



System/Network Power Management in Underwater Sensor Networks

Energy-efficient and Lifetime-aware Routing Algorithm Using
Markov Decision Process

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Overview



- Introduction
- Energy-efficient and lifetime-aware routing protocol
 - Stochastic model
 - Network solutions
- Future research plans

Research Direction

- Extend the network lifetime through energy-efficient networking protocols (e.g., routing, localization, etc.) and effective system power management

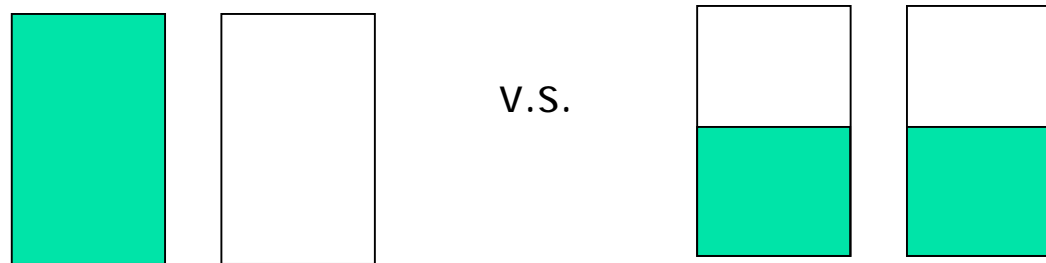
- Lifetime definitions:
 - When the first sensor node powers down
 - When a portion of the network nodes are dead
 - When the wireless network loses coverage for the first time
 - The mean expiration time
 - In terms of packet delivery rate
 - In terms of the number of alive flows

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Energy-efficient and Lifetime-aware Routing

- Routing protocol

- Energy-efficient: the minimum energy consumption for certain routing requests
- Lifetime-aware: avoid unevenly energy distribution among sensor nodes



Related Work – Power Management



- Power management mechanisms directed by certain policy to save energy consumption in sensor nodes
- Related work
 - Dynamically managing various components in computer systems
 - ◆ Disk drive, CPU, memory, network card, display, etc.
 - ◆ Transition between different power states (e.g., DVFS)
 - Policy: when to transition to what low power state
 - ◆ Time-out
 - ◆ Greedy N-policy
 - ◆ Markov decision process based stochastic models
 - ❖ Discrete time approach by L. Benini, A. Bogliolo, G. Paleologo & G. Micheli
 - ❖ Continuous time approach by Qinru Qiu & Massoud Pedram
- Advantages of stochastic models
 - Using Markov decision process to find the optimum policy which minimizes the power consumption of a single computer system
 - The dynamic states of system can be effectively captured by the Markov chain model

Related Work - General Routing Protocols

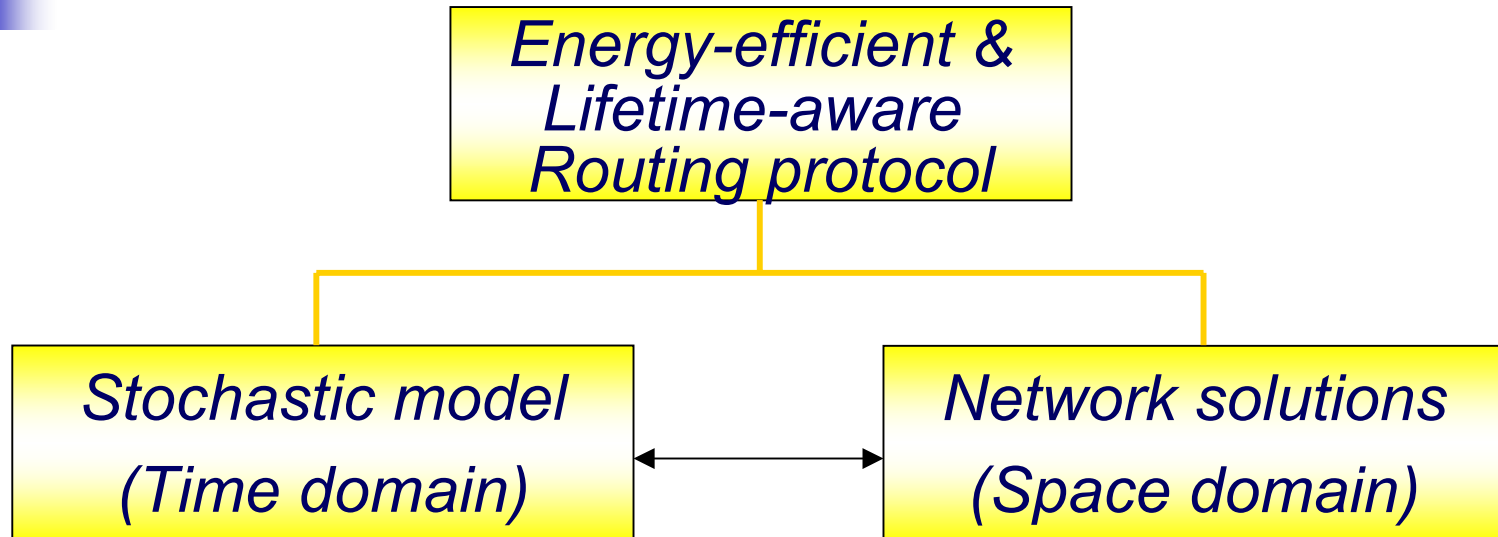


- Geographical routing by P. Xie & J. Cui
 - Using geographical information of sensors to choose forwarding nodes and save energy for the networks
 - Minimum number of hops from the candidate node to destination
 - Distance between the candidate and destination & some angle info
 - ◆ By reducing the number of hops from source to destination node, overall energy consumption will be reduced
- Maximizing network lifetime by J. Chang & L. Tassiulas
 - The residual energy is factored in when selecting forwarding nodes
 - Higher priority is given to nodes with higher power levels for forwarding
 - Advantages
 - ◆ The consideration of residual energy of each node will distribute the routing tasks more evenly in the network, thus network lifetime may be extended

Our Approach

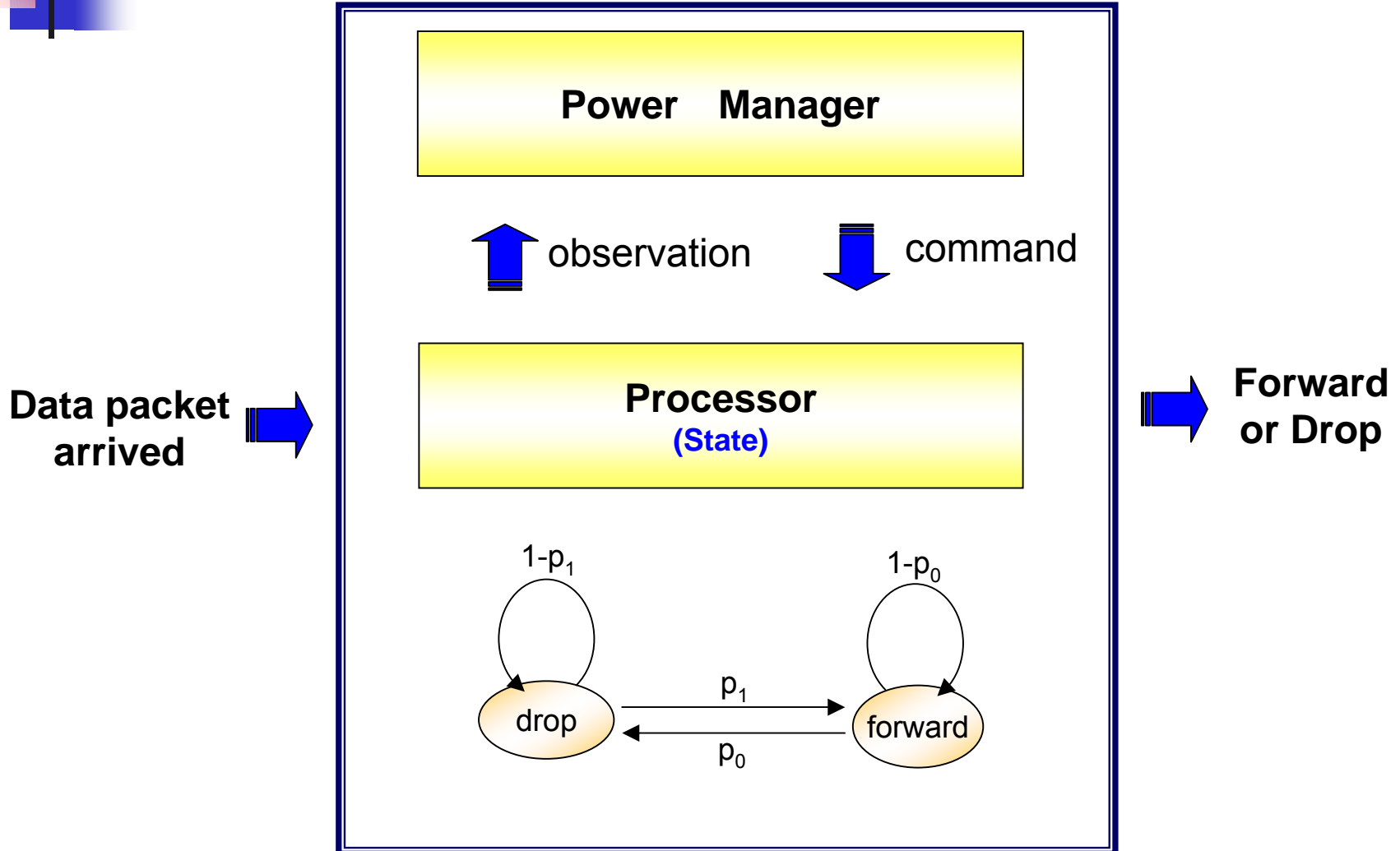
- The power management technique is extended from a single node to the whole network in determining routing paths
- We apply the Markov decision process to find an optimal policy for data forwarding in underwater sensor networks (where and when to forward/drop)
 - The possible action of each node is simple
 - ◆ Two dynamic states: forward or drop
 - Parameters to represent the state of each node
 - ◆ Geographical position (d and Θ)
 - ◆ Residual energy (E_r)
 - ◆ Recent forwarding history

Our Approach



- Markov process
 - Find optimum forwarding policy with minimum routing cost
- Routing parameters
 - Position info. (distance, angle)
 - Residual energy
 - Forwarding history
- Two-dimension
- Lifetime measurement
 - Variance of residual energy in nodes

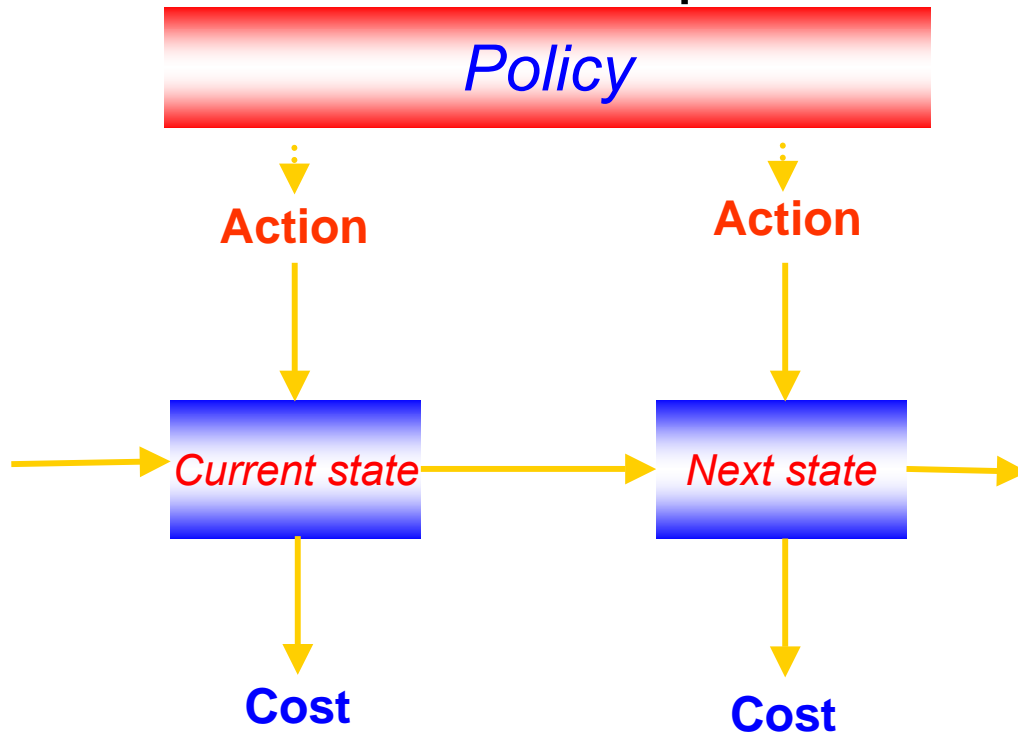
System Model



Stochastic Model



Markov decision process



For discrete states $i=1,2,\dots,N$

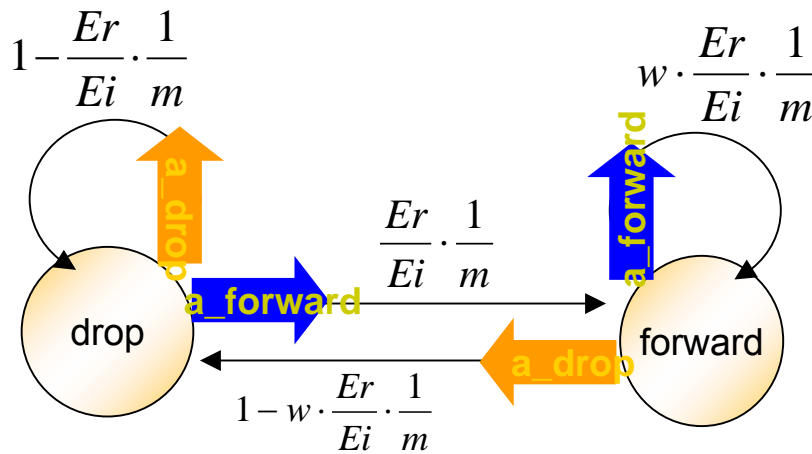
- A policy set $\pi = \{\pi_i\}$
- An action set $A = \{a_i\}$
- A state set $S = \{s_i\}$
- A cost set $C = \{c_i\}$
- Discount factor $=\beta$, $0 < \beta < 1$

“How to find the policy that can minimize the cost?”

●
Discounted factor (inflation, error , etc.)

Our Stochastic Model

- A Markov decision process model



- A state set $S = \{drop, forward\}$
- A cost set $C = \{\log(m)/m \text{ (or } m/\exp(m)), 1\}$
- An action set $A = \{a_drop, a_forward\}$
- A discount factor $\beta \rightarrow 0 < \beta < 1$
- A policy set $\pi = \{\pi_1, \pi_2, \pi_3, \pi_4\}$

- A transition probability function

$P_{ij}^a = \text{probability}(\text{next}=j | \text{current}=i, \text{action } a)$

$p_drop \quad p_forward$

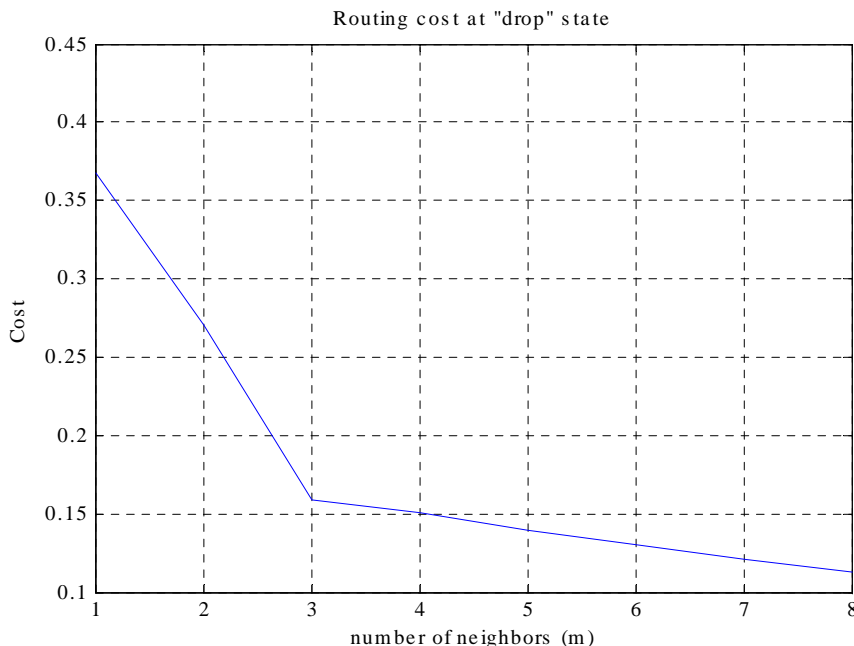
$$\begin{matrix} drop \\ forward \end{matrix} \begin{pmatrix} 1 - \frac{Er}{Ei} \cdot \frac{1}{m} & \frac{Er}{Ei} \cdot \frac{1}{m} \\ 1 - w \cdot \frac{Er}{Ei} \cdot \frac{1}{m} & w \cdot \frac{Er}{Ei} \cdot \frac{1}{m} \end{pmatrix} \text{ where } Er: \text{ residual energy} \\ Ei: \text{ initial energy} \\ m: \# \text{ of neighbors} \\ w: \text{ weight, } 0 < w < 1$$

	state	action		state	action
π_1	drop	a_drop	π_2	drop	a_drop
	forward	a_drop		forward	a_forward
π_3	drop	a_forwa rd	π_4	drop	a_forward
	forward	a_drop		forward	a_forward

Parameter Selection

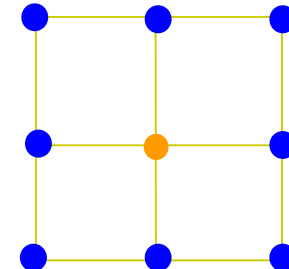
■ Routing cost (power & connectivity)

- Connectivity cost $CC = \log(m)/m$, state = drop & $m \geq 3$;
 $m/\exp(m)$, state = drop & $0 < m < 3$;
 0 , otherwise
- One hop power consumption $CP = 1$, state = forward;
 0 , otherwise
- Total cost $C = CC + CP$



Max. number of neighbors = 8

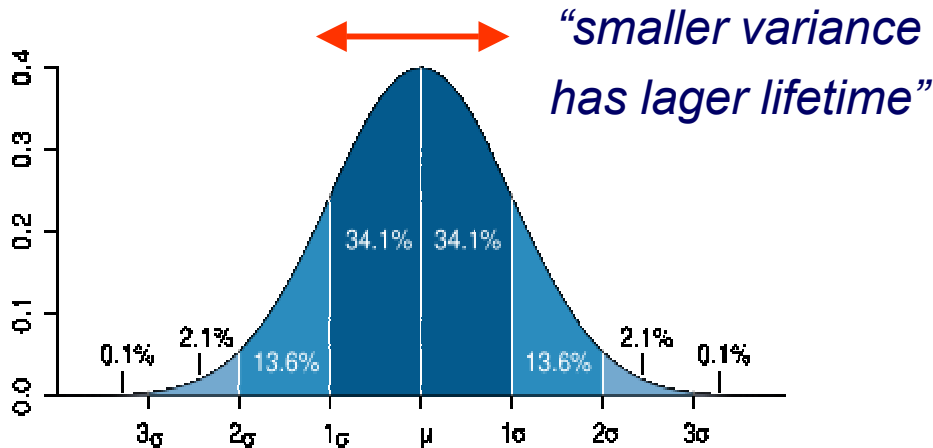
- Current node
- Neighbor node



Network Solutions

- From time-domain to space-domain
 - Multi-dimensional Markov process (?)

- Lifetime measurement
 - Variance of residual energy in nodes, or can be simplified as the entropy measure



$$Entropy = \sum_{j=1}^n \left| \log(Er_j / Ei_j) \right|$$

Discussions

For MDP-based routing algorithm:

- How to decide parameters in the MDP model?
- Which algorithm may be effective for network solution?
 - How to incorporate position information, residual energy, etc. in the cost function?

Future Work

- Apply stochastic models to other networking algorithms, e.g., MAC, localization, etc., for energy saving and lifetime extension
- Refine the lifetime definition
- Lifetime estimation model and simulation

Appendix



Markov Process

- Definition: the future value is independent of the past values given the present value:

For $t_1 < t_2 < \dots < t_n$

$$P[\underbrace{x(t_n) \leq x_n}_{\text{future}} | \underbrace{x(t_{n-1}), x(t_{n-2}), \dots, x(t_1)}_{\text{past}}] = P\{\underbrace{x(t_n) \leq x_n}_{\text{depend only on present value}} | x(t_{n-1})\}$$

- Class of Markov processes

$x(t)$ \ t	Continuous	Discrete
Continuous	Markov process	Markov Sequence
Discrete	Continuous time Markov Chain	Markov Chain