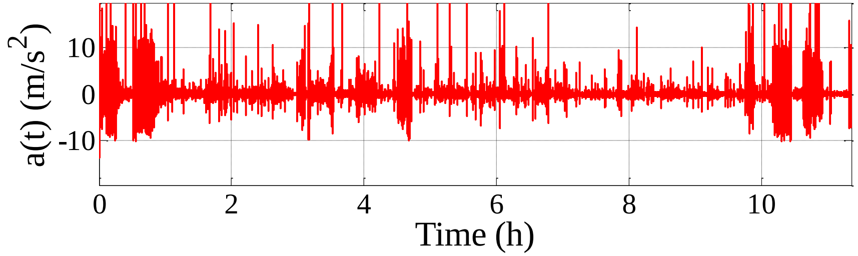
- Running - P for taller half of participants is 20% higher than for the shorter half

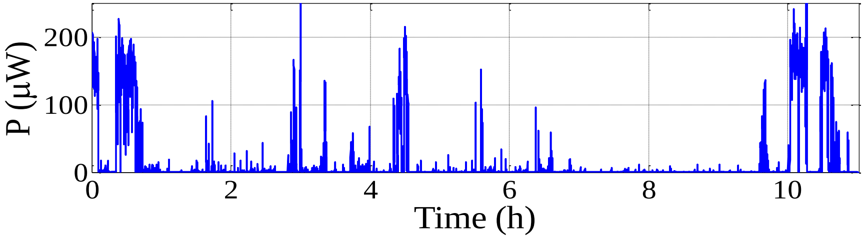
- Develop different harvesters for different demographics
- Provide performance guarantees based on human parameters

Day-long Human Motion: Methodology

- Daily human routines
- Previous studies: *Yun'11*
  - Study under different assumptions
- We needed: insights into energy harvesting adaptive algorithm design

- 5-participant study
  - Carried sensing units where convenient





- 25 days, over 200 hours of acceleration information

- Data available on CRAWDAD: M. Cong, K. Kim, M. Gorlatova, J. Sarik, J. Kymissis, G. Zussman, Dataset: Kinetic Energy Measurements **CRAWDAD dataset**, May 2014.

Day-long Human Motion: Power Budgets

- P_d - average power generated over 24-hour interval
- r_d – corresponding **continuous** data rates

Part.	# days	Total dur. (h)	P_d (μW), min/avg/max	r_d, avg (Kb/s)
M1	5	60.4	4.8 / 6.5 / 8.1	1.3
M2	3	27.7	8.4 / 11.5 / 17.7	2.3
M3	9	62.0	0.6 / 2.02 / 3.6	0.4
M4	7	80.1	0.6 / 5.6 / 10.7	1.1
M5	1	11.0	7.5	1.5

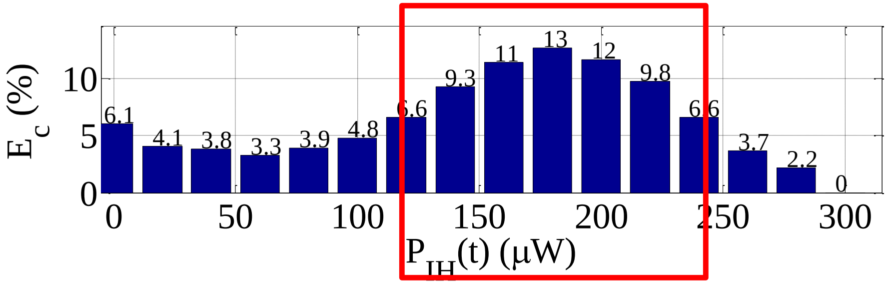
1 gram harvester proof mass
10 mm harvester size
20% efficiency
1nJ/bit communication cost

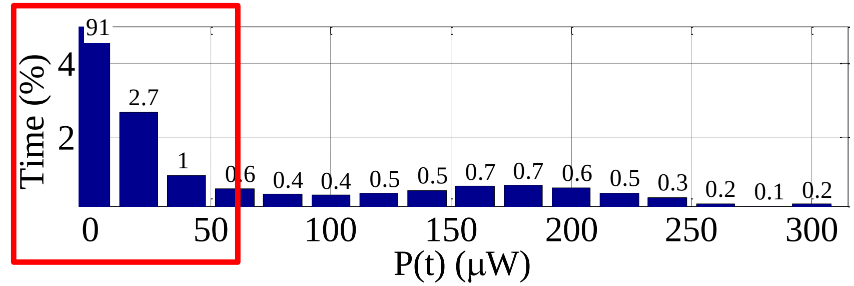
- Normal daily activities: **1-2 Kb/s**
  - Comparable with dim indoor lights
- Low energy availability → working from home
- Daily routines with a lot of walking → higher energy availability

❑ Data available on CRAWDAD: M. Cong, K. Kim, M. Gorlatova, J. Sarik, J. Kymissis, G. Zussman, Dataset: Kinetic Energy Measurements **CRAWDAD dataset**, May 2014.

Day-long Human Motion: Variability and Properties

- People are stationary the vast majority of the time
  - >95% energy collected during 4-7% of the day





- P_{onoff} process: P_{onoff} ←ON if $P(t) > \gamma$, P_{onoff} ← OFF otherwise

Part.	# days	Total dur. (h)	% ON, min/avg/max
M1	5	60.4	5.4 / 9.9 / 12.2
M2	3	27.7	13.6 / 16.1 / 18.4
M3	9	62.0	3.6 / 6.0 / 9.95
M4	7	80.1	2.8 / 12.7 / 18.1
M5	1	11.0	11.5

% ON: typically low

- 30 min of activity per day: ~ 9% of an 11-hour trace

ON intervals: typically short

- 78-89% shorter than 30 seconds
- Median intervals: 5 – 9.5s
- Longer intervals are rare (1 – 3%), correspond to commuting

- Overall, $P(t)$ low the majority of the time; if high, stays high for a short interval

Need energy harvesting adaptive algorithms

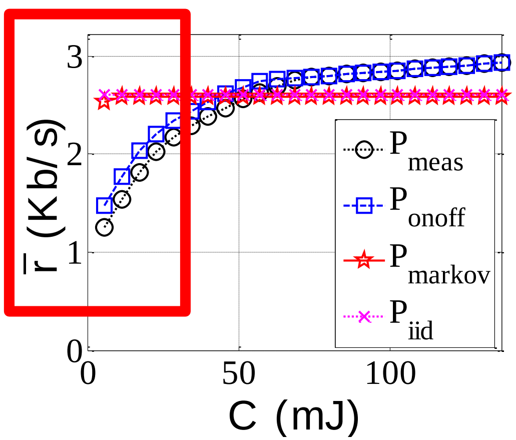
Harvesting Process vs. i.i.d. and Markov Processes

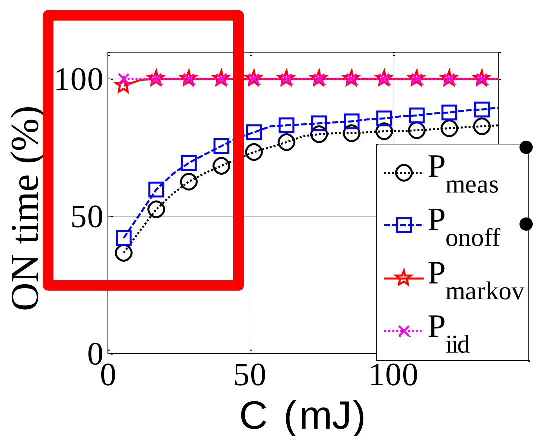
- Many energy harvesting adaptive algorithms developed for i.i.d. or Markov energy sources *Huang'13, Wang'13*
- Kinetic motion process: *not i.i.d. or Markov*
  - $p(P(t) > \gamma \mid P(t\text{-}1) > \gamma) \neq p(P(t) > \gamma \mid P(t\text{-}1) > \gamma, P(t\text{-}2) < \gamma)$
- Performance **not** similar to i.i.d. or Markovian processes

Example: Scheme-LB policy, *Chen'12*

- Controls: energy spending
- Decision made on: average incoming energy, energy in storage

- Examine Scheme-LB for different energy storage sizes C
  - P_{meas}, P_{onoff}: observed processes
  - P_{iid}, P_{markov}: derived processes



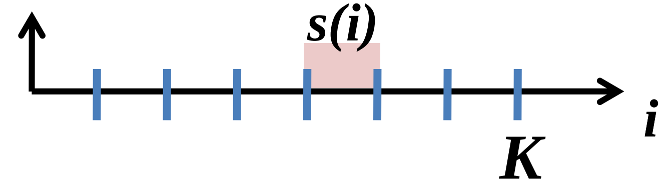


- Dramatic performance differences
- Different performance **trends**
  - No dependency on C for P_{iid}, P_{markov}

Need to evaluate policy performance with real traces

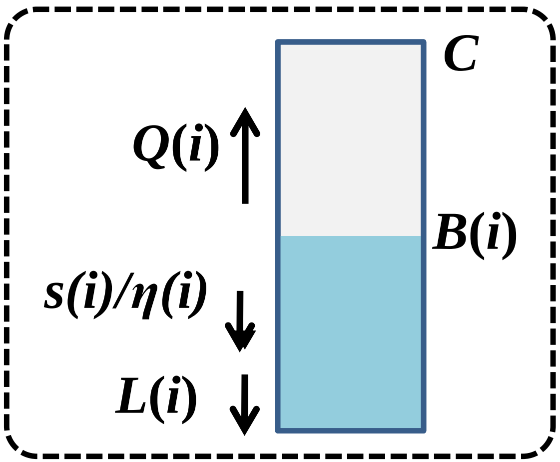
Energy Allocation (EA) Problem Formulation

- Model: an ultra low power **Internet of Things** node
  - ➢ Limited set of energy spending modes → Energy spending $s(i)$ in a finite set S
  - ➢ Different options for communicating with a particular energy spending level $s(i)$ → Arbitrary utility function $U(s(i))$
  - ➢ **Capacitor** possible for energy storage → Allowing for **non-linearity** in energy storage
- EA problem: max $\sum U(s(i))$, s.t.
  - ➢ Starting and ending energy levels B_0, B_K
  - ➢ Energy availability
  - ➢ Energy storage evolution dynamics
- Integer optimization problem



s(i): energy spending, in finite set S

Energy Storage



Theorem: EA problem is NP-hard.

- Even for “easy” cases, e.g., battery energy storage and linear utility function

Energy Allocation Algorithms

- **Dynamic programming-based algorithm**, offline
  - Complexity $O(K^2 \cdot U(s_{max}) \cdot |S|)$
- **FPTAS**, offline
  - Scaling factor $\mu = \varepsilon \cdot U(s_{max})/K$, utility function $\overline{U} = \lfloor U(s)/\mu \rfloor$
  - Invoke dynamic programming algorithms for $\overline{U}$

Theorem: The algorithm runs in times $poly\left(\frac{1}{\varepsilon}, K\right)$. The solution is a $1 - \varepsilon$ approximation.

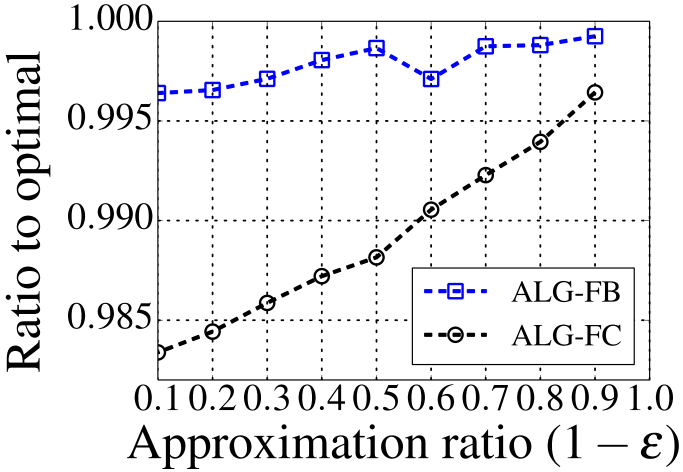
- **Greedy** online algorithm
  - In every time slot, maximizes the utility, while not letting the energy storage go below B_K

Theorem: The algorithm is optimal for battery energy storage model, if $B_K = 0$, $U(x+y) = U(x) + U(y), S = \{j \cdot s, j = 1, \dots, |S|\}$.

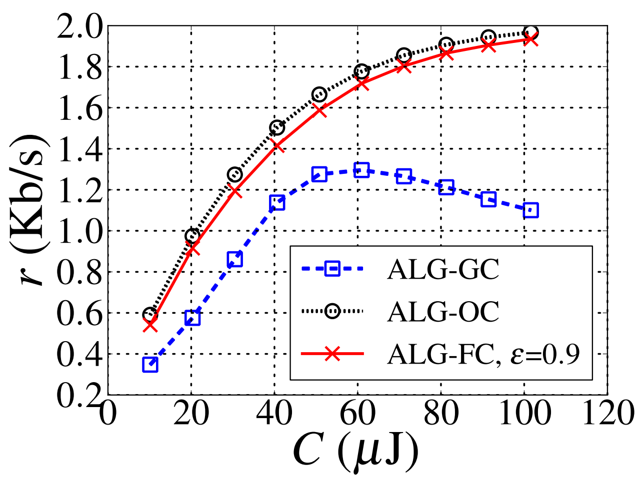
  - E.g., node using a fixed power level, changing its transmission rate by transmitting a different number of equal-sized packets

Trace-based Algorithm Performance Evaluations

- Each data point: one run of algorithm with a day-long trace



- Ratio of FPTAS to optimal solution, as a function of the approximation ratio
  - ➢ For both battery (ALG-FB) and capacitor (ALG-FC)
  - ➢ Performance is close to the optimal
  - ➢ Much closer than the theoretical bound



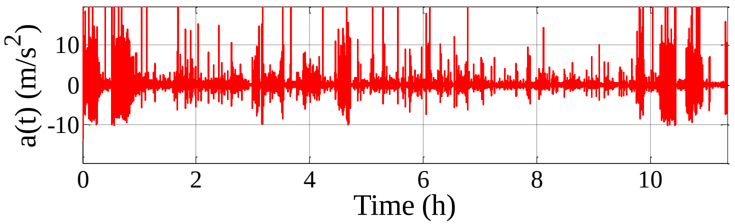
- Capacitor: Average data rates for ALG-GC (greedy), ALG-OC (optimal), and ALG-FC (FPTAS), for different energy storage sizes C
  - ➢ FPTAS performs similar to the optimal
  - ➢ For the greedy algorithm, performance decreases as C increases

For a capacitor, larger energy storage may worsen the overall performance

Kinetic Energy Availability for the Internet of Things

- Measurement-based study of object and human motion
- Examine implications for IoT node and algorithm design
  - ➢ Demonstrate energy budgets
  - ➢ Demonstrate dependency of energy on different parameters
  - ➢ Examine properties of energy generation process

- Consider an IoT node model, and design and evaluate energy allocation algorithms
- Traces available via CRAWDAD



- Big thanks to contributors!
  - ➢ Sonal Shetkar, Craig Gutterman, Chang Sun, Kanghwan Kim
- Questions?
  - ➢ Please e-mail me at: maria.gorlatova@caa.columbia.edu
  - ➢ Project website: **enhants.ee.columbia.edu**

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