Large Scale Energy Harvesting Sensor Networks with Applications in Smart Cities

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Abstract. Wireless sensor networks (WSNs), with a wide range of applications in smart cities (e.g. environmental monitoring, intelligent traffic management, healthcare), have energy self-sufficiency as one of the main bottlenecks in their implementation. Thanks to the recent advances in energy harvesting (EH), i.e., capturing energy from ambient *renewable* sources, it is now a promising solution for low-power and low-rate WNSs. In this paper, we consider two open problems of practical importance to the data quality optimization problem. In this paper, first the probabilistic energy causality constraint for the online consideration of the EH scenarios is proposed. Our realistic assumptions consider causal energy state information, instead of the non-causal cases and the ones based on offline prediction studied in literature. In addition, we propose a novel EH-aware routing protocol, based on opportunistic relaying. This routing protocol is shown to have significant benefits in finding the best path with no prior knowledge of the topology and with minimal overhead, making it an efficient protocol for EH-WSNs.

Keywords: Energy harvesting · Energy outage rate · Probabilistic energy causality constraint · EH-aware opportunistic routing

1 Introduction

Wireless sensor networks with their wide range of applications in smart cities including environmental monitoring, intelligent traffic management, healthcare, target tracking, etc., have received significant attention in the last decade. Some of the most important issues which limit WSNs' functionality are the scale, lifetime, and ease of physical access to replenish their power sources. Therefore energy self-sufficiency is one of the main bottlenecks in the implementation of sensor network applications in smart cities.

Energy harvesting, which is the capture and storage of energy from ambient *renewable* sources, allows for self sustainable and environmentally-friendly operations in low-power wireless sensor networks. This environmental energy

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(e.g., solar energy, thermal energy, vibration), harnessed at the EH communication nodes, needs to be utilized efficiently for data transmission. The recent advances in EH technologies makes it a promising and viable solution for the aforementioned problems in WSNs.

2 State-of-the-art and Scope

The existing works on EH are classified based on the causal or non-causal knowledge of the energy state information and the channel state information at the transmitter (called ESIT and CSIT, respectively) [1,2].

The related works considering EH in the WSNs are mainly on routing and medium access control (MAC) protocol design, power management, topology design, etc. The main state-of-the-art on the mentioned subjects has considered only the application or network layer without being aware of the other layers' adaptation to EH [3–6].

Different layers are strongly coupled in EH-WSNs while there are only a few works considering cross-layer design problems in such networks. These studies mainly consider the throughput maximization problem while guaranteeing the routing feasibility [7,8].

The main work on EH-WSNs as a cross-layer problem is [9] where the data quality maximization problem in EH-WSNs is considered. [9] uses EH prediction methods instead of considering the causal ESIT which leads to high prediction errors when the energy conditions change significantly. The work also does not provide an efficient routing protocol for the data quality maximization problem considering the EH constraints. In this paper, we consider two open problems in the area of EH-WSNs that help us practically consider the data quality maximization problem in such networks which is an important problem in the applications of EH-WSNs in smart cities.

First, we propose an online scenario, i.e., the causal ESIT case in point to point fading channels and then generalize it to EH-WSNs. We propose a novel problem formulation, in which instead of minimizing the outage probability as is done in [10], we consider the rate maximization problem in [1] but with probabilistic constraints. We show that our problem is non-convex and thus, based on the properties of our problem constraints, we find a convex transformation which results in the optimal solution. The convex transformation of our problem is shown to have a similar form as the problem mentioned in [1]. Therefore, we can find the closed form solution of our problem using the same approach as in [1]. Finally, we compare our results with that of the main EH rate optimization problem proposed in [1] and we quantize loss in the throughput as a result of having only the distribution of the harvested energies.

Second, unlike the work in [9] that deals with the data quality problem, we are also seeking a customized routing protocol, which considers the constraints of EH to maximize data quality in large scale networks as another tool for considering the data quality problem in EH-WSNs. Our proposed protocol considers the packet concatenation and fair bandwidth share as well as decision making based on the EH nature of the network.

The remainder of the paper is organized as follows. The system model and problem formulation are provided in Sect. 3. Then, our online EH scenario is presented in Sect. 4. Section 5 describes the proposed EH-aware routing protocol. Our simulation results are shown in Sect. 6 and finally, Sect. 7 concludes the paper.

3 System Model and Problem Formulation

3.1 System Model

Our system consists of N sensor nodes, one base station (BS), and a user-side application. The sensor nodes are distributed randomly in the monitored area. They harvest energy from the environment and also sense the physical properties of their surroundings. In our model, we consider that the nodes have an infinite battery capacity and a finite buffer for storing the received packets. Each node is assumed to have a fixed transmission region, denoted as R_t. The nodes are randomly distributed inside a circle of radius R.

The user-side application sets constraints on the data in the form of an acceptable error margin and conveys this information to the BS. This is then broadcasted by the BS to the sensor nodes. The sensor nodes sense the physical changes in the environment until the sensed data deviates from the past value by more than the acceptable error margin. This data is then transmitted to the BS. In addition to transmitting its own data, each node also performs the task of forwarding other nodes' data to the BS. Therefore, the total number of messages each node should transmit to the BS in a certain time interval is a function of the error margin and also depends on the routing protocol used in the network. The total number of messages node i transmits during the t^{th} timeslot is denoted as $M(t, e_i)$, where e_i is the error margin defined at this node.

The total energy consumption for each node in a certain time interval is a function of the total number of messages that the node transmits. This has to be less than or equal to the amount of energy harvested by the node in that period of time. Therefore, the EH rate limits the data quality level of the system. Our last term goal is to find the closest we can get to the determined accuracy level while taking into account the EH constraints in large scale EH-WSNs. The energy causality constraint for node i in the data quality maximization problem discussed above is as follows.

$$\sum_{t=1}^{k} M(t, e_i) \times E_p \leq \sum_{t=1}^{k} E_H(t),\ k = 1, 2, \ldots, t_{max}, \tag{1}$$

where $E_H(t)$ is the amount of harvested energy in t^{th} timeslot and E_p is the energy required for transmission of one packet. Note that in the causal ESIT case, $E_H(t)$ is not available for the future timeslots.

3.2 Design Challenges

The randomness in the arrival times and in the amount of energy harvested in addition to fluctuations in the communication channel pose a challenge in the identification of the optimal transmission policy. In order to maintain network connectivity and reliable data delivery, topology design and control across the network is required. Fair bandwidth share is another challenge especially in our case of large scale networks. Nodes which are far from the BS may starve the nodes closer to the BS in order to forward their packets [11]. Since the energy level of each EH node is not high, the nodes closer to the BS do not have enough energy for data transmission which decreases their data quality level. Thus, there is a requirement for an efficient EH-aware routing protocol.

Another challenge due to the energy causality constraint in Eq. (1) is consideration of the causal ESIT. As stated in the previous section, [9] uses prediction methods for this purpose and in the following section, we propose the idea of probabilistic energy causality constraint which helps us consider the online EH scenario for the constraint (1).

4 Online EH Scenario

In this section we propose the probabilistic energy causality constraint as a tool for online consideration of the EH applications.

We propose our online scenario for the rate maximization problem for a single transmitter and a fading channel in a point to point wireless communication system where the harvested energy is harnessed, stored and utilized for data transmission purposes.

We look to maximize the throughput over a finite time horizon and partition this time horizon into M time intervals, where l_i is the length of the i^{th} time interval. The bandwidth is assumed to be sufficiently wide so that we may approximate this slotted time system to a continuous time system. Furthermore, it has been shown that the optimal transmission policy is constant between energy arrivals or change in fading events. Each time interval can, thus, be referred to as a transmission block where the energy arrivals occur at the beginning of the transmission blocks.

Thus, considering the number of channel uses in each block to be large enough [1], the data transmission rate in each block is given by

$$\frac{1}{2}\log\left(1+|h_i|^2 P_i\right), \tag{2}$$

where h_i is the fading coefficient and P_i is the power allocated to block i. The channel state information, h_i, of the fading channel, is constant over each time interval i and is known at the transmitter. The amount of energy harnessed at the beginning of the time interval, E_i, is random in nature, but constant over the time interval and thus, we model the energy arrivals to be in accordance with a certain probabilistic distribution as only the past and current energy state information (ESI) is known.

We, thus, wish to identify the optimal power, P_i, to be allocated to each time interval subject to causality constraints which dictate that the total power allocated at the end of each interval should not exceed the total energy that is available at that time, which can be shown as follows

$$\int_0^{t_i^e} P(u)du \leq \sum_{j=1}^{i} E_j, \tag{3}$$

where t_i^e is the duration of i energy harvesting timeslots. Because of the concavity of rate in power the transmit power is to be kept constant during each time interval [12], and hence the causality constraints is reduced to

$$\sum_{i=1}^{k} P_i \leq \sum_{i=1}^{k} E_i,\ k = 1, 2, \ldots, M. \tag{4}$$

4.1 Problem Formulation

The optimization problem for maximizing the total throughput via optimal power allocation subject to energy causality constraints is as follows.

$$\begin{aligned} \max_{p_i} \ & \sum_{i=1}^{M} \frac{1}{2} \log(1 + P_i \left|h_i^2\right|) \\ s.t. \ & \sum_{i=1}^{k} l_i P_i \leq \sum_{i=1}^{k} E_i,\ k = 1, 2, \ldots, M. \\ & 0 \leq P_i \end{aligned} \tag{5}$$

Since the amount of energy harvested is random in nature, we can only consider probabilistic information about the energy. Instead of minimizing the outage probability of the rate as it is done in existing works, we modify to consider probabilistic energy causality constraints where the rate of violation of each constraint is ϵ, which is the energy outage rate. The optimization problem is, thus, reformulated as follows

$$\begin{aligned} \max_{p_i} \ & \sum_{i=1}^{M} \frac{1}{2} \log(1 + P_i \left|h_i^2\right|) \\ s.t. \ & Pr(\sum_{i=1}^{k} E_i \leq \sum_{i=1}^{k} l_i P_i) \leq \epsilon,\ k = 1, 2, \ldots, M. \\ & 0 \leq P_i \end{aligned} \tag{6}$$

The time interval lengths, l_i, can be taken to be unity for simplicity.

4.2 Optimal Solution

The objective function in problem (6) is a concave function but the first constraint which is in the form of the CDF of $\sum_{i=1}^{k} E_i$ is not a convex function. The CDF for most distributions is of the form of unimodal distribution functions, i.e., it is convex for some x in the range less than m and concave for $x > m$.

The non-decreasing behavior of CDF makes the probabilistic constraint in problem (6) quasiconvex in nature causing the feasible set of this problem to be convex [13]. However, we propose another method to find the convex transformation of this problem. Based on the non-decreasing behavior of CDF, it is possible to find the inverse CDF using the closed form CDF or the CDF lookup tables. In the following, we consider the case with the harvested energies to be independent and identically distributed (i.i.d.) random variables with exponential distribution. Since the sum of i.i.d. exponential random variables has Erlang distribution, the CDF of the sum of harvested energies is as follows.

$$F(x;k,\lambda) = \frac{\gamma(k,\lambda x)}{(k-1)!}, \tag{7}$$

where $\gamma(.)$ is the lower incomplete gamma function defined as

$$\gamma(s,x) = \int_0^x t^{s-1}\, e^{-t}\, \mathrm{d}t. \tag{8}$$

The Erlang distribution is a unimodal distribution function. Hence, we should transform the constraint in problem (6) to a convex constraint. The Eq. (7) can be assumed as a function of $\sum_i p_i$. Therefore, the best approach is to find the inverse of the Erlang CDF which results in an affine inequality constraint.

$$F_k\left(\sum_{i=1}^{k} P_i\right) \leq \epsilon,\ k = 1, 2, \ldots, M, \tag{9}$$

where $F_k(.)$ is the CDF of the sum of i.i.d. E_i's, $i = 1, 2, \ldots, k$.

According to the inequality (9), we have

$$\sum_{i=1}^{k} P_i \leq F_k^{-1}(\epsilon), \tag{10}$$

where $F_k^{-1}(.)$ is the inverse CDF of the sum of i.i.d. E_i's, $i = 1, 2, \ldots, k$.

Given the closed form CDF, it is easy to find the inverse function. Alternatively, because of the non-decreasing behaviour of CDF, we can use the bisection method to find the inverse CDF. Another way of finding the inverse function is to use inverse CDF tables such as the gamma function tables that we used in our simulations.

4.3 Closed Form Solution

After finding the convex form of our optimization problem, now we can obtain the closed form solution by applying the Karush-Kuhn-Tucker (KKT) conditions.

The Lagrangian for (6) using Lagrange multipliers ϵ_i and μ_i can be obtained as

$$L = \sum_{i=1}^{M} \log(1 + |h_i|^2 P_i) - \sum_{j=1}^{M} \lambda_j \left(\sum_{i=1}^{j} P_i - F_j^{-1}(\epsilon) \right) + \sum_{i=1}^{M} \mu_j P_j. \tag{11}$$

Thus, the complimentary slackness conditions can be given by

$$\lambda_j \left(\sum_{i=1}^{j} P_i - F_j^{-1}(\epsilon) \right) = 0, \tag{12}$$

$$\mu_j P_j = 0. \tag{13}$$

It follows that the optimal power for the i^{th} transmission block is

$$P_i^{\star} = \left[\nu_i - \frac{1}{|h_i|^2} \right]^{+}, \tag{14}$$

where the water level is given by

$$\nu_i = \frac{1}{\sum_{j=i}^{M} \lambda_j}. \tag{15}$$

The above solution can be obtained using *directional water-filling* algorithm as in [1].

4.4 Updating Scenario

The optimal power allocation, which faces violations, needs to be modified to give the practically achievable alloceted power, that is, one which is in keeping with the causality constraints. The updating scenario we propose here in order to satisfy the energy causality constraint for the optimal allocated power is that for each timeslot j that the energy causality constraint does violate we limit P_j to the total available energy harvested at the j^{th} timeslot.

4.5 Online Scenario in EH-WSNs

The proposed method in this section can be applied as a tool for considering online EH scenario in EH-WSNs since data transmission between two nodes in WSNs can be considered similar to the point to point case. To achieve this objective we just need to change the energy causality constraint in (1) to the probabilistic constraint similar to what we mentioned in the point to point case. Therefore, using the probabilistic knowledge of the harvested energy no offline prediction is required.

5 Proposed Opportunistic Routing

In the previous section we investigated transmission strategies for a single link in the WSN. This section investigates a complementary issue: the route data packets must take to be received at the BS. We propose a new EH-aware routing protocol in order to find the best route from each node toward the BS. As opposed to the other routing protocols applied for EH scenarios which are either only distance-dependent or are just for specific network topologies (e.g., linear, grid), ours considers the remaining energy for each node and the statistics of the channel based on instantaneous channel measurements where nodes are randomly distributed in environment.

Our protocol does not require prior knowledge of the network topology and operates in a distributed fashion. Each EH node is assumed to have a fixed transmission region, a circle of radius R_t. EH nodes are distributed randomly inside a circle of radius R. In addition to transmitting its own data, each EH node is also capable of relaying other nodes' messages to the BS. Each EH node is only aware of its own location and consequently, its distance from the BS. As mentioned in the system model, nodes are battery operated and have a finite size buffer to store packets for future transmission.

Our opportunistic routing protocol exploits the opportunistic relaying scheme proposed and analyzed in [14]. The overall overhead is an important aspect that needs to be taken into account in large scale EH-WSNs. The opportunistic relaying scheme in [14] is based on time and is shown to have the minimal overhead. Each node may have a few neighbouring nodes, i.e., nodes that are present in its transmission region. These neighbouring nodes could be active or in sleep mode (waiting to harvest sufficient energy to transmit data) based on their remaining energy. We define a threshold, E_{th}, so that only those EH nodes with remaining energy more than E_{th} are capable of receiving data (active mode).

Nodes which have a packet to transmit will broadcast it if they have enough energy for data transmission. The active neighbors receive this data and store it in their buffer. Nodes are equipped with an internal timer which starts after they receive data from their neighbours. In our model, as soon as each node receives a message, it goes to the listening mode and starts a timer based on its SNR received at the BS, at each timeslot. Therefore, the timer of the relaying node with the maximum SNR (best end-to-end path between the relaying node and the BS) expires first, thereby choosing the max-SNR node to relay the data (if it has enough energy for data transmission). It then sends a packet to all of its neighbours indicating that they can drop their received data. In this way, the probability of the collision is also decreased.

A node with location vector (a_i, b_i) from the BS and remaining energy E_r should wait T_i seconds after data reception, where T_i is defined as

$$T_i = \frac{\lambda}{SNR_i}, \tag{16}$$

and SNR_i is the signal to noise ratio for the EH node i *at the BS*, and λ is a constant which is defined based on the channel coherence time. For choosing the best path through maximum SNR neighbour selection using the described protocol, not only are the remaining energy of the EH nodes and the channel state information taken into account, but other features like distance to BS are inherently considered.

6 Simulation Results

6.1 Online EH Scenario

In this section we first simulate the rate optimization problem proposed in Sect. 4. The optimal rates have been simulated in order to observe their variation with change in average energy harvesting rate per time interval, using MATLAB CVX toolbox [15].

First, to check the correctness of our model, we simulate random energy arrivals and observe the rate of violation of the causality constraints by the power allocated. The results show that this rate matches the value of ϵ (violation rate) that we set for the probabilistic constraint in our problem thus, justifying the accuracy of the model.

Figure 1 compares the performance of the offline scenario, given in Eq. (5), with our online scenario for ϵ equals to 0.1. In this figure the channel is random fading. The greedy curve is also depicted in the figure, where all the available energy is allocated for data transmission at each timeslot. It can be observed that there is reduction in rate for the reformulated problem due to availability of only probabilistic information regarding the amount of energy as compared to the deterministic scenario addressed in the original problem.

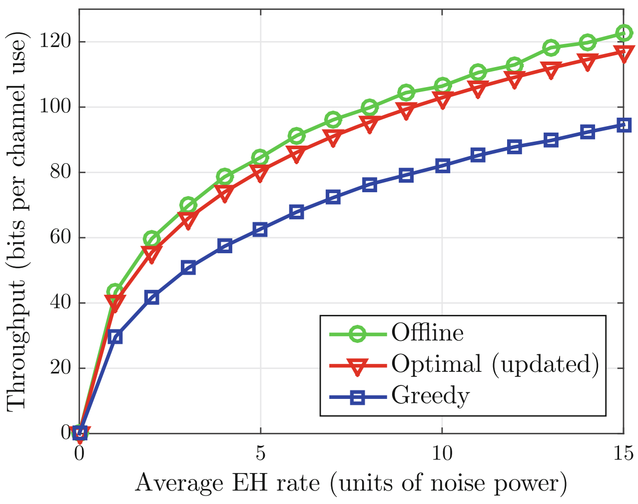

Fig. 1. Comparing achievable rates

6.2 EH-aware Routing Protocol

We simulate our proposed EH-aware routing protocol for different network densities. Our main goal here is to find the expected number of messages transmitted per node as a function of distance from the BS. This can be used for calculation of $M(t, e_i)$ in the energy causality constraint, mentioned in (1), of the data quality maximization problem.

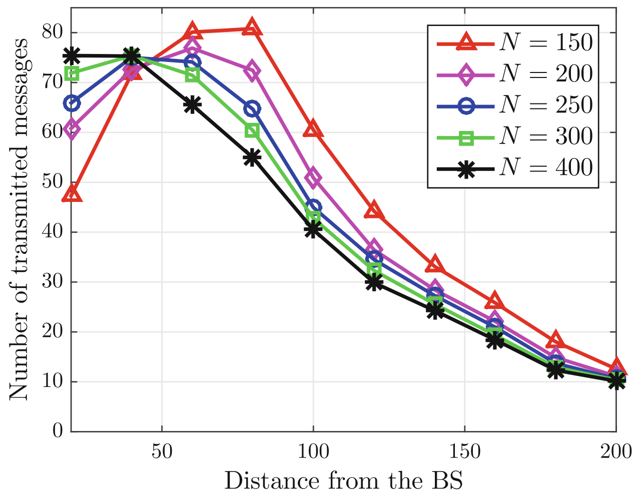

Fig. 2. Opportunistic routing for different network densities

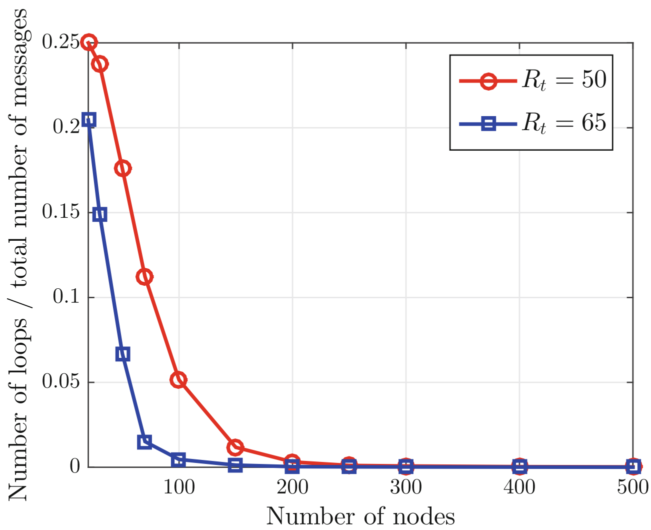

Fig. 3. Number of loops as a function of network density (for nodes with different transmission regions)

Figure 2 depicts the total transmitted messages versus the distance from the BS. We simulate a network with radius of $R = 200$ and for nodes with transmission region $R_t = 50$. The harvested energy is assumed to have exponential distribution.

We run the routing protocol for 100 timeslots and the total number of the initial messages for each node is considered to be 10 packets that are randomly generated within the running time. We also define a limited buffer size of 20 packets for each node.

Another feature of our proposed protocol is the number of loops that occur during data transmission. We define a loop as the occurrence when a node receives back its own initial transmitted packet as a part of the other nodes' data. Figure 3 demonstrates the number of loops for the EH-aware routing protocol. As we see, for high densities the total number of loops is negligible which means that the protocol works well for large scale EH-WSNs.

7 Conclusion

In this paper, we considered the data quality maximization problem in EH-WSNs. The growing interest in smart cities make the analysis of such networks important. This paper results in a practical framework for the application of WSNs in smart cities. Our realistic assumptions consider causal ESIT instead of non-causal cases and those methods using offline prediction studied in literature. We also propose an EH-aware routing protocol as an efficient routing protocol for the data quality maximization problem in EH-WSNs. To the best of our knowledge, this is the first work on the data quality maximization problem in large scale EH-WSNs as a cross-layer optimization problem considering the causal ESIT knowledge of each node which benefits from an efficient EH-aware routing protocol.

References

1. Ozel, O., Tutuncuoglu, K., Yang, J., Ulukus, S., Yener, A.: Transmission with energy harvesting nodes in fading wireless channels: optimal policies. IEEE J. Sel. Areas Commun. **29**(8), 1732–1743 (2011)
2. Li, H., Xu, J., Zhang, R., Cui, S.: A general utility optimization framework for energy harvesting based wireless communications. IEEE Commun. Mag. **53**(4), 79–85 (2015)
3. Dang, N., Bozorgzadeh, E., Venkatasubramanian, N.: QuARES: quality-aware data collection in energy harvesting sensor networks. In: 2011 International on Green Computing Conference and Workshops (IGCC), pp. 1–9, 25–28 July 2011
4. Hasenfratz, D., Meier, A., Moser, C., Chen, J.J., Thiele, L.: Analysis, comparison, and optimization of routing protocols for energy harvesting wireless sensor networks. In: 2010 IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing (SUTC), pp. 19–26, 7–9 June 2010
5. Eu, Z.A., Tan, H.-P., Seah, W.K.: Opportunistic routing in wireless sensor networks powered by ambient energy harvesting. Comput. Netw. **54**(17), 2943–2966 (2010)

6. Eu, Z.A., Seah, W.K., Tan, H.-P.: A study of MAC schemes for wireless sensor networks powered by ambient energy harvesting. In: Proceedings of the 4th Annual International Conference on Wireless Internet, p. 78. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering) (2008)
7. Zhang, B., Simon, R., Aydin, H.: Maximal utility rate allocation for energy harvesting wireless sensor networks. In: 14th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (2011)
8. Fan, K.W., Zheng, Z., Sinha, P.: Steady and fair rate allocation for rechargeable sensors in perpetual sensor networks. In: Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems, pp. 239–252. ACM (2008)
9. Dang, N., Roshanaei, M., Bozorgzadeh, E., Venkatasubramanian, N.: Adapting data quality with multihop routing for energy harvesting wireless sensor networks. In: 2013 International on Green Computing Conference (IGCC), pp. 1–6, 27–29 June 2013
10. Wei, S., Guan, W., Liu, K.J.R.: Outage probability optimization with equal and unequal transmission rates under energy harvesting constraints. In: Global Communications Conference, GLOBECOM 2013, pp. 2520–2525. IEEE, 9–13 December 2013
11. Seah, W.K.G., Eu, Z.A., Tan, H.: Wireless sensor networks powered by ambient energy harvesting (WSN-HEAP) - survey and challenges. In: 1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace & Electronic Systems Technology, Wireless VITAE 2009, pp. 1–5, 17–20 May 2009
12. Yang, J., Ulukus, S.: Transmission completion time minimization in an energy harvesting system. In: 2010 44th Annual Conference on Information Sciences and Systems (CISS), pp. 1–6, 17–19 March 2010
13. Boyd, S., Vandenberghe, L.: Convex Optimization. Cambridge University Press, Cambridge (2004)
14. Bletsas, A., Khisti, A., Reed, D.P., Lippman, A.: A simple cooperative diversity method based on network path selection. IEEE J. Sel. Areas Commun. **24**(3), 659–672 (2006)
15. Grant, M., Boyd, S., Ye, Y.: CVX: Matlab software for disciplined convex programming (2008)