

Scheduling an Energy harvesting Network

Balaprasad B

Guide : Dr. Chandra R. Murthy



SPC Lab

Department of Electrical Communication Engineering
Indian Institute of Science

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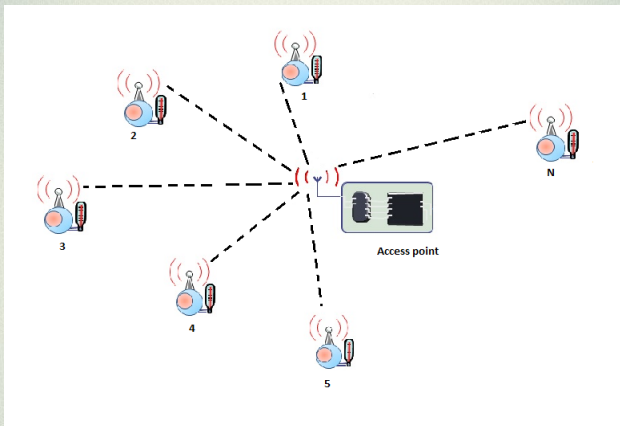
Agenda

- Motivation
- System Model
- Problem statement
- MDP Formulation
- Simulation Results

Motivation

- Cyber-physical system typically employ wireless sensors for keeping track of physical processes such as temperature and pressure. These nodes then transmit data packets containing measurements back to the access point.
- The Time between successive deliveries of packets is an important metric.
- Wireless sensors are battery powered. Thus, energy-efficiency is also important.

System Model



- All ' N ' Sensor Nodes are Energy Harvesting sensors.
- Access point(AP) is Powered by External Battery.

Problem statement

- Atmost $L(<N)$ sensors can simultaneously transmit in a time slot.
- A Control message is sent at the beginning by the AP to select L sensors out of N sensors.

A scheduling algorithm for N wireless energy harvesting nodes is to be designed to the following constraints:

- Uniform sized packets arrive at random times at each node(each node has queue associated with it). Each packet has a deadline by which it needs to be delivered.
- The best delivery ratios we can support?

Assumptions:

- Battery state of all the EH sensor nodes is known.
- Packet success probability of all the EH sensor nodes is known.
- The Energy Harvesting Rate of all the nodes is known.
- The Energy required to transmit a packet is 1 unit.
- The Energy Harvested in a given time slot is 1 unit.

MDP Formulation:

Goal: Scheduling the nodes based on the battery energy level, Success Probability and Time elapsed since the latest delivery of the client n 's packet.

a) *State space:*

- $B = \{0, 1, \dots, b_{max}\}$ is the set of Battery states.
 $B(t) := (b_1(t), \dots, b_N(t))$, Where $b_n(t)$ is the Battery of client n 's in time slot t .
- $X(t) := (x_1(t), \dots, x_N(t))$, Where $x_n(t)$ is the time elapsed since the latest delivery of client n 's packet.
- $O(t) := (o_1(t), \dots, o_N(t))$, Where $o_n(t)$ is the Packet reception state of client n 's in time slot t .

b) *Action space:* $U(t) := (u_1(t), \dots, u_N(t))$, Where $u_n(t)$ is the Action taken for client n , in time slot t .

$$\sum_{n=1}^N u_n(t) \leq L \quad (1)$$

$$u_n(t) = \begin{cases} 1 & \text{if client } n \text{ is selected to transmit in slot } t \\ 0 & \text{otherwise} \end{cases}$$

- c) *State Transition Function*: Let Two arbitrary states in S be $s = (B, X, O)$ and $s' = (B', X', O')$. The state Transition function is the probability that the system starts in state s , takes an action U , and lands in state s' .

The system state evolves as,

$$x_n(t+1) = \begin{cases} 0 & \text{if a packet of client } n \text{ is delivered in } t \\ x_n(t) + 1 & \text{otherwise} \end{cases}$$

$$b_n(t+1) = \begin{cases} \min(b_n(t) + 1, b_{n(max)}) & \text{with probability } \rho \text{ of client } n \text{ in } t \\ b_n(t) & \text{with probability } 1 - \rho \text{ of client } n \text{ in } t \end{cases}$$

- Considering A small Network consisting of Two EHS nodes and an Access point.
- Scheduling policy: Access point can schedule at the most Only one sensor Node. $N=2, L=\{0,1\}$

$$B = (b_1, b_2), X = (x_1, x_2), U = (u_1, u_2), O = (o_1, o_2)$$

$$(b_1, b_2, x_1, x_2, o_1, o_2) \xrightarrow{(u_1, u_2)} (b'_1, b'_2, x'_1, x'_2, o'_1, o'_2)$$

$$\text{Possible Action set: } (u_1, u_2) = \{(0, 0), (1, 0), (0, 1)\}$$

- Energy harvesting rate of Node1= ρ_1
- Energy harvesting rate of Node2= ρ_2
- Success Probability of Node1= p_1
- Success Probability of Node2= p_2

The State Transition Probability is given by,

$$\psi((B, X, O), U, (B', X', O')) = P((B', X', O')|(B, X, O))$$

$$P((B', X', O')|(B, X, O)) \\ = P(b'_1 = j_1, b'_2 = j_2, x'_1 = y_1, x'_2 = y_2, o'_1 = s_1, o'_2 = s_2 | b_1 = i_1, b_2 = i_2, x_1, x_2, o_1 = r_1, o_2 = r_2)$$

$$P((B', X', O') | (B, X, O)) =$$

Case-1: $U = (u_1 = 0, u_2 = 0)$ None of the Nodes are Scheduled.

- In this case No need to of the observation vector.

$$= \begin{cases} \rho_1 \rho_2, & j_1 = \min(i_1 + 1, b_{1max}), j_2 = \min(i_2 + 1, b_{2max}), y_1 = x_1 + 1, \\ & y_2 = x_2 + 1, \\ (1 - \rho_1) \rho_2, & j_1 = i_1, j_2 = \min(i_2 + 1, b_{2max}), y_1 = x_1 + 1, y_2 = x_2 + 1, \\ \rho_1 (1 - \rho_2), & j_1 = \min(i_1 + 1, b_{1max}), j_2 = i_2, y_1 = x_1 + 1, y_2 = x_2 + 1, \\ (1 - \rho_1)(1 - \rho_2), & j_1 = i_1, j_2 = i_2, y_1 = x_1 + 1, y_2 = x_2 + 1, \\ 0, & \text{else.} \end{cases}$$

Case-2: $U = (u_1 = 1, u_2 = 0)$ Node1 is scheduled.

$$= \left\{ \begin{array}{l} (1 - \rho_1)\rho_1\rho_2, j_1 = \min(i_1 + 1 - 1, b_{1max}), j_2 = \min(i_2 + 1, b_{2max}), \\ \quad y_1 = x_1 + 1, y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ (1 - \rho_1)(1 - \rho_1)\rho_2, j_1 = \max(i_1 - 1, 0), j_2 = \min(i_2 + 1, b_{2max}), \\ \quad y_1 = x_1 + 1, y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ (1 - \rho_1)\rho_1(1 - \rho_2), (j_1 = \min(i_1 + 1 - 1, b_{1max}), j_2 = i_2, y_1 = x_1 + 1, \\ \quad y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ (1 - \rho_1)(1 - \rho_1)(1 - \rho_2), j_1 = \max(i_1 - 1, 0), j_2 = i_2, y_1 = x_1 + 1, \\ \quad y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ 0, \quad \text{else.} \end{array} \right.$$

$$= \left\{ \begin{array}{l} \rho_1 \rho_1 \rho_2, j_1 = \min(i_1 + 1 - 1, b_{1max}), j_2 = \min(i_2 + 1, b_{2max}), \\ \quad y_1 = 0, y_2 = x_2 + 1, s_1 = 1, s_2 = 0, \\ \\ \rho_1(1 - \rho_1)\rho_2, j_1 = \max(i_1 - 1, 0), j_2 = \min(i_2 + 1, b_{2max}), \\ \quad y_1 = 0, y_2 = x_2 + 1, s_1 = 1, s_2 = 0, \\ \\ \rho_1 \rho_1(1 - \rho_2), (j_1 = \min(i_1 + 1 - 1, b_{1max}), j_2 = i_2, y_1 = 0, \\ \quad y_2 = x_2 + 1, s_1 = 1, s_2 = 0, \\ \\ \rho_1(1 - \rho_1)(1 - \rho_2), j_1 = \max(i_1 - 1, 0), j_2 = i_2, y_1 = 0, y_2 = x_2 + 1, \\ \quad s_1 = 1, s_2 = 0, \\ \\ 0, \quad \text{else.} \end{array} \right.$$

Case-3: $U = (u_1 = 0, u_2 = 1)$ Node2 is scheduled.

$$= \left\{ \begin{array}{l} (1 - \rho_2)\rho_1\rho_2, j_1 = \min(i_1 + 1, b_{1max}), j_2 = \min(i_2 + 1 - 1, b_{2max}), \\ \quad y_1 = x_1 + 1, y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ (1 - \rho_2)(1 - \rho_1)\rho_2, j_1 = i_1, j_2 = \min(i_2 + 1 - 1, b_{2max}), \\ \quad y_1 = x_1 + 1, y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ (1 - \rho_2)\rho_1(1 - \rho_2), j_1 = \min(i_1 + 1, b_{1max}), j_2 = \max(i_2 - 1, 0), \\ \quad y_1 = x_1 + 1, y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ (1 - \rho_2)(1 - \rho_1)(1 - \rho_2), j_1 = i_1, j_2 = \max(i_2 - 1, 0), y_1 = x_1 + 1, \\ \quad y_2 = x_2 + 1, s_1 = 0, s_2 = 0, \\ \\ 0, \quad \textit{else.} \end{array} \right.$$

$$= \left\{ \begin{array}{l} p_2 \rho_1 \rho_2, j_1 = \min(i_1 + 1, b_{1max}), j_2 = \min(i_2 + 1 - 1, b_{2max}), \\ \quad y_1 = x_1 + 1, y_2 = 0, s_1 = 0, s_2 = 1, \\ \\ p_2(1 - \rho_1)\rho_2, j_1 = \max(i_1 - 1, 0), j_2 = \min(i_2 + 1, b_{2max}), \\ \quad y_1 = x_1 + 1, y_2 = 0, s_1 = 0, s_2 = 1, \\ \\ p_2 \rho_1(1 - \rho_2), (j_1 = \min(i_1 + 1 - 1, b_{1max}), j_2 = i_2, y_1 = x_1 + 1, \\ \quad y_2 = 0, s_1 = 0, s_2 = 1, \\ \\ p_2(1 - \rho_1)(1 - \rho_2), j_1 = \max(i_1 - 1, 0), j_2 = i_2, y_1 = x_1 + 1, y_2 = 0, \\ \quad s_1 = 0, s_2 = 1, \\ \\ 0, \quad \text{else.} \end{array} \right.$$

Cost: Let $s = (B, X, O)$ be the state of the system.

The expected immediate cost is defined as,

$c(S, U)$

$$= \begin{cases} 10 & \text{if } b_n < E, u_n = 1 \text{ and } x_n \geq \tau_n \\ 10 & \text{if } b_n < E, u_n = 1 \text{ and } x_n < \tau_n \\ 1 & \text{if } b_n < E, u_n = 0 \text{ and } x_n \geq \tau_n \\ 0 & \text{if } b_n < E, u_n = 0 \text{ and } x_n < \tau_n \\ 1 & \text{if } b_n \geq E, u_n = 1 \text{ and } x_n \geq \tau_n \\ 0 & \text{if } b_n \geq E, u_n = 1 \text{ and } x_n < \tau_n \\ 2 & \text{if } b_n \geq E, u_n = 0 \text{ and } x_n \geq \tau_n \\ 0 & \text{if } b_n \geq E, u_n = 0 \text{ and } x_n < \tau_n \end{cases}$$

Heuristic policy

The Cost function used for Heuristic policy:

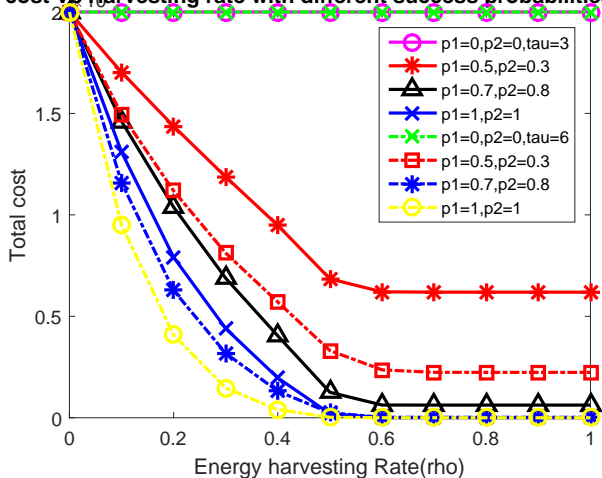
Cost Function:

The T-horizon optimal cost-to-go from initial state x is given by,

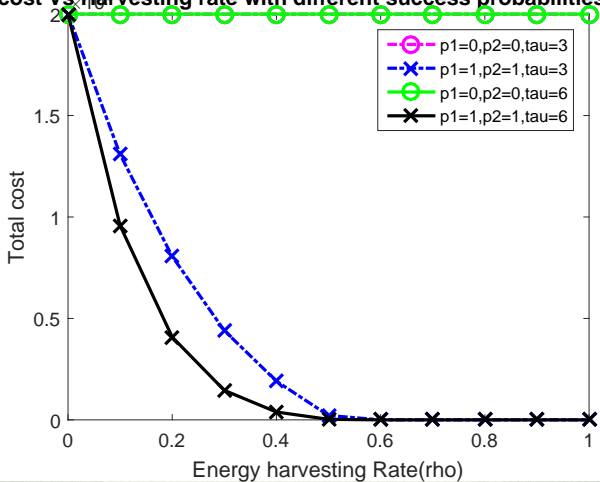
$$V_T(x) := E \left[\sum_{n=1}^N \left(\sum_{i=1}^{M_T^{(n)}} (D_i^{(n)} - \tau_n)^+ + \left(T - t_{D_{M_T^{(n)}}^{(n)}} - \tau_n \right)^+ \right) \right] \quad (2)$$

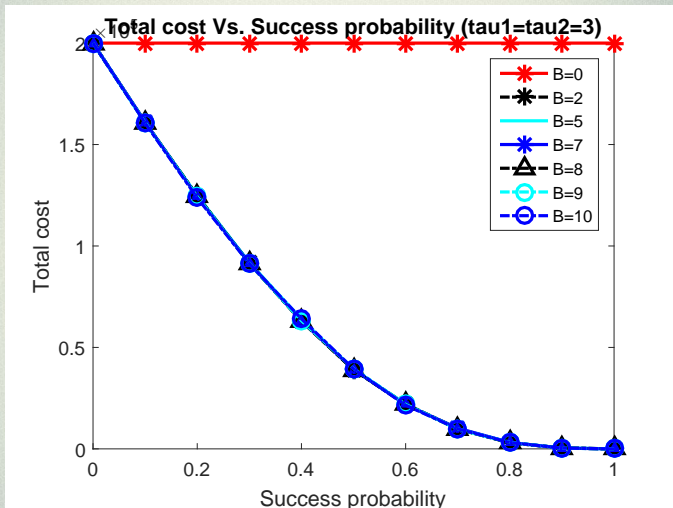
Heuristic policy Simulation Results:

Total cost Vs Harvesting rate with different success probabilities($\tau=3$ & 6)








Total cost Vs Harvesting rate with different success probabilities($\tau=3$ & 6)





Bibliography

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Thank You