Modulation Optimization for Energy Harvesting Transmitters with Compound Poisson Energy Arrivals

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***Abstract*—With the development of the energy harvesting technology, communication devices nowadays can be powered by the electrical energy obtained by converting different forms of energy from their ambience. The energy that becomes available to such transceivers varies both in time and amount, the exact information of which is usually unknown to the transceivers. We consider in this work the point-to-point communication between an energy harvesting transmitter and a receiver over a block-fading channel, where the transmitter has statistical and causal knowledge about the energy arrivals as well as the channel conditions. The stochastic energy arriving process is assumed compound Poisson, which provides both good mathematical tractability and enough physical generality. With the objective of maximizing the average throughput over a long operation time, we model the system as a Markov decision process and apply the policy-iteration algorithm to optimize the transmission policies with respect to all discretized system states. Several transmission strategies are proposed and compared from the aspects of ease of control, performance, and computational complexity.**

I. Introduction

The energy harvesting technology has emerged as a feasible and promising solution [1] to the increasing demands of longer operation time and better energy efficiency for wireless communication devices. Different from the constant power supply available for conventional devices, the energy that becomes available to an energy harvesting transceiver is dependent on the environment, varies with time in randomness, and can be even unpredictable. To this end, new optimization frameworks and resource allocation algorithms are required for energy harvesting transceivers to make more efficient use of the harvested energy. In [2], an information-theoretic framework for maximizing the short-term throughput of an energy harvesting transmitter is established, where full, non-causal knowledge of the energy arrivals is assumed. The model as well as the study on the optimal resource allocation strategy are extended in [3] and [4], where the main contributions are the inclusion of circuit power into the model, and the employment and optimization of discrete modulation schemes, respectively. The more practical scenario that the transmitter has only statistical and causal knowledge about the energy arrivals has been investigated in [5] and [6], both based on an information-theoretic approach. The main features of the work we present here include: the employment of a system setup with time-varying channel, discrete modulation orders and concrete modeling of circuit power, the formulation of an average throughput maximization problem with infinite horizon, and the modeling of the system as a discrete-time Markov decision process via discretization of the state space, which enables application of the policy-iteration algorithm. The optimized transmission policies we obtain yield the maximal average throughput under a given short-term resource allocation strategy.

The paper is organized in a standard fashion. We introduce the system model and problem formulation in Sec. II, explain the policy-iteration algorithm and propose different transmission strategies in Sec. III. Simulation results are shown in Sec. IV before the paper is concluded in Sec. V.

II. System Model and Problem Formulation

Consider the point-to-point communication between an energy harvesting transmitter and a receiver. The transmitter, which is assumed to have enough data to convey to the receiver, modulates the information bits with the *quadrature amplitude modulation* (QAM) scheme and transmits them without coding. In this section, we first establish the dependency between the instantaneous data rate and the power consumption at the transmitter, then introduce the energy arrival process which brings in the new dimension of time, and finally formulate the average throughput maximization problem, the solution of which is the focus of this paper.

A. Data transmission over block-fading channel

For the wireless communication channel, both path loss and shadow fading are considered for the radio propagation effect. Let $p_{\rm tx}$ be the transmit power and $p_{\rm rx}$ be the corresponding receive power. The receive SNR can be written as [7]

$$\gamma = \frac{p_{\rm rx}}{N_0 B} = \frac{1}{N_0 B M_{\rm l} G_1} \cdot \frac{p_{\rm tx}}{10^{\psi/10} d^{\kappa}}, \qquad (1)$$

where $\frac{N_0}{2}$ is the noise power spectrum density, B denotes the transmission bandwidth which is approximately equal to the inverse of the symbol duration $T_{\rm s}$, κ is the path loss exponent, d stands for the distance between the transmitter and the receiver, and G_1 is the the power gain at the reference distance of 1 meter. The effect of shadowing is characterized in dB by the random variable ψ which is Gaussian distributed with zero mean and variance σ_ψ^2 [8]. We assume that the shadow fading condition stays constant within a block of length $T_{\rm B}$, and changes independently from block to block. With d being constant which leads to invariant path loss, the modeled wireless channel is block-fading governed by the parameter ψ. Interference, other background noise, and internal hardware loss are compensated with the link margin M_l.

The uncoded bit error probability for M-QAM, where M denotes the constellation size, is upper bounded by [7]

$$\pi_\mathrm{b} \leq \frac{4}{\log_2 M} \cdot \left(1 - \frac{1}{\sqrt{M}}\right) \cdot \mathrm{e}^{-\frac{3}{M-1} \cdot \frac{\gamma}{2}}. \qquad (2)$$

Given a target BER $\pi_\mathrm{b}^{(\mathrm{rq})}$, the required minimum receive SNR can be computed via (2), and the corresponding p_tx can be obtained from (1) as dependent on d, ψ, and M. The instantaneous data rate in bit/sec is given by $r = B(1-\pi_\mathrm{b}^{(\mathrm{rq})}) \log_2 M$.

B. Power and Energy Consumption

The transmitter works possibly in three modes: the *active* mode during which it transmits data, the *sleep* mode during which it does not send any signal, and the *transient* mode which is the switch between the active and the sleep modes. We neglect here the power consumption of the sleep mode and the transient mode, for it is usually much smaller than that of the active mode, and neglect also the time required for the transient mode. The total power consumption p of the transmitter in active mode consists of 3 parts, as given by [7]

$$p = p_\mathrm{tx} + p_\mathrm{amp} + p_\mathrm{ct} = (1+\alpha)p_\mathrm{tx} + p_\mathrm{ct}.$$

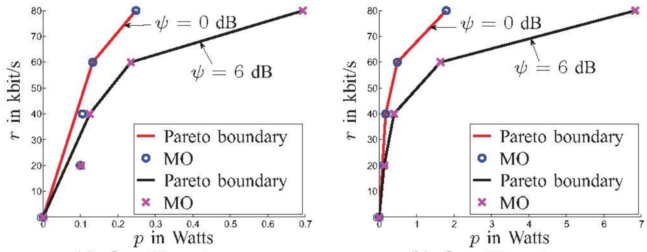
Besides the transmit power p_tx, an important part of p comes from the power amplifier given as $p_\mathrm{amp} = \alpha \cdot p_\mathrm{tx}$. The scaling factor $\alpha = \frac{\xi}{\eta} - 1$, where η is the drain efficiency of the power amplifier, and $\xi = 3 \cdot \frac{\sqrt{M}-1}{\sqrt{M}+1}$ is the peak-to-average ratio which depends on the constellation size M. The power consumptions of the D/A converter, the transmit filters, the mixer, and the frequency synthesizer are included as a whole in p_ct and they constitute the constant part of p. We summarize the notations and values of the system parameters in Table I.

Table I. SYSTEM AND SIMULATION PARAMETERS

$\kappa = 3.5$ GHz	$B = 10$ kHz	$N_0/2 = -174$ dBm/Hz
$\sigma_\psi = 3$	$M_\mathrm{l} = 30$ dB	$G_1 = 40$ dB
$\pi_\mathrm{b}^{(\mathrm{rq})} = 10^{-3}$	$T_\mathrm{B} = 4$ sec	$M \in \mathcal{M} = \{4, 16, 64, 256\}$
$\eta = 0.35$	$P_\mathrm{ct} = 98.2$ mW	$1/\lambda_0 = 30$ sec
$T = 10^5$ sec	$\delta = 0.1$ Joule	$E_\mathrm{max} = 30$ Joule
$N_\mathrm{C} = 7$	$T_0 = 4$ sec	

With the derivations and system parameters we clarify so far, one power-rate pair can be specified with each given constellation size M, shadow fading parameter ψ, and transmission distance d. In Figure 1, we plot the (p, r) points corresponding to all available modulation orders (MO) for $d \in \{20, 40\}$ meters, and $\psi \in \{0, 6\}$ dB. The origin of the graph corresponds to the sleep mode. Any two (p, r) points can be connected with a straight line, where each point on the line is achieved by the time-sharing usage of the two end points. To this end, the *Pareto boundary* of the power-rate pairs can be determined, which is a concave curve representing the maximal rate that can be achieved with each power consumption. If the power-rate pair of a MO lies on the Pareto boundary, we call it an *energy-efficient* MO. It can be seen that with shorter transmission distance and good channel condition, lower modulation levels are typically energy-inefficient.

Without loss of generality, we let the system begin operation from the time instance $t_0 = 0$. The modulation level



(a) $d = 20$ meters (b) $d = 40$ meters

Figure 1. Pareto boundaries of power-rate pairs and energy-efficient MO

employed at time t is indicated by $M(t), t \geq 0$. The cumulative energy consumption of the node is then given by the function

$$W(t) = \int_0^t p(\tau, M(\tau))\, \mathrm{d}\tau, \quad t \geq 0,$$

where the explicit dependency of the power consumption p on time accounts for the time-varying channel. Naturally, we have the initial condition $W(0) = 0$, and function $W(t)$ is also subject to a causality constraint which is explained next.

C. Compound Poisson energy arrival process

We consider that the harvested energy becomes available to the node in the form of *energy packets*, *i.e.*, the energy arrives at discrete time instances with various amounts. Let U_n and t_n denote the size of the nth packet and the time instance at which it arrives, $n = 1, 2, \ldots$, respectively. The cumulative harvested energy is given by the function

$$U(t) = A_0 + \sum_{n=1}^{N(t)} U_n, \quad t \geq 0,$$

where A_0 stands for the amount of stored energy at t_0, and function $N(t)$ indicates the number of arrivals until time t.

The values of U_n, $n = 1, 2, \ldots$ are determined by the ambience of the node and the energy harvesting technology it is using. Due to the limited capacity of the energy storage, the actual amount of energy input at each arrival, denoted with A_n, is upper bounded by U_n. Let E_max be the maximum amount of energy that the node is able to store which is a finite constant. The state of energy storage at time t, represented by the function $Z(t)$, is assumed perfectly known by the node at any $t \geq 0$. The sequence of energy inputs A_n, $n = 1, 2, \ldots$, the cumulative energy input function $A(t)$, as well as the relation between $Z(t)$, $A(t)$ and $W(t)$, are expressed by the equations

$$A_n = \min\left(U_n, E_\mathrm{max} - Z(t_n^-)\right), \quad n = 1, 2, \ldots,$$

$$A(t) = A_0 + \sum_{n=1}^{N(t)} A_n, \quad Z(t) = A(t) - W(t), \quad t \geq 0,$$

Note that $Z(t)$ and $A(t)$ are influenced by the MO the node chooses to use over time, *i.e.*, the function $M(t)$. The causality restriction requires $W(t) \leq A(t)$ to hold for any $t \geq 0$.

In practice, when and how much energy can be harvested is generally random and not exactly predictable at the transmitting node. We assume here that the energy harvesting node has perfect causal information about the energy arrivals as well as their statistics, and this statistical information does not

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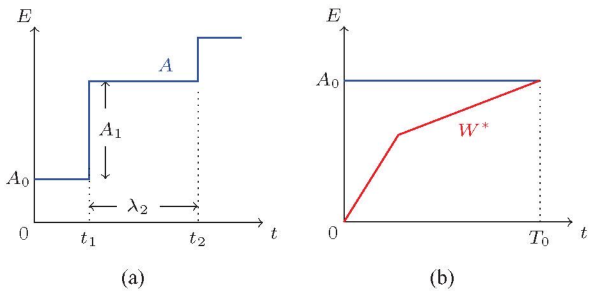

Figure 2. Energy arrival process and optimal solution to the basic problem

change over time. To be more specific, the energy arrivals follow a stationary Poisson process with known intensity λ_0, *i.e.*, the inter-arrival times $\lambda_n = t_n - t_{n-1}$ are exponentially distributed with $1/\lambda_0$ as their mean value. The quantities of energy arrivals U_n, $n = 1, 2, \ldots$ are i.i.d. random variables taking positive values, and the availability of the probability density function is assumed. The stochastic process indicated by $U(t)$ is compound Poisson under these conditions.

We illustrate the energy arrival process on a time-energy graph with a simple example in Figure 2(a). The causality constraint requires the trajectory W to lie below the curve A.

D. Average throughput maximization

The maximization of throughput on a given finite time slot $[0, T]$ for an energy harvesting transmitter has been proposed in [2]. When the system is to operate for a long time or there is no specific termination time, it is more appropriate to maximize the *average throughput* instead. To this end, based on the knowledge of energy arrival statistics, the energy harvesting node aims at solving the following optimization

$$\begin{aligned} \max_{M} \quad & \lim_{T\to\infty} \frac{1}{T}\int_0^T r(t, M)\,\mathrm{d}t \\ \text{s.t.} \quad & W \le A, \quad W(0) = 0, \end{aligned} \tag{3}$$

where the time index t is omitted due to convention, and the function M can only take values from the discrete set $\mathcal{M}$.

Equivalently, we can define a *stage* of fixed length T_0 and maximize the *average throughput per stage* over infinitely many stages. Assuming that T_B is an integer multiple of T_0, we synchronize the beginning of each block with a stage so that the channel condition stays constant on each stage. Consequently, the following optimization can be formulated

$$\begin{aligned} \max_{M} \quad & \lim_{S\to\infty} \frac{1}{S}\sum_{s=1}^{S}\int_{(s-1)T_0}^{sT_0} r(\psi_s, M)\,\mathrm{d}t \\ \text{s.t.} \quad & W \le A, \quad W(0) = 0, \end{aligned} \tag{4}$$

where ψ_s is the shadow fading factor on stage s. As we will analyse and solve the optimization within the theoretical framework of Markov decision processes, it is more convenient to employ the equivalent formulation (4) instead of using (3).

III. Policy-Iteration Algorithm

With the established system model, the energy harvesting transmitter is influenced by the energy arrival events and channel variations both in a discrete manner. We therefore propose to control the transmitter on a per stage basis, which means that the transmitter can change its *transmission policy* at the beginning of a stage, and the specific resource allocation strategy employed during each stage is dependent on this transmission policy in a predefined way. Such a design not only allows us to view the system as a discrete-time Markov decision process, but is also simple and robust from an operation point of view. Generally speaking, a transmission policy determines, based on the system state, how much resources to be allocated on the current stage, which is influenced conversely by the *transmission strategy* employed during the stage. We optimize the transmission policies corresponding to all possible system states with the policy-iteration algorithm. On the other hand, different transmission strategies can be proposed based on the analysis on the single-stage throughput maximization problem, and are assumed unchanged during operation. We mainly focus on two transmission strategies in this work, namely, the *fixed modulation order* (FMO) strategy, and the *time-sharing* (TS) strategy, which are explained next.

A. Single-stage strategies

According to our design, a single stage is a time period of length T_0 over which the channel condition is invariant. When there is no energy arrival during the stage, the throughput-maximizing transmission strategy is given by the time-sharing of the two energy-efficient MO's that are adjacent to the power value A_0/T_0, where A_0 denotes the available energy for the stage [4]. This static problem is termed as the *basic problem* and is illustrated in Figure 2(b). The optimal energy consumption trajectory W^* consists of two straight line segments, the slopes of which correspond to the power consumptions of the two involved energy-efficient MO's. Intuitively, this time-sharing (TS) solution provides a candidate single-stage strategy, where the transmitter needs to specify the total energy consumption E of the stage where $E \le A_0$. Optimizing E with respect to each system state is then the task of the policy-iteration algorithm. Although using the allocated energy to optimality, the TS strategy does not react to possible energy arrivals during the stage. We design the strategy in this way with the main concern on complexity. In fact, as we need to describe the dynamics of the system with transition probabilities between states for the policy-iteration algorithm, it is convenient to restrict T_0 such that the probability of an energy arrival within the stage is very small, and the probability of two energy arrivals is almost negligible. As a consequence, the penalty for using the static TS strategy is partly limited.

We consider another single-stage strategy, the effect of which, to the contrary of the TS strategy, is not completely determined at the beginning of the stage. It uses a certain fixed modulation order during the stage, whenever there is still energy in the storage. Therefore, the arrival of an energy packet might cause the transmitter to turn from sleep mode to active mode, or prolong the active time of the transmitter. For this fixed modulation order (FMO) strategy, a transmission policy refers to the modulation order employed during the stage.

B. Policy-iteration algorithm and its application

The problem of maximizing the average throughput per stage (4) involves an infinite number of stages on which the stationary system operates. With such a scenario and optimization goal, the *policy-iteration* technique is more favourable

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than the common dynamic programming technique based on *value-iteration* [9]. In this context, we consider the control of the energy harvesting transmitter as a finite-state Markov decision process. At the beginning of each stage, the node can change its transmission policy based on the *state* of the system, which consists of the instantaneous energy storage level, the channel condition for the stage, and the position of the stage within the corresponding block. The system state at the beginning of stage s is specified by the triple (Z_s, ψ_s, I_s), where $Z_s = Z((s-1)T_0)$, $I_s \in \left\{1, 2, \ldots, T_B/T_0 \triangleq N_\mathrm{I}\right\}$. The continuous state spaces $[0, E_{\max}]$ for Z_s and $\mathbb{R}$ for ψ_s need to be discretized in order to have finite states of the system. To this end, we approximate Z_s with N_E representative values resulting from the uniform quantization of $[0, E_{\max}]$. Let the granularity of the quantization be δ, we have $Z_s \in \{0, \delta, 2\delta, \ldots, (N_\mathrm{E}-1)\delta\}$, where $N_\mathrm{E} = \lfloor E_{\max}/\delta \rfloor + 1$. Since the random variable ψ_s is Gaussian distributed, we use the Lloyd-Max quantizer for its discretization for less loss of precision. Let N_C denote the number of quantization levels for ψ_s. In total, the system has $N_\mathrm{S} = N_\mathrm{E} \times N_\mathrm{C} \times N_\mathrm{I}$ states.

With the goal of maximizing average throughput, a reasonable transmitter would try to use the available energy steadily, and yet reduce the occurrence of energy miss events defined by $A_n < U_n$. Based on the statistical properties of the energy arrival process and the shadow fading parameter, it can be observed that the Markov process underlying such a transmitter has only one recurrent chain and is completely ergodic. This means, the initial state of the system does not influence the maximal average throughput that can be achieved.

The policy-iteration algorithm consists of the *value-determination operation* and the *policy-improvement routine* in each of its iteration cycles [10]. In the value-determination phase, the system operates under a given set of policies so that for each state of the system, the throughput to be expected on the current stage can be computed. In addition, the transition probability of the system from the current state to any possible next state is specified. The possibility of having two energy arrivals within one stage is neglected given T_0 sufficiently small. Let i, j be the state indices of the current and the next stage. A set of N_S linear equations is established as

$$\rho + v_i = q_i + \sum_{j=1}^{N_\mathrm{S}} P_{ij} v_j, \quad i = 1, \ldots, N_\mathrm{S}, \tag{5}$$

where ρ is the average throughput per stage achieved with the given policy, P_{ij} stands for the transition probability from state i to state j, and q_i stands for the expected immediate throughput with state i. It is obvious from (5) that shifting the unknowns $v_1, \ldots, v_{N_\mathrm{S}}$ by the same constant amount does not change the equations since $\sum_{j=1}^{N_\mathrm{S}} P_{ij} = 1$. Therefore, we can set the unknown v_1 to 0 which results in exactly N_S unknowns to be solved by the equation system. The resulting solutions $v_2, \ldots, v_{N_\mathrm{S}}$ are called the *relative values* of the given set of policies and serve as inputs to the policy-improvement routine.

The policy-improvement routine produces new policies as a function of input relative values. Mathematically, it solves for each state the following optimization w.r.t all feasible policies

$$\max_{M} \quad q_i(M) + \sum_{j=1}^{N_\mathrm{S}} P_{ij}(M) v_j, \quad i = 1, \ldots, N_\mathrm{S}. \tag{6}$$

The optimal policy for each state is then recorded and fed to the value-determination routine, where the transition probabilities are re-evaluated, and new relative values are computed. For each iteration cycle, the obtained average throughput per stage is improved [10]. We find via numerical experiments that the algorithm converges quite quickly, taking from 4 to around 20 iterations before the improvement of ρ drops below 10^{-4} over one iteration. We show in Figure 3 the performance of the FMO and the TS strategies, as well as their myopic counterparts, denoted with m-FMO and m-TS respectively, which correspond to the policies that maximize the expected immediate throughput on one stage. The size of each energy packet is identically u, and the achieved average throughput per stage ρ is normalized with the stage length T_0 to ϱ, which has the unit of kbit/s. The transmission distance is set to 50 meters, and other simulation parameters can be found in Table I. The significant improvement of applying the policy-iteration algorithm to optimize the transmission policies can be observed from the figure, whereas the performances of the FMO and the TS strategies are almost equal.

The most computationally demanding part of the policy-iteration algorithm is to solve the equation system (5) for the relative values, the complexity of which goes beyond the square of N_S. Therefore, reducing the number of system states is crucial to the computational complexity of the algorithm. We have the degrees of freedom in choosing the parameters δ and T_0, which directly determines N_E and N_I. The number of channel states N_C is usually small and might be agreed on by the transmitter and the receiver, hence we do not consider altering it. With smaller stage length, the transmitter has more frequent control over the system, and our approximation that there is at most one energy arrival on each stage is more accurate. However, reducing T_0 not only increases N_I, but also requires finer energy quantization which leads to larger N_E. In Figure 4, we compare the results of choosing different values for δ and T_0, where $T_\mathrm{B} = 16$ sec, identical energy arrivals of the amount of 15 Joules are assumed, and the FMO strategy is employed. Apparently, the policy-iteration algorithm gives very poor performance when the stage length is set small but a rough energy quantization is used. Although with a granularity fine enough in energy, smaller T_0 leads to better performance, the payoff in computations is tremendous and even unaffordable. In fact, we can find a trade-off between the accuracy of system description, which translates to the performance of the policy-iteration algorithm, and the computational complexity. The most favourable choice for us appears to be a fine energy quantization and a not-so-short stage length, as compared to the mean inter-arrival time of the energy packets.

An alternative way of reducing the number of system states is to unify the transmission policies used for different channel conditions and stage positions in a block. This is implemented by averaging the achieved throughput with the corresponding probabilities of channel conditions. As a result, the system has only N_E possible states. Both FMO and TS strategies have their averaged versions, which we call the AFMO and the ATS strategies. Unlike the FMO strategy, the modulation order indicated by an optimized AFMO policy is not always an energy-efficient MO, as all channel conditions are treated with the same transmission policy. It should be noted that the policy-iteration algorithm provides the optimal transmission policies with respect to the given transmission strategy, but not necessarily the global optimal solution to (4).

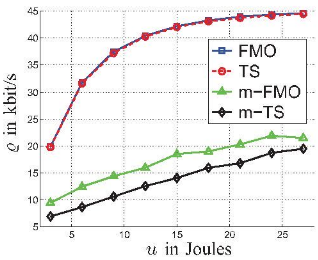


Figure 3. Opt. vs. myopic policies

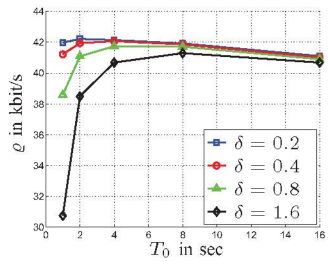


Figure 4. Impact of δ and T_0

IV. Simulation Results

We have proposed four transmission strategies: FMO, TS, AFMO, and ATS, all of which can be optimized with the policy-iteration algorithm so that the best transmission policy can be chosen for each stage. Based on the obtained results, we run simulations for 10^5 seconds and compare the achieved average data rates ϱ, where the transmission distance d and the distribution of energy packet size are varied. Besides identical energy arrivals, we also consider uniformly distributed energy packet size ranging from u_1 to u_2. The maximal data rates that can be achieved with non-causal knowledge about energy arrivals as well as channel conditions are given in Table II for reference, which are computed by using the critical slope based construction algorithm [3] and the linear programming technique. Note that the simulation time is only 5000 seconds in this case due to the high complexity of the algorithm.

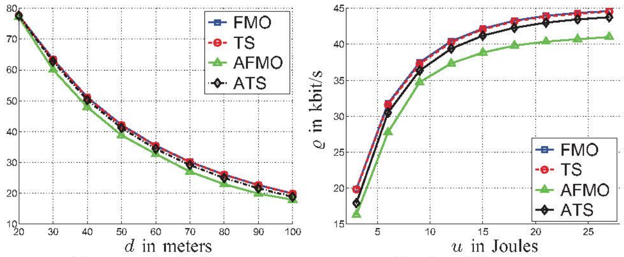
Table II. Maximal Average Data Rate Achieved with Full Knowledge of Energy Arrivals and Channel Conditions

Identical energy arrivals, $u = 15$ Joules									
d	20	30	40	50	60	70	80	90	100
ϱ	79.9200	78.6134	69.7674	59.9295	51.6222	45.2499	39.8696	35.0895	31.1931
Uniform energy arrivals, $u_1 = 10$, $u_2 = 20$ Joules									
d	20	30	40	50	60	70	80	90	100
ϱ	79.9200	78.6132	69.5944	59.7622	51.4450	45.0930	39.7534	34.9390	31.0423
Identical energy arrivals, $d = 50$ meters									
u	3	6	9	12	15	18	21	24	27
ϱ	27.9023	45.2950	52.4553	56.8949	59.9295	61.8967	63.3122	64.3277	65.0799
Uniform energy arrivals, $d = 50$ meters									
$u_2 - u_1$		0	4	8	12	16	20	24	28
ϱ		59.9295	59.9206	59.8425	59.6551	59.5643	58.9433	58.4761	58.3828

Similar performance of the FMO and the TS strategies can again be observed in Figure 5 and 6, where the FMO strategy has a slight advantage. Yet the averaged version of the TS strategy outperforms that of FMO, especially in a scenario with abundant energy. In general, the performance gap between the averaged strategy and the original strategy is quite small. Besides, a drop in the maximal average data rate can be seen in Figure 6(b), when the deviation of the energy arrivals becomes larger. Typical performance loss due to the lack of non-causal energy arrival and channel knowledge is around 30-35%.

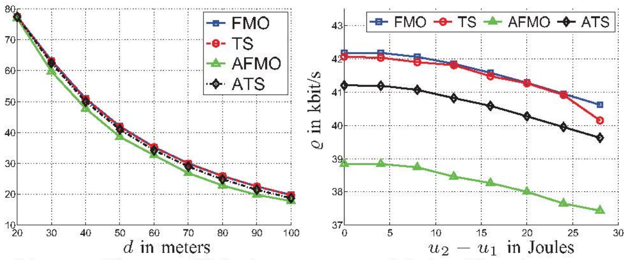
V. Conclusion

We investigate the average throughput maximization problem of an energy harvesting transmitter, which sends data to a receiver over a block-fading channel and has only statistical knowledge about the energy arriving process. A fixed length stage is defined as the minimal period that one control decision



(a) $u = 15$ Joules (b) $d = 50$ meters

Figure 5. Maximal average data rate achieved with identical energy arrivals



(a) $u_1 = 10$, $u_2 = 20$ Joules (b) $d = 50$ meters

Figure 6. Maximal average data rate achieved with uniform energy arrivals

is put into action. Based on this, the system is modeled as a discrete-time Markov decision process, for which we apply the policy-iteration algorithm to optimize the transmission policies for each system state. The FMO, TS, AFMO, and ATS transmission strategies are proposed and evaluated via simulations. While being simpler from a control point of view, the FMO strategy slightly outperforms the TS strategy. The ATS is also a promising strategy due to its lower complexity and acceptable performance degradation compared to TS.

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