HANDBOOK ON GREEN INFORMATION AND COMMUNICATION SYSTEMS

Chapter on:

Energy-efficient Green Radio Communications for Delay Tolerant Applications

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Outline

Importance of Green Design

Demand for Energy and Increase in CO_2 Emission

- With the continual increase of dependence on electrical systems in our daily lives, the consumption of electrical energy is increasing at a rapid pace.
- Information and communication technology (ICT) industry sector is responsible for a significant portion (6%) of total global CO_2 emission and global warming.
- To save mother earth from green house gas, it is therefore crucial to optimize and schedule energy consumption in every use in our daily life.

Importance of Green Wireless Design

- Wireless devices communicate over air medium whose gain is randomly varying with time, space and frequency.
- Sometime, the channel gain is too low, which causes erroneous reception at the receiver and requires higher transmitter power for a given QoS requirement.
- Other time, the gain of the channel is very high, which permits use of lower power or permits using higher order modulation and higher error control rate.
- Therefore, the intelligent and efficient techniques are specially crucial for transmission over the wireless channel to minimize power usage for delay tolerant data services.

Importance of Cross-layer Green Wireless Design

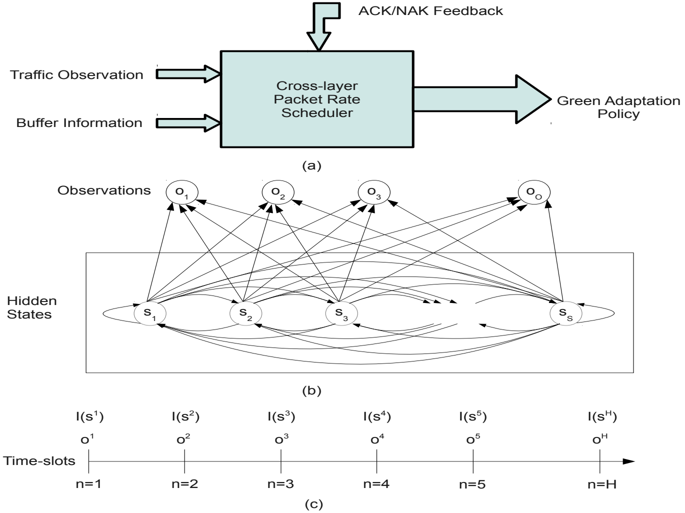
- In order to achieve reliable and energy-efficient transmission over wireless channel, a plethora of
  - adaptation
  - scheduling and
  - radio resource management (RRM) schemes

  have been proposed and utilized in different layers.
- However, in a traditional network, the optimization is usually carried out considering respective layer's objectives based on only local information ignoring other layers' design parameters or information.
- This fact gives locally optimal, but globally suboptimal solution.

Importance of Cross-layer Green Wireless Design

- In the recent years, significant attention has been received from the wireless research community on cross-layer optimization due to the promising system level performance improvements.
- These techniques exploit
  - inter-dependency and interaction among PHY, MAC and higher layers in an integrated manner.
- In cross-layer techniques, a layer interacts and exchanges information with other layers to set up its own strategy.
- A brief discussion on the energy-efficient green design of cross-layer techniques are presented in the chapter.
- In sequel, we discuss a green cross-layer scheduling technique.

Diagram of the State Transitions, Observations and Policy



General Description

- We consider a communication system over a time-slotted Gilbert-Elliot channel.
- A transmitter terminal with finite buffering capacity of B packets is communicating with its receiver terminal. The buffer maintains FIFO service strategy.
- Let T_s denotes the length of a time-slot in second. One radio frame has N_f time-slots.
- Packets are coming from the upper-layer application and are consisting of N_p bits/packet.

Traffic Model

- A Markov model is usually used to capture both the memory and burstiness of the network traffic.
- Let $\mathcal{F} = \{f_1, f_2, \cdots, f_F\}$ denote the state space of the traffic, where $f_i,\ i = 1, 2, \cdots, F$ denotes the i^{th} state.
- The states of the traffic states are governed by an underlying Markov chain $\mathcal{P}_f$, where P_{f_i, f_j} represents the transition probability.
- Incoming packet arrival may follow uniform, Poisson, Bernoulli, etc distribution.
- Hidden Markov model is usually used for the situations when states are hidden.

Channel Model

- The randomly varying gains are correlated and is usually captured using FSMC model.
- Gilbert-Elliot Markov channel model has two states $\mathcal{C} = \{c_1, \ c_2\}$) with P_{c_i,c_j} denotes the transition probability.
- The channel gains are partitioned so that the channels are equally probable.
- P_{c_i,c_j} can be approximated by the ratio of the expected number of level crossings at the received SNR γ_k and the steady state probability of channel state c_i.

Buffer Model

- For a particular action u_i and traffic state f_j, the probability of occupying buffer state $b^{n+1} = b_z$ from state $b^n = b_l$ is given by,

$$P_{b_l,b_z} = \sum_{x=0}^{x=A} \delta(b_z - b_l - a_x + \Psi(u_i))P(a_x|f_j), \ \forall c_k \in \mathcal{C} \quad (1)$$

  where function $\delta(x)$ returns 1 when $x = 0$ and returns 0 otherwise, and $P(a_x|f_j)$ is the probability of a_x arrivals in state f_j.
- Superscript n denote the value of a variable at time-slot n.

POMDP

- POMDP is a generalized framework for formulating problems where a controller takes dynamic decision based on the belief of the hidden state.
- POMDP formulations have been used to solve various wireless networking decision making problems.
- Our challenge is to find a policy given the state information of buffer and observations of the traffic and channel.
- A POMDP problem can be defined by a tuple $(\mathcal{S}, \mathcal{U}, \mathcal{P}_s, \mathcal{G}, \mathcal{O}, \mathcal{P}_o)$.

States

- The state of the system is composite and consists of
  - traffic
  - channel and
  - buffer states.
- We can write the system state space as $\mathcal{S} = \mathcal{F} \times \mathcal{C} \times \mathcal{B} = \{s_1, s_2, \cdots, s_S\}$ with total number of states being $S = F \times C \times (B + 1)$, where $s_l,\ l = 1, 2, \cdots, S$.
- The system state at time-slot n can be given by $s^n = C(B + 1)(f^n - 1) + (B + 1)(c^n - 1) + b^n$

Actions

- Actions describe the task of the scheduler to be performed at a particular state.
- The scheduler may have different choices and also the choices may be different in different state.
- We denote the set of all actions by $\mathcal{U} = \{u_1,\ u_2, \cdots, u_U\}$, where U is the total number of possible actions available.
- Let $\mathcal{X} = \{X_1,\ X_2, \cdots, X_U\}$ denote the set of transmission rate in bits/symbol, where rate X_i corresponds to action u_i.

Transitions Probabilities

- The transitions among the system states are governed by the system state transition probabilities.
- It depends on the individual transition probabilities for traffic arrivals, channel transition and buffer transition as follows,

$$\begin{aligned}\mathbf{P}_s(u_i) &= \mathbf{P}_a(u_i) \otimes \mathbf{P}_c(u_i) \otimes \mathbf{P}_b(u_i) \\ &= \begin{bmatrix} P_{s_1,s_1}(u_i) & P_{s_1,s_2}(u_i) & \cdots & P_{s_1,s_S}(u_i) \\ P_{s_2,s_1}(u_i) & P_{s_2,s_2}(u_i) & \cdots & P_{s_2,s_S}(u_i) \\ \vdots & \vdots & \ddots & \vdots \\ P_{s_S,s_1}(u_i) & P_{s_S,s_2}(u_i) & \cdots & P_{s_S,s_S}(u_i) \end{bmatrix}\end{aligned} \tag{2}$$

where the transition probability P_{s_q,s_r} for action $u^n = u_i$ can be given by,

$$P_{s_q,s_r}(u_i) = P_{a_j,a_x} P_{c_k,c_y} P_{b_l,b_z} \tag{3}$$

Costs

- The choice for an action in state is driven by associated costs. The scheduler chooses the action that incurs lowest cost.
- The transmitter power in a particular slot determines the power cost, $G_P(s_i, u_j) = P_t$
- Delay cost can be written as $G_D(s_i, u_j) = \frac{b_k - 1}{\bar{A}_l}$, where b_k is the corresponding buffer state and $\bar{A}_l$ is the average packet arrival rate.
- The overflow cost is equal to the number of packets dropped from the buffer as a result of insufficient storage, $G_O(s^n, u^n) = b^n - w^n + a^n$.

Observations

- The observation for the problem consists of traffic observation a^n and channel feedback observation ω^n.
- The observation probability for an action u_k can be written as $P_o = P(a_l|f_i) \times P(\omega_m|c_j, u_k)$.
- The packet arrivals can be uniformly, Bernoulli, Poisson, etc distributed. For uniformly distributed traffic, $P(a_l|f_i) = 1/\bar{A}_i$.
- The positive acknowledgement (ACK) probability for channel state-action pair (c_i, u_j) can be written as,

$$P_A(c_i, u_j) = (1 - \bar{P}_b(c_i, u_j))^{X_j N_f} \tag{4}$$

Fully Observable Optimal Policy (FOOP)

- We formulate the problem as an infinite horizon average cost UMDP problem and solved using dynamic programming algorithm (e.g., policy iteration).
- Our objective is to minimize a weighted sum of the three discussed cost functions,
  $G_T(s^n, u^n) = G_P(s^n, u^n) + \beta_1 G_D(s^n, u^n) + \beta_2 G_O(s^n, u^n)$.
- The Bellman equation for the dynamic programming algorithm can be written as,

$$\lambda + h(s_i) = \min_{u \in \mathcal{U}_{s_i}} \left[G_T(s_i, u) + \sum_{s_j \in \mathcal{S}} P_{s_i, s_j}(u) h(s_j) \right] \qquad (5)$$

where λ is the optimal average cost, $h(s_i)$ is the differential cost for state $s_i \in \mathcal{S}$ w.r.t. a reference state s_r.

Maximum-Likelihood Heuristic Policy (MLHP)

- Let $\mathcal{Z} = \{z_1, z_2, \cdots, z_S\}$ denote the belief of the states, where $z^n = z_i = I(s_i) = P(s_i)$ is the probability of a physical system state $s^n = s_i \in \mathcal{S}$.
- In MLHP, the policy can be represented as

$$\mu_{\text{ML}}(z^n) = \mu^*_{\text{MDP}}(\arg\max_{s^n \in \mathcal{S}} \; I(s^n)) \quad (6)$$

where, $\mu^*_{\text{MDP}}(s_i)$ is the optimal policy for state s_i of the system as computed for FOOP.
- The new belief, $I(s^{n+1})$ for state $s^{n+1} = s_j$ is updated using the following filtering formula,

$$I(s^{n+1}) = \alpha P(o^n | s^{n+1}, u^n) \sum_{s^n} P_{s^n, s^{n+1}}(u^n) I(s^n), \; \forall s^{n+1} \in \mathcal{S} \quad (7)$$

where α is a normalizing constant that makes the belief sum to 1.

Data for Monte-Carlo Simulations

We use following data for the Monte-Carlo simulations:

- Horizon $H = 10^5$, Number of Channel, Buffer and Traffic States, $C = 2$, $B = 50$ and $F = 2$
- Poisson distributed traffic with average arrival rate, $\bar{A}_1 = \bar{A}_2 = 1.0$. The traffic states are equally likely.
- Number of transmitter and receiver antennas, $n_T = 2$ and $n_R = 1$, normalized Doppler frequency, $f_m T_s = 0.1$, normalized average channel gain, $\bar{\gamma} = 1$, Nakagami-m parameter, $m = 1$, average BER, $\bar{P}_b = 10^{-4}$,
- Number of action, $U = 4$, Transmission rate set, $\mathcal{X} = \{0,\ 2,\ 4,\ 6\}$ bits/symbol, Number of symbols/block, $N_f = 1000$, the packet size in bits/packet, $N_p = 1000$
- Information code rate of STBC, $R_c = 1$

Monte-Carlo Simulations

- For simulations, without loss of generality, we assume that channel states are hidden, but traffic and buffer states are known.
- The optimal policies of the underlying fully observable MDP are found using weighting factors, β_1 varied from 0.1 to 100, and $\beta_2 = 0$.
- For each combinations, of the weighting factors, we get an unique policy using policy iteration algorithm.

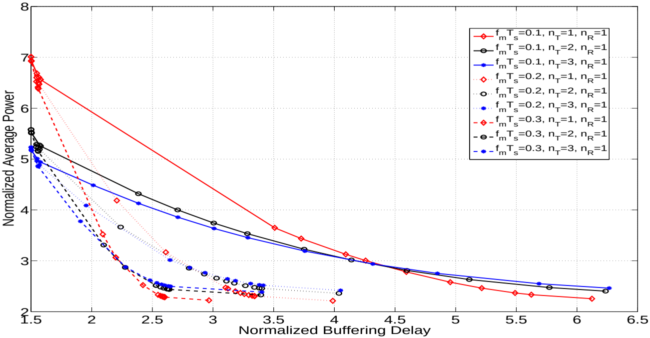
Monte-Carlo Simulations: FOOP

- For FOOP Monte-Carlo simulations, the samples of the traffic state and the channel state for the whole horizon are generated using their respective transition matrix and uniform initial state probabilities.
- Initial buffer state is assumed to be b_0 and it is updated in each time-slot using the packet arrival and packet transmission information.
- The optimal policy for the system state is applied.

Monte-Carlo Simulations: MLHP

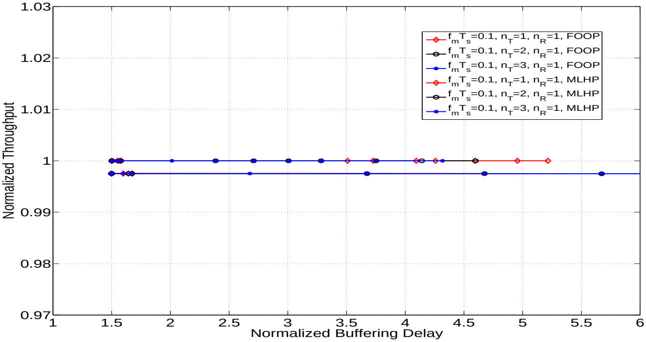
- For MLHP Monte-Carlo simulations, the channel state is assumed to be unknown and it is estimated and updated using belief update formula (7).
- The packets received in error are dropped and not retransmitted, however ACK/NAK feedback is sent to the transmitter to update belief on the channel.
- The channel state with maximum probability in a given time-slot is assumed to be the underlying channel.
- Using the generated traffic state and updated buffer state as FOOP, and estimated channel state from belief state, the system state is found and the optimal action for the system state is applied.

Power vs. Delay Tradeoff for Different n_T and $f_m T_B$



- A majority of the high bandwidth wireless traffic is relatively delay insensitive. When the delay limit is increased, the power consumption can be decreased.
- When the fading rate increases, the fall of power with increased delay limit is faster.

Throughput comparison of FOOP vs. MLHP



- The MLHP performs almost the same as the FOOP. Only slight less throughput is due to suboptimal nature of the heuristic policy.
- The throughput remains the same irrespective of fading rate and/or transmitter antenna diversity.

Summary

- We discussed two packet schedulers over correlated wireless channels in order to optimize energy using POMDP framework for future green radio communication.
- First scheduler, called FOOP, deals with the situation when all the states information are known at the transmitter.
- To deal with some practical situations, where the exact traffic and channel states may not be known, second heuristic policy, namely MLHP, is discussed.
- We discussed the problem formulations, solutions and simulation results. We also presented pertinent literature review on energy-efficient cross-layer techniques and future direction on the topic.