ECROPS: Minimum Energy with Maximum Harvesting for Optimal Communications

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2020 ICT Carbon ➔ 1.43BTONNES CO₂
2007 ICT = 0.83BTONNES CO₂
~Aviation = 2%
Growth 4%
EU 2012 →
ICT = 4.7% of Electricity Worldwide
1000 TeraW-hrs/year > Japan’s Electricity

Figure 3-1: Worldwide use phase electricity consumption of communication networks, personal computers and data centers. Their combined share in the total worldwide electricity consumption has grown from about 4% in 2007 to 4.7% in 2012.
High-Level Contributions of ECROPS

- Focus on Energy Harvesting and its Optimisation
- Introduction of a Discrete State-Space Model for Energy and Communications
- Random Processes Represent both Energy Flow and Data Flow
- Energy-Packets & Data Packets
- Discrete Storage Batteries & Data Buffers
- Leading to Easy Access to Convenient Mathematical Tools: Random Walks, Queueing Theory, and Dynamic Programming
Example Problem: Optimum Power to Minimize Energy Consumption per Successfully Received Data Packet

• Cooperating (Wireless) Transmitters
• Choose the *individual transmission power* to Minimize the *Energy Consumed per Correctly Received Packet*
Power Level, Interference and Errors

- Identical Wireless Transmitters
- Transmit $D$ packets at rate $v$: Transmission Time $D/v$
- Power Consumption $P(v)$

$$P_{\text{Electronics}} + P_{\text{Transm}} + \text{Packet Queue}$$
Optimum Energy Efficiency vs Power

- Error Probability: $\sim 1 - f\left(\frac{rP_T}{B(\text{noise}) + \text{Interference}}\right)$

- Effective Transmission Time: $T_{\text{eff}} = \frac{D}{\nu \cdot f(\cdot)} = \frac{rP_T}{B + I}$

- Efficiency: Number of Effectively Transmitted Packets per Energy Unit (NOT Power Unit)

$$D(P_T) = \frac{D}{(P_E + P_T) \cdot T_{\text{eff}}} = v \cdot \frac{f\left(\frac{rP_T}{B + I}\right)}{(P_E + P_T)}$$

$P_{\text{Electronics}} + P_{\text{Transm}} + \text{Packet Queue}$
Generally $f$ needs to be determined empirically, or with detailed analysis, but in simple cases:

- Single Bipolar Binary Bit $\{+1,-1\}$ Transmission

$$1 - Q \left( \sqrt{\frac{r P_T}{B + \alpha P_T}} \right).$$

- Uncoded Block of $n$ Bipolar Bits

$$[1 - Q \left( \sqrt{\bar{x}} \right)]^n.$$

- Where

$$Q(x) = \frac{1}{\sqrt{2}} \int_{-x}^{x} e^{-t^2/2} dt.$$
Identical Multi-Users: Optimum Energy Efficiency vs Power

- Error Probability

$$\sim 1 - f\left(\frac{rP_T}{B(\text{noise}) + \text{Interference}}\right)$$

- Efficiency – Number of Packets Correctly transmitted per Unit of Energy

$$D(P_T) = \frac{D}{(P_E + P_T)T_{\text{eff}}} = v \frac{f\left(\frac{rP_T}{B + P_T}\right)}{(P_E + P_T)}$$

When $I = a P_T$, We are only interested in $f(x)$ with $0 \leq x \leq r/a$, and the optimum $P_T$ that maximizes Efficiency satisfies

$$\frac{f(x)}{x} = \frac{(B + P_T)^2}{rB(P_E + P_T)} \cdot f(x), \text{ where } x = \frac{r P_T}{B + P_T}$$
Identical Multi-Users with n-bit un-encoded packets

- Error Probability

\[ \sim 1 - f(x), \quad f(x) = \left[ 1 - Q(\sqrt{x}) \right]^n, \quad x = \frac{rP_T}{B + P_T} \]

- Energy Efficiency – Number of Packets Correctly transmitted per Unit of Energy

\[ D(P_T) = \frac{D}{(P_E + P_T)T_{\text{eff}}} = v \frac{f\left(\frac{rP_T}{B + P_T}\right)}{(P_E + P_T)} \]

When \( I = aP_T \), the optimum \( P_T \) that Maximizes Energy Efficiency will satisfy

\[ \frac{f(x)}{x} = \frac{(B + P_T)^2}{rB(P_E + P_T)} \cdot f(x), \quad \text{where} \quad x = \frac{rP_T}{B + P_T} \]

Fig. 4. Optimal transmission power with scaled interference power for varying levels of interference (\( \alpha = 0.1, 0.5, 0.9 \)). Data is transmitted in an uncoded fashion using BPSK modulation with packet length \( n = 100 \), processing power \( P_E = 2 \), channel gain \( r = 1 \) and noise variance \( B = 1 \).
If Transmitter Knows when Bit is in Error

\[ p_e = \text{Prob}[V + |R| \leq 0] + \text{Prob}[V - |R| \geq 0] \]

\[ = 1 - \frac{2}{\sigma \sqrt{2 \pi}} \int_0^{\frac{\sqrt{rP_T}}{\sigma}} dx e^{-\frac{x^2}{2\sigma^2}} \]

Energy Consumed Per Correctly Received Bit

\[ J = \frac{P_E + P_T}{\text{verf} \left( \sqrt{\frac{rP_T}{2(B+1)}} \right)} . \]

Proposition 1 For the set of communicating wireless devices, if \( B > 0 \) and \( P_E > 0 \), then there is a \( P_T^0 > 0 \) that minimises \( J(P_T) \) for \( P_T \geq 0 \).
On Chip Wired Comms
Energy per Correctly Transmitted Bit

\[ J(V_c) = \frac{P_E + CV_c^2}{\text{verf} \left( V_c \sqrt{\frac{r}{2(B+1)}} \right)} \]

\[ I = \alpha P_c + \beta P_E = C\alpha V_c^2 + b\beta V_E^2 \]

When all the voltages in the system are the same, if we can neglect the effect of noise, and the interference is due to crosstalk, then we see from (27) that we should take the voltage to be as small as possible. When noise power is non-zero \( B > 0 \), since for \( V = 0 \) we have \( J = +\infty \), and similarly \( J \to +\infty \) for \( V \to +\infty \), we can see that there will be a value of \( V \), call it \( V^0 \), that minimizes \( J \).
How about the Energy for Storage in Queue??

$$E[Q] = \lim_{t \to \infty} E[Q(t)] = \rho + \frac{\rho^2 + \lambda^2 \text{Var}(\tau)}{2(1 - \rho)}$$

$$\Pi = c[\rho + \frac{\rho^2 + \lambda^2 \text{Var}(\tau)}{2(1 - \rho)}] + P_E + P_T$$

$$J_B = c[E[\tau] + \frac{\rho E[\tau] + \lambda \text{Var}(\tau)}{2(1 - \rho)}] + \left(\frac{P_E + P_T}{\lambda}\right)$$

Figure 6. Average number of data packets in the queue $Q(t)$ as a function of the transmission power $P_T$ and channel state $\tau$. The optimal transmission power $P_T^*$ is determined by minimizing $J_B$. The effect of channel fading and channel state information on the optimal transmission power and the system performance.
Improvements in Energy Harvesters

- Design and characterization of EM energy harvester for charging rechargeable batteries on time

- Life-time of a MicaZ mote can be prolonged more than **10-times** by using energy harvesting
Vibration characteristics

2.56 Hz

2.8 Hz

2.56 Hz
Energy Harvesting Node

EM harvester characterized according to wrist vibration

Diagram of energy harvesting node with circuit diagram and energy harvesting components.
Energy Harvesting WSN

- Path
- Base station
- Energy Harvesting Sensor Node + Temperature Sensor
- N1 (Running Node)
- N2 (Walking Node)

Graph:
- Buffer Voltage (V) vs. Time (s)
- Temperature (°C)
- Data points for TEMP_Node2, TEMP_Node_1, TINT_Node_1, VOLT_Node_2, VOLT_Node_1, TINT_Node_2
Self-adaptive MicaZ mote:

**Quasi-random vibration excitation** *(Green line)* generated through shaker table.

**Energy status of the buffer** measured by Data Acquisition Board *(blue line)*

**Measured Data** Received through Base-station *(red line)*
Competitive Design of Online Policies: System Model

- PtP slotted communications
- $T$: Frame transmission duration
- $N$: Number of slots/frame
- $E_n = H \left( n \frac{T}{N} \right)$
- $U_n = U \left( n \frac{T}{N} \right)$

- Offline Rate: $R_O(E)$ (Maximum rate assuming future energy arrivals are known)
- Online Rate: $R_U(E)$ (Maximum rate assuming the energy arrival process is unknown)

Competitive Analysis: Worst case design

$$g = \min_u \max_{E \in \{0, \mathbb{R}_+\}^N} R_O(E) - R_U(E)$$
Designing Online Scheduling Policies

Competitive Design of Online Policies: Simulation Results

Main result: $g \leq \log_2(N)$

- Upper-bound
- Myopic Policy
- Proposed Policy
- Lower-Bound

Graph showing the relationship between $\max R_O - R_U$ and the number of slots $N$, with points indicating the performance of different policies relative to the upper and lower bounds.
System Model

► Goal: Derive online algorithms capable of learning the optimal policy by observing the harvested energy in previous days (without statistical knowledge of the energy harvesting process).

► At each day $t$, the node selects a power allocation policy $x^t$ without knowing the harvested energy $e^t$ with the aim of maximizing the rate.

\[
\min_{x \in \mathcal{X}} \quad f^t(x) \triangleq -\sum_{n=1}^{N} \log \left( 1 + \frac{h_n^t}{T_x} \sum_{j=1}^{n} x_j(n) e_j^t \right), \quad (5)
\]

► $x_j(n)$ stands for the fraction of energy harvested at the $j$-th slot that is consumed at the $n$-th slot.

► The environmental conditions then set the channel state $h_n^t$ and harvested energy $e^t$, $\forall n, j = 1, \ldots, N$. 

![Graph showing harvested energy over time]
Online power allocation algorithms

- We propose three low-complexity online algorithms:
  - Online Gradient Descent (OGD),
  - Exponentiated gradient (EG),
  - Online Newton step (ONS).

- The efficiency of these algorithms, \( \{x^t\}_{t=1}^T \), is characterized relative to a comparator sequence \( \{\bar{x}^t\}_{t=1}^T \) in terms of regret,

\[
\text{Regret}_T(A, \{\bar{x}^t\}_{t=1}^T) = \sum_{t=1}^T f^t(x^t) - f^t(\bar{x}^t).
\]

- Static comparator: \( \bar{x}_S^t = \arg\min_x \sum_{t=1}^T f^t(x), \forall t; \)
  Dynamic comparator (Directional WaterFilling): \( \bar{x}_D^t = \arg\min_x f^t(x). \)

- All the algorithms achieve sublinear regret with respect to the total number of days \( T \), which means that the average asymptotic performance is as good as the one of the static comparator.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Regret bound (static comparator)</th>
<th>Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>OGD</td>
<td>( \gamma_{\text{Max}} N \sqrt{(N+1)T} )</td>
<td>( O(X) )</td>
</tr>
<tr>
<td>EG</td>
<td>( \gamma_{\text{Max}} \sqrt{2TN \log \left( \frac{N+1}{2} \right)} )</td>
<td>( O(X^2) )</td>
</tr>
<tr>
<td>ONS</td>
<td>( 5 \left( 1 + \gamma_{\text{Max}} N \sqrt{N+1} \right) \frac{N(N+1)}{2} \log(T) )</td>
<td>( O(X^2) ) and polynomial time pre...</td>
</tr>
</tbody>
</table>

with \( \gamma_{\text{Max}} \) being the maximum SNR and \( X \) the length of \( x \).


Simulation results- Solar Harvesting

- The proposed algorithms are evaluated with respect to: (i) the myopic policy, (ii) the Competitive Rate Gap (CRG).
- We consider a node equipped with a solar panel of dimension $100\text{cm}^2$ and 10% efficiency. Real solar harvesting traces are obtained from Columbia/Enhants.
- $N = 48$ time slots of duration 30 minutes.
- OGD, EG, and ONS algorithms are initialized with Myopic policy.
- Average regret w.r.t. static (solid lines) and dynamic (dashed lines) comparators.
Finite Horizon Energy-Efficient Scheduling with EH Transmitters over Fading Channels

- Generalized Problem:
  - considers energy and data arrivals together over a finite time horizon
  - generic capacity function based on channel SNR

- $f(x)$ is concave, increasing and differentiable.
- $f(1) = 0$, $f'(1 + x) < \infty$ and $\lim_{x \to \infty} f'(1 + x) = 0.$

Update Equation for the Energy Buffer:

\[ e_{n+1} = e_n + H_n - s\rho_n, \] \[ s\rho_n \leq e_n, \text{ for all } n. \] \[ (1) \]

Update Equation for the Data Buffer:

\[ b_{n+1} = b_n + B_n - f(1 + \rho_n\gamma_n), \] \[ f(1 + \rho_n\gamma_n) \leq b_n, \text{ for all } n. \] \[ (2) \]
Finite Horizon Energy-Efficient Scheduling with EH Transmitters over Fading Channels

- Online Approach:
  - Stochastic approach that incorporates the offline solution as a reference process
  - Improves on the classical stochastic dynamic programming solution
Offline Optimization for Interference Channels
  Sum-rate maximization for EH Interference channel with a generalized power consumption model

Sensors with EH constraints
  Source Reconstruction
  Sensor Selection
  Correlated Sampling

Online Policies
  Competitive Design (Worst case)
  Online Learning
The Energy Packet Network (EPN): Systems Level Discrete Model for Large Scale Systems of Intermittent Energy Sources and Intermittent Energy Consumers
\[ Q_i = \frac{\lambda_i + \sum_{j=1}^{n} \sum_{l=1}^{m} q_l w(l,j) Q_j P_{ji}}{\sum_{l=1}^{m} q_l w(l,i) + \beta_i}, \quad (1) \]

where the rate of service at \( W_i \) is determined by the rate at which it receives energy, and \( q_l \) is the probability that energy storage station \( E_l \) has at least one EP in store:

\[ q_l = \frac{\gamma_l + \sum_{k=1}^{m} q_k W(k,l)}{\tau_l + \pi_l}. \quad (2) \]

The above equations also allow us to state the following result [35]:

**Theorem 1** Assume that the external arrivals of jobs, and the arrivals of EPs from renewable energy sources, are independent Poisson processes with rates \( \lambda_i \), and \( \gamma_l \). Suppose that the \( \tau_i \), \( \pi_i \) and \( \beta_i \) are the parameters of mutually independent exponentially distributed random variables. Then if \((K_1, \ldots, K_n) \geq (0, \ldots, 0)\) and \((k_1, \ldots, k_m) \geq (0, \ldots, 0)\) represent the backlogs of jobs to be executed at the workstations, and the number of energy packets stored at the ESs, respectively. Then

\[
\lim_{t \to \infty} P[K_1(t) = K_1, \ldots, K_n(t) = K_n; k_1(t) = k_1, \ldots, k_m(t) = k_m] = \prod_{i=1}^{n} Q_i^{K_i}(1 - Q_i) \prod_{i=1}^{m} q_i^{k_i}(1 - q_i).
\]

**Corollary 1** Because in steady-state the joint probability distribution of the number of jobs waiting, and energy packets stored, at each of the WS and ES, is the product of the marginal distributions, we have:

\[
\lim_{t \to \infty} P[K_i(t) \geq K_i] = Q_i^{K_i}, \quad \lim_{t \to \infty} P[k_i(t) \geq k_i] = q_i^{k_i}.
\]
Obviously, we wish to limit the backlog of work at the workstations, while we also want to have some reserve of energy since there may be unpredictable needs. Thus a sensible cost or utility function would have the form:

\[ U_1 = \sum_{i=1}^{n} a_i Q_i^{K_i} + \sum_{l=1}^{m} b_l (1 - q_l^{k_l}) \]  

which is the weighted probability that the backlogs of work exceed the values \( K_i \) at each workstation \( i \), and the weighted probabilities that there are not at least \( k_l \) energy packets at ES \( l \), where the \( a_i \) and \( b_l \) are non-negative real numbers (the weights). A simpler utility that may be minimised is the weighted probabilities that there is some backlog at the workstations, plus that there is no energy in reserve, which is \( U_1 \) when \( K_i = 1 \) and \( k_l = 1 \) for all \( i, l \):

\[ U_1^0 = \sum_{i=1}^{n} a_i Q_i + \sum_{l=1}^{m} b_l (1 - q_l) \]

A cost function other than \( U_1 \) defined above that we may wish to minimise is:

\[ U_2 = \sum_{i=1}^{n} a_i \left[ \frac{\sum_{l=1}^{m} q_l w(l, i) + \beta_i}{1 - Q_i} \right]^{-1} + \sum_{l=1}^{m} b_l (1 - q_l^{k_l}) \]

which differs from \( U_1 \) only in the first sum which is simply the weighted sum of the average response time of jobs waiting to be served at each of the workstations.
### TABLE II
**Optimised EP flow rates for the different utility functions**
when $b_1, b_2 = 100$, the $r_1, r_2$ are not constant and the other numerical parameters are given in Table I

<table>
<thead>
<tr>
<th>Control parameters</th>
<th>Optimised rates for $U_1^0$</th>
<th>Optimised rates for $U_1$</th>
<th>Optimised rates for $U_2$</th>
<th>Optimised rates for $U_3$</th>
</tr>
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<tbody>
<tr>
<td>$w^*(1, 1)/r_1^M$</td>
<td>0.15</td>
<td>0.15</td>
<td>0.15</td>
<td>0.30</td>
</tr>
<tr>
<td>$w^*(1, 2)/r_1^M$</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>0.05</td>
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<tr>
<td>$w^*(1, 3)/r_1^M$</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>$w^*(2, 1)/r_2^M$</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.30</td>
</tr>
<tr>
<td>$w^*(2, 2)/r_2^M$</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.20</td>
</tr>
<tr>
<td>$w^*(2, 3)/r_2^M$</td>
<td>0.05</td>
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### TABLE III
**Optimised EP flow rates for the different utility functions**
when $b_1, b_2 = 10$, the $r_1, r_2$ are not constant and the other numerical parameters are given in Table I

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<thead>
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<td>0.15</td>
<td>0.15</td>
<td>0.15</td>
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<tr>
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<td>$w^*(1, 3)/r_1^M$</td>
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<tr>
<td>$w^*(2, 1)/r_2^M$</td>
<td>0.45</td>
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<tr>
<td>$w^*(2, 2)/r_2^M$</td>
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<tr>
<td>$w^*(2, 3)/r_2^M$</td>
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<td>0.05</td>
<td>0.05</td>
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### TABLE VII
**Optimised EP flow rates for the different utility functions**
when $b_1, b_2 = 10$, the $r_1, r_2$ are constant and the other numerical parameters are given in Table I

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<tbody>
<tr>
<td>$w^*(1, 1)/r_1^M$</td>
<td>0.40</td>
<td>0.30</td>
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<tr>
<td>$w^*(1, 3)/r_1^M$</td>
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</tr>
<tr>
<td>$w^*(2, 1)/r_2^M$</td>
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<td>0.30</td>
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</tr>
<tr>
<td>$w^*(2, 2)/r_2^M$</td>
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</tr>
<tr>
<td>$w^*(2, 3)/r_2^M$</td>
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<td>0.05</td>
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<td>0.05</td>
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<tr>
<td>$W^*(1, 2)/r_1^M$</td>
<td>0.50</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
</tr>
<tr>
<td>$W^*(2, 1)/r_2^M$</td>
<td>0.50</td>
<td>0.60</td>
<td>0.60</td>
<td>0.60</td>
</tr>
</tbody>
</table>
ECROPS – Some Novel Ideas & Results

- Discrete Probability Models for Energy-Data Transmission Optimisation (Energy Packet Networks) – Queues are Batteries and Data Buffers
- Holistic Energy Optimisation for the Onboard and Wireless Parts including Interference, Fading, etc.
- Design On-Board-On-Chip Real Hardware Harvesters and Optimisers
- Develop On-Line Real-Time Decision Algorithms to manage Energy and Data Transmission
- Introduce the “Crazy Idea” of Femto-Power Communications with Spins
Successes

• 3 ERCs – Haluk Kulah, METU; Deniz Gunduz, Imperial; David Gesbert, Eurecom
• Imperial & CTTC won with European universities and National Instruments, Toshiba Research, Athonet, Worldsensing .. a H2020 Marie Sklodowska-Curie European Training Network on “Sustainable Cellular Networks Harvesting Ambient Energy - SCAVENGE” (2016- 2020)
• Imperial won a UK MoD Grant for ICT Energy Optimisation
• Institutional Links Project Imperial & Sabanci University on “Collaborative Research on Harnessing Renewable Energy Sources for Communications” (UK British Council)
• Other Collaborations: University of Venice Ca` Foscari (Italy), NYU and NJIT (USA)

Publications in Journals (~20)


Publications

Journals (More)


Numerous Conferences (over 40)


Thanks, Merci ... CHIST-ERA !

http://san.ee.ic.ac.uk