# Optimization of Energy Harvesting Wireless Sensor Networks

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March 2013 | Energy Harvesting 2013 | London, UK

## Summary

We design novel communication protocols for wireless sensor networks with energy harvesting nodes. Our main contribution is a machine-learning based communication protocol for an energy-harvesting sensor node that optimizes the total amount of transmitted data without any prior knowledge regarding the energy harvesting process.

## Wireless Sensor Networks (WSNs)

A WSN consists of spatially deployed sensor devices that measure physical or environmental phenomena. Sensor nodes transmit their measurements wirelessly to an access point where the data is stored and/or analysed. **Applications**: health monitoring, earth monitoring, structure monitoring, agriculture, smart homes and many other industrial applications.

### Battery Powered Nodes

- The energy stored in the battery is used to operate the sensor node (e.g., to power up sensing device, microprocessors, ADCs and radio frequency amplifiers).
- Much effort has been put into designing low-power communication protocols to extend the life time of wireless sensor nodes limited by the battery capacity.
- However, eventually the **battery drains** and the **sensor node becomes useless** until the battery is replaced.

### Problems

- Batteries are expensive, and take space,
- Batteries eventually die:
  - In large networks it is expensive to change batteries manually,
  - In remote or embedded networks it is difficult to access the nodes (i.e., vibration sensors monitoring embedded in a bridge or environmental monitoring).

### Energy Harvesting Powered

- Energy harvesting devices and rechargeable batteries complement WSN by allowing, in principle, perpetual operation of the sensor nodes.
- Most of the available energy sources are limited and sporadic.
- New communication protocols that adapt to the randomness of the energy source, and take the maximum out of the scarce energy available are needed.

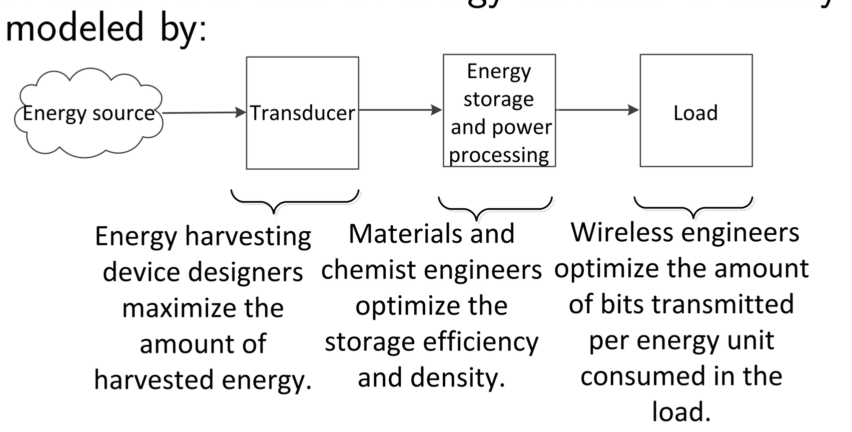
### Problems

- Increasing the amount of harvested energy usually requires to increasing the cost/size of the harvester.
- Storage units may be inefficient and leak energy.
- Fixed or non-intelligent communication protocols for WSNs may waste the energy harvested at the nodes.

## System Model

### Wireless Sensor Node Model

A sensor node with an energy harvester is usually modeled by:

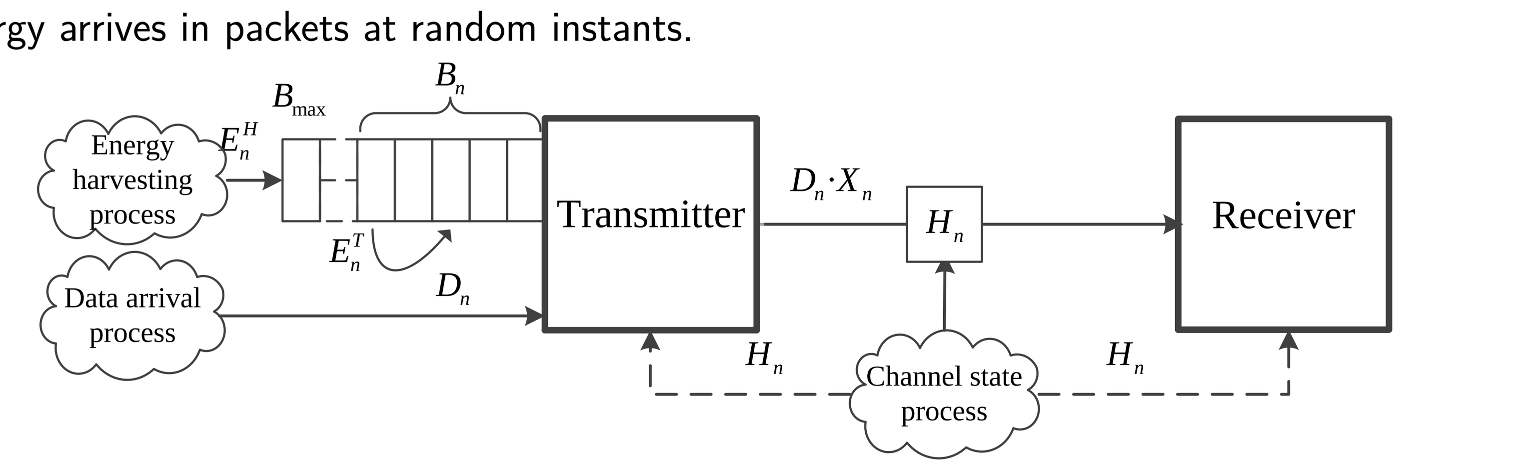



The load block depends on:

- Measured data (e.g., amount of data to be transmitted),
- State of the wireless channel (e.g., the channel is blocked or there is line of sight),
- Communication protocol (e.g., modulation scheme, transmit power, ACK-retransmission protocol),
- Electronics of the wireless transmitter (e.g., RF amplifiers and antenna hardware).

### Our Wireless Sensor Node Model

- The **load block** is modeled by a time-varying wireless channel, data measurements of random size, and the communication protocol implemented in the receiver.
- The **transducer and energy storage blocks** are modeled by an ideal battery in which the energy arrives in packets at random instants.




- System is time slotted (TS),
- Transmitter has a rechargeable battery of size $B_{max}$,
- Energy arrives in packets, and $E_n^H$ energy units are harvested and stored in the battery at TS $n$,
- Data packet of size $D_n$ arrives at the transmitter in TS $n$,
- Wireless channel is block fading, and $H_n$ is the channel state in TS $n$,
- Cost of transmission in TS $n$ is $E_n^T$ energy units: $E_n^T$ is a function of $H_n$ and $D_n$,
- $D_n$, $E_n^H$ and $H_n$ are modeled by Markov processes.

### Wireless Communication Problem

At the beginning of each TS, the transmitter makes a binary decision: to transmit or to drop the incoming packet, with the **objective** of **maximizing the total amount of transmitted data** to destination during its activation time:

$$\max_{\{X_i\}_{i=0}^{\infty}} \lim_{N\to\infty} \mathbb{E}\left[\sum_{n=0}^{N}\gamma^n X_n D_n\right],$$

$$\text{s.t. } B_{n+1}=\min\{B_n - X_n E_n^T + E_n^H, B_{max}\},$$

$$X_n E_n^T \le B_n,$$

$$X_n \in \{0,1\}.$$

## Contribution and Results

We find the best wireless communication protocol based on three different assumptions regarding the knowledge about the energy, data and wireless channel state processes at the transmitter.

### Offline Optimization

Everything is known in advance:

- the instants and amounts of the energy/data arrivals and channel states are known in advance (non-causal knowledge),
- the optimization problem can be solved numerically using the Branch and Bound algorithm.

### Online Optimization

Statistical knowledge:

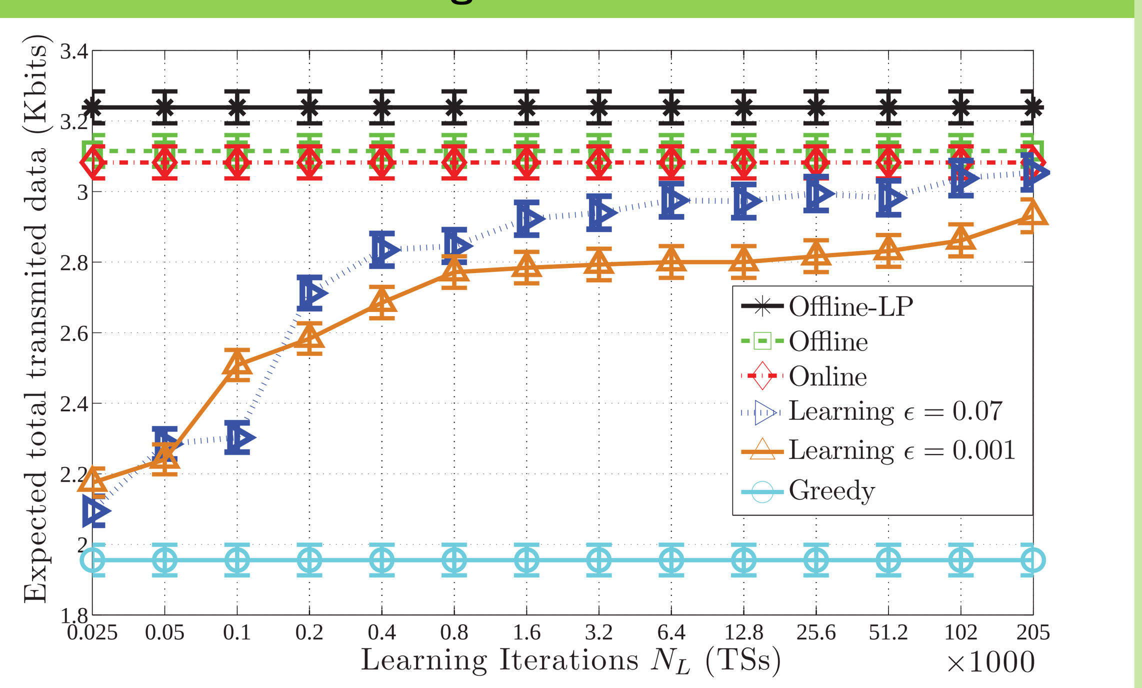
- Energy/data arrival and channel are modeled as Markov processes,
- Parameters of this processes are known,
- Optimization problem is solved using Dynamic Programming.

### Machine Learning Optimization

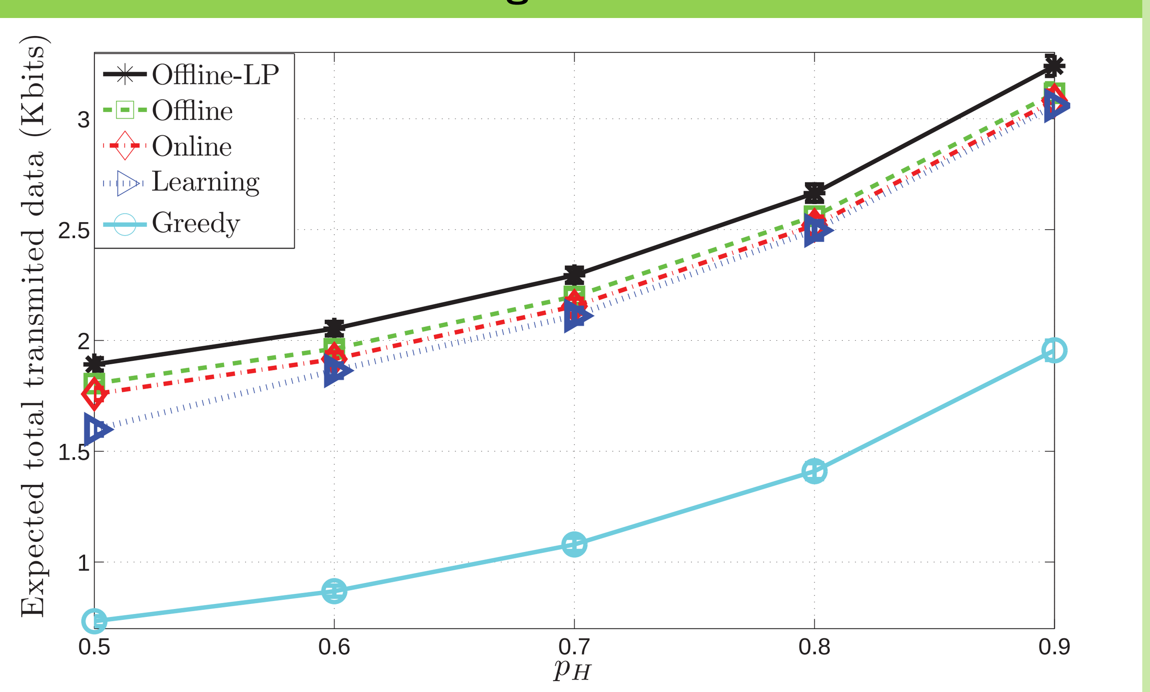
Transmitter has **no** knowledge:

- Parameters of the energy/data and channel process are not known,
- We use Q-learning to find the optimal transmission policy,
- Q-learning learns iteratively, the statistics of the underlying Markov process and, after some learning iterations, converges to the optimal policy of the online optimization.

### The effect of the Learning Time




### The Effect of the Harvesting Rate




### Conclusions

- Energy harvesting WSNs require communication protocols that can adapt to the scarce and stochastic energy source,
- Energy harvesting process is stochastic: what is known about this process is critical,
- **Machine learning optimization** is important for practical applications because it optimizes the communication protocols without information regarding the energy source,
- We have shown that Q-learning quickly learns the system parameters and approaches the online optimization upperbound.