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Efficient Power Management in Wireless Communication

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Abstract— Data transmission in point to point wireless communication degrades the energy efficiency. One of the primary solutions to overcome this problem is to minimize the power consumption. Here, the delay sensitive data (e.g., multimedia data) are transmitted over a wireless channel. Delay sensitive communication system operates in dynamic environment conditions. A new Q-learning algorithm which dynamically adapts to the environment to achieve power management .The Q-learning based power management is more flexible and highly adaptive. It is a simple update step performed at the end of each time slot. The dynamic power management is to reduce power consumption without affecting the overall performance of the device. But only the disadvantage of this algorithm is holding cost and packet overflows are increased. In order to reduce the cost and energy consumption the transmission scheduling algorithm is proposed. This type of algorithm schedules the amount of data for desired users with a view of minimizing the energy consumption of a wireless device and prolonging its battery lifetime.

Keywords— Energy Efficient Wireless Communication, Dynamic Power Management, Power-Control, Adaptive Modulation and Coding, Markov Decision Process, Reinforcement Learning.

I. Introduction

Wireless communication is the transfer of information between two or more points that are not connected by an electrical conductor. Delay sensitive communication system operates in dynamic environment conditions (e.g., fading channel) and dynamic traffic loads (e.g,. variable bit-rate). In such systems, the primary concern has typically been the reliable delivery of data to the receiver within a tolerable delay. Increasingly, however, battery-operated mobile devices are becoming the primary means by which people consume , author, and share delay-sensitive content (e.g., real-time streaming of multimedia data, videoconferencing, gaming etc.). Consequently, energy-efficiency is becoming an increasingly important design consideration. To balance the competing requirements of energy-efficiency and low delay, fast learning algorithms are needed to quickly adapt the transmission decisions to the time-varying and a priori unknown traffic and channel conditions.

In this paper, let as consider one type of cost (delay, throughput, etc...) is to be minimized while keeping the other types of costs (power, delay, etc.) below some given bounds. Posed in this way, our control problem can be viewed as a constrained optimization problem over a given class of policies. Telecommunications networks are designed to enable the simultaneous transmission of different types of traffic: voice, file transfers, interactive messages, video, etc. Typical performance measures are the transmission delay, power consumption, throughput, transmission error probabilities, etc. Different types of traffic differ from each other by their statistical properties, as well by their performance requirements. For example, for interactive messages it is necessary that the average end-to-end delay be limited. Strict delay constraints are important for voice traffic; there, we impose a delay limit of 0.1 second. When the delay increases beyond this limit, it becomes quickly intolerable. For non-interactive file transfer, we often wish to minimize delays or to maximize throughput.

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A .PHYSICAL LAYER: ADAPTIVE MODULATION AND POWER-CONTROL

Power control is the intelligent selection of transmit power in a communication system for achieving best performance within the system. The physical layer is assumed to be a single-carrier single-input single-output (SISO) system with fixed symbol rate of 1/Ts (symbols per second). The transmitter sends at a data rate β^n /Ts (bits/s) to the receiver, where $\beta^n \geq 1$ is the number of bits per symbol determined by the modulation scheme in the AMC component shown in Fig. 1. All packets are assumed to have packet length L (bits) and the symbol period Ts is fixed.

The proposed framework can be applied to any modulation and coding schemes. Our only assumptions are that the bit-error probability (BEP) at the output of the maximum likelihood detector of the receiver, denoted by BEP^n, and the transmission power, denoted by P_{tx}^n , can be expressed as

$$BEP^n = BEP(h^n, P_{tx}^n, z^n) \quad (1)$$

and

$$P_{tx}^n = P_{tx}(h^n, BEP^n, z^n) \quad (2)$$

Where zn is the packet throughput in packets per time slot. Assuming independent bit-errors, the packet loss rate (PLR) for a packet of size L can be easily computed from the BEP as $PLR^n = 1 - (1 - BEP^n)^L$.

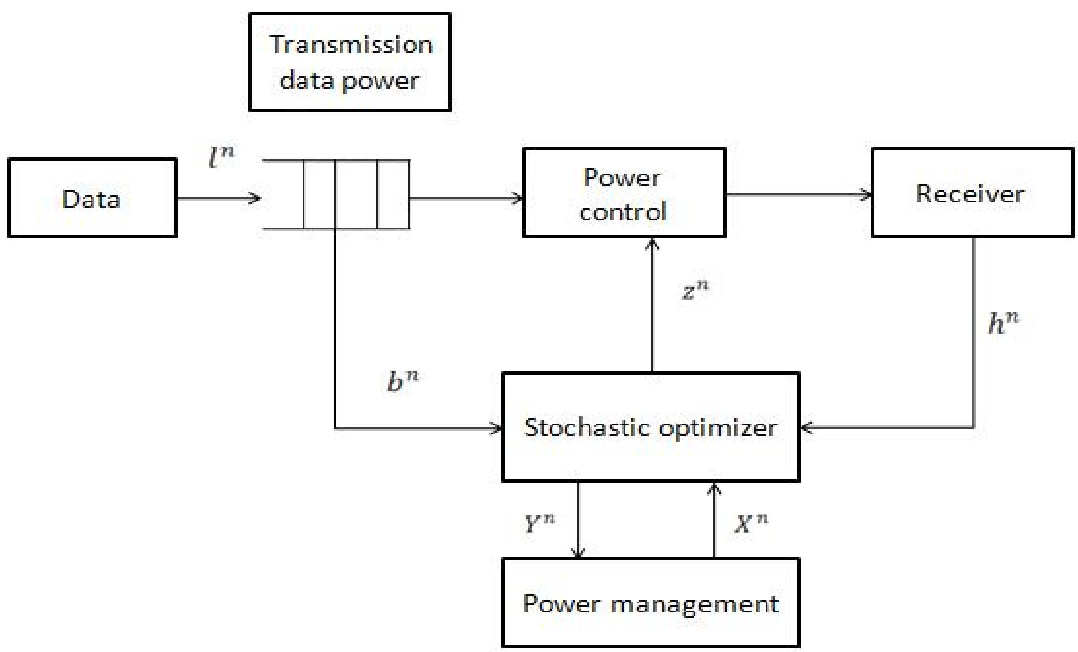

Fig 1: Wireless Transmission System

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(i). Transmission Data Buffer:

The transmission buffer is a first-in first-out queue. Each packet is of size L bits and the arrival process {n=0,1…} is assumed to be independent and identically distributed .The arriving packets are stored in a finite-length buffer, which can hold a maximum of B packets. The packet transmitted without error, which depends on the throughput .If the buffer is stable, then the holding cost is proportional to the queuing delay. If the buffer is not stable then the overflow cost imposes a penalty of efficiency for each dropped packet. Although PHY-centric solutions are effective at minimizing Transmission power, they ignore the fact that it costs Power to keep the wireless card on and ready to transmit; therefore, a significant amount of power can be wasted even .When there are no packets being transmitted. System-level Solutions address this problem.

(ii). Power – Control:

The set of channel states H is discrete and finite, and that the channel state is constant for the duration of a time .The packet length L (bits) and the symbol period Ts is fixed. The packet throughput, which determine the number of bit per symbol and channel state h(n) ,transmission power p(tx).The Bit-error probability calculated transmission power parameter function.

(iii).**Power management**:

Power consumption has become a major concern in the design of computing systems today. High power consumption increases cooling cost, degrades the system reliability and also reduces the battery life in portable devices. Modern computing/communication devices support multiple power modes which enable power and performance tradeoff. Dynamic power management (DPM) has proven to be an effective technique for power reduction at system level. The Q-learning which determine the active transmission of power Management. The power can be managed in to the x= {on, off}.The two power management actions in the set y={s-on, s-off}.The power consumed by the wireless card in the "on" and "off" states respectively, and p (tx) watts.

(iv). Stochastic Optimizer:

Stochastic optimization (SO) methods are optimization methods that generate and use random variables. The injected randomness may enable the method to escape a local minimum and eventually to approach a global optimum.

B. CONVENTIONAL Q-LEARNING ALGORITHM

Q-learning assumes that the unknown cost and transition probability functions depend on the action. Q-learning obvious what the best action is to take in each state during the learning process. Q can be learned by randomly exploring the available actions in each state. Q-learning updates, the action-value function for a single state action pair in each time slot. It, does not exploit known information about the system's dynamics. Using Q-learning, it is not obvious what the best action is to take in each state during the learning process. On the one hand, Q can be learned by randomly exploring the available actions in each state. Unfortunately, unguided randomized exploration cannot guarantee acceptable runtime performance because suboptimal actions will be taken frequently. On the other hand, taking greedy actions, which exploit the available information in Qn, can guarantee a certain level of performance, but exploiting what is already known about the system prevents the discovery of better actions. Many techniques are available in the literature to judiciously tradeoff exploration and exploitation. In this Paper, we use the so-called "-greedy action selection method, but other techniques such as Boltzmann exploration Can also be deployed. Importantly, the only reason why exploration is required is because Q-learning assumes that the unknown cost and transition probability functions depend on the action. In the remainder of this section, we will describe circumstances under which exploiting partial information about the system can obviate the need for action exploration.

Q-learning is a model-free reinforcement learning technique. Specifically, Q-learning can be used to find an optimal action-selection policy for any given (finite) Markov decision process (MDP). It works by learning an action-value function that ultimately gives the expected utility of taking a given action in a given state and following the optimal policy thereafter. When such an action-value function is learned, the optimal policy can be constructed by simply selecting the action with the highest value in each state. One of the strengths of Q-learning is that it is able to compare the expected utility of the available actions without requiring a model of the environment. Additionally, Q-learning can handle problems with stochastic transitions and rewards, without requiring any adaptations. It has been proven that for any finite MDP, Q-learning eventually finds an optimal policy.

$$Q^{n+1}(s^n,a^n) = (1-\alpha^n)Q^n(s^n,a^n) + \alpha^n[c^n + \gamma \min Q^n(s^{n+1},a') \quad (3)$$

Where,

s and a are state and action performed in time slot, respectively.
c is the corresponding cost .
a' is the greedy action in state.

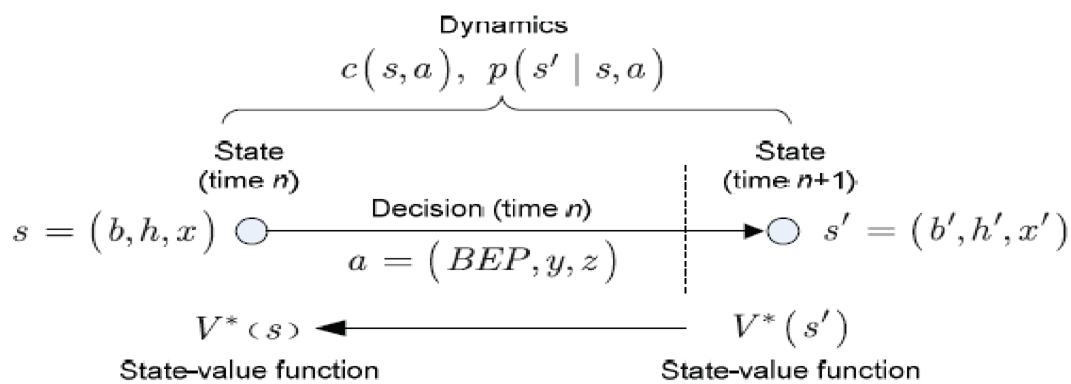

Fig 2: State Diagram

Since Q-learning is an iterative algorithm, it implicitly assumes an initial condition before the first update occurs. A high (infinite) initial value, also known as "optimistic initial conditions", can encourage exploration: no matter what action will take place, the update rule will cause it to have lower values than the other alternative, thus increasing their choice probability. Recently, it was suggested that the first reward r could be used to reset the initial conditions. According to this idea, the first time an action is taken the reward is used to set the value of Q. This will allow immediate learning in case of fix deterministic rewards. Surprisingly, this resetting-of-initial-conditions (RIC) approach seems to be consistent with human behaviour in repeated binary choice experiments.

C.PROPOSED METHOD

The proposed algorithm is based on energy-efficient opportunistic transmission scheduler considering the following two different approaches: 1) the minimization of the expected energy consumption (E2OTS − I) and 2) the minimization of the average energy consumption per unit of time (E2OTS − II). The proposed method deals with minimizing the energy consumption by using transmission scheduling algorithm. This type of algorithm schedules the amount of data for desired users with a view of minimizing the energy consumption of a wireless device and prolonging its battery lifetime. The lifetime of the batteries in wireless networks depends on the energy consumption of the devices. This energy consumption

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is effectively minimized using the multilevel queue scheduling. The energy consumption depends on the channel state because the channels are time variant. To achieve higher utilization of energy in wireless communications by exploiting good channel conditions. To accomplish this goal, we use distributed opportunistic transmission scheduling to prolong the battery lifetime of a wireless device. Therefore, according to the proposed scheduling techniques, we postpone communication until we find the best expected channel conditions to transmit, also taking into account a given tolerable time deadline and a required power level at the receiver . .Compare to the conventional algorithm power consumption are minimized in scheduling algorithm.

D.RESULT AND IMPLEMENTATION

Compare to conventional q-learning algorithm the power consumption is minimized energy –efficient transmission scheduling algorithm.

The power minimization in conventional Q-learning algorithm is 33%

The power minimization in transmission-scheduling algorithm is 41%

Output for conventional Q-learning algorithm

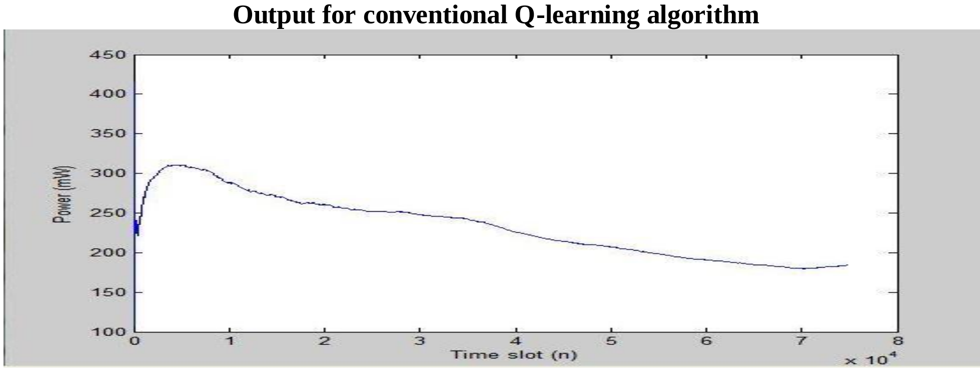

Fig 3: Cumulative average power versus timeslot

Output for transmission scheduling algorithm

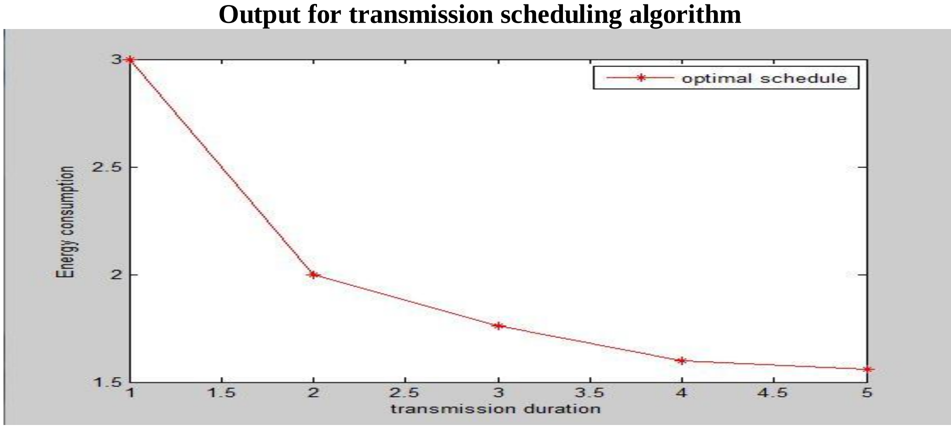

Fig 4: Impact of the CSI acquisition's energy consumption in the total average power consumption.

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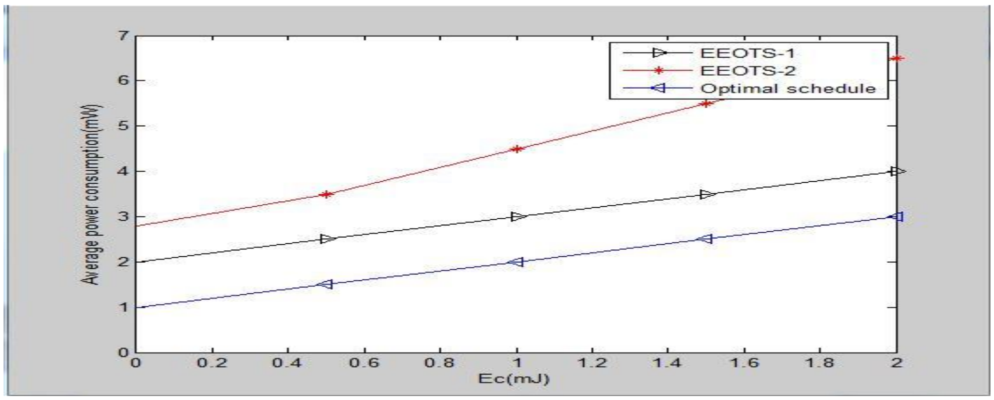

Fig 5: Impact of the CSI acquisition's energy consumption in the average performance.

II.CONCLUSION

Data transmission in point to point wireless communication degrades the energy efficiency. One of the primary solutions to overcome this problem is to minimize the power consumption with delay constraints. we have contributed minimal power consumption using transmission scheduling algorithm when compared to conventional Q-learning algorithm through MATLAB simulation.

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