Journal of Engineering Sciences

Vol 13, Issue 06, JUNE/2022

ISSN NO:0377-9254

EFFICIENT ENERGY SCHEDULING BY USING OPTIMAL SOLUTION METHODS IN WIRLESS POWER NETWORKS

SALI ANUHYA[1], J.V. PRABHAKAR RAO[2]

[1]M.Tech [MW&RE], Department of ECE, KLR Engineering College, Palvancha, Telangana.

[2] M.Tech, MISTE assoc professor & HOD, Department of ECE , KLR Engineering College, Palvancha, Telangana

Abstract: Radio frequency (RF) energy harvesting has the potential to provide perpetual energy to the nodes in communication networks. In this paper, we study the optimization problem for the scheduling of the RF energy harvesting to satisfy the energy demands of the links in a wireless powered network containing a multi-antenna hybrid beam forming base station and multi-antenna users: The time is divided into multiple slots, where different beam forming weights are assigned to each slot. Upon formulation of the problem as a non-convex quadratic ally constrained linear program, we propose a solution method based on alternating minimization algorithm. We demonstrate via simulations that the additional degrees of freedom introduced by the scheduling algorithm can reduce the number of required RF chains in the hybrid beam forming structure for a certain delay performance, resulting in significant cost savings.

Key words: RF energy harvesting, hybrid beam forming, scheduling, non-scheduling, WPSN.

1.INTRODUCTION

Energy harvesting via radio-frequency (RF) signals has emerged as a groundbreaking technique to prolong the network lifetime. The idea is to extend the lifetime of the network via wireless energy harvesting instead of replacing their batteries or recharging the devices through conventional methods [1–3]. Although other ambient energy harvesting methods such as thermoelectric effects, solar, vibrations, and the wind can also be used to recharge the batteries [4, 5], these conventional techniques are not very reliable and highly variable [6]. From the perspective of RF energy harvesting, the main advantage is that RF signals can simultaneously carry both information and energy. Thus, the energy-constrained nodes in the network can scavenge energy and process the information at the same time [7, 8]. Note that, in a wireless energy harvesting enabled network, the nodes can harvest energy from both a dedicated RF source and an ambient RF source. The idea of wireless energy harvesting offers a practical solution to extend the lifetime of energy constrained networks and also improves communication reliability. Due to these features, recent research works have widely studied its use in state-of-the-art next-generation technologies such as machine-to-machine communications (M2M), Internet of Things (IoT), MIMO, and 5G cellular networks [9–12]. Moreover, it is also well-known that relays can extend the coverage, improve quality-of-service (QoS), and improve capacity of networks by dividing the direct source-to-destination communication channel into two appropriate source-to-relay and relay-to-destination communication paths [13]. In conventional relay networks, relay node uses its own battery power to forward the information received from the source node. However, in the case of energy-constrained relay nodes, the network lifetime is significantly compromised. Luckily, recent advances and state-of-the-art technology in next-generation cooperative networks have paved the way for wireless

energy cooperation between communicating nodes in which the idea is to power up the relay node through wireless energy harvesting

2.SYSTEM MODEL

We consider a WPCN containing an access point equipped with M antennas and N users equipped with R antennas. The access point is connected to a power supply with capability of transferring RF energy to the users. Users do not possess any power supply and harvest energy from the RF transmission of the access point. The communication protocol is assumed to employ a half-duplex dynamic time-division multiple access (TDMA), where each TDMA frame is partitioned into S slots of variable duration for the wireless energy transmission of the access point to the users in the downlink, followed by the slots of variable duration allocated for the information transmission of the users to the access point in the uplink using the harvested energy. We assume that the energy requirement of user n is fixed and equal to En for n 2 [1; N] to avoid the complexity in the first step of the study and better illustrate the gain from the scheduling of energy harvesting. We aim to minimize the total duration of energy harvesting to meet these energy requirements.

We consider an RF energy harvesting-based multichannel multipair DF relay network as shown in Figure 1. In the proposed network, we define S={Sm I Sm=1,2,3…,M} and D={Dnm I Sm=1,2,3…,N} as the sets of source and destination nodes in the network with cardinality and , respectively. In our proposed scheme, information is transmitted from source node (where) to its respective destination node (), via an intermediate energy-constrained DF relay node R using orthogonal channels. It is assumed that there is no direct link between the source and destination nodes, and the respective SNRs of the channels between the communicating nodes are less than the minimum required threshold SNR for effective communication. Therefore, to assist the information transmission between communicating nodes, an intermediate relay node (R) is used [40].

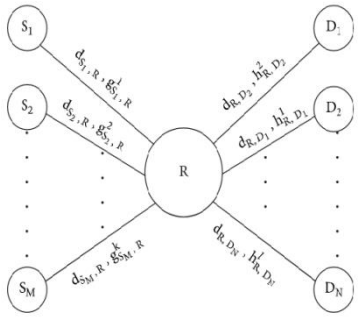

FIG 2 : System model of energy harvesting-based multichannel relay network.

In Figure 2, and represent the distance and channel coefficient between source node and relay node R via frequency channel respectively. Similarly, and represent the distance and channel coefficient between relay node R and destination node via channel (where), respectively. Note that, since each node is using a single orthogonal frequency channel for communication, the total numbers of source-to-relay and relay-to-destination channels are equal to the total number of source nodes and destination nodes, respectively. The orthogonal channels are considered in order to avoid co channel interference. The channel coefficients are assumed to be quasi-static block-fading, which means that the channel state is constant and does not vary over a transmission block time . It is also assumed that they are independent and identically distributed in each time block following a Rayleigh distribution. The path-loss model considered in this paper is a distance-dependent path-loss model , where is the path-loss exponent and is the propagation distance. The use of such path-loss and channel model is motivated by the previous work done in this research area. For the sake of readers' convenience, all the notations used in this paper are summarized in Further more, we assume

that the relay node R is an energy-constrained node. Therefore, it first harvests energy from the received source signals and then utilizes this harvested energy to forward these received signals to their respective destinations.

3. EXISTING SYSTEM

PILOT CONTAMINATION

It is nothing but one cell is corrupted by channel between base station and user. PC has a more severe impact on the system performance than channel noise.

DRAW BACKS

- **Frequency reuse**
- **Path loss**
- **Data diverting problems**

4.PROPOSED SYSTEM

ENERGY Harvesting And Information Processing In PS Based DF Relay

In this section, a generalized energy harvesting and information processing procedure for a PS-based energy-constrained DF relay network is provided. In order to harvest energy at relay node R, we consider the PS-based relaying (PSR) protocol proposed in [16, 17]. According to PSR protocol, the entire received power of the source signal is split into two portions by using a power splitter. One portion of power is used for energy harvesting while the other is used for information processing. Figures 2(a) and 2(b) depict the transmission time-block structure and block diagram, respectively, for PSR protocol. Please note that P^k_{SmR} denotes the power of the signal received from source node S_m via channel K and T stands for the total transmission time which is divided into two halves; the first T/2 half is used for source-to-relay transmission, and the second T/2 half is used for relay-to-destination transmission. According to PSR protocol, during the first half a certain fraction of the received signal power P^k_{SmR} is used for energy harvesting and the remaining power $(1-p^m)$ P^k_{SmR} is used for information processing, where p^m denotes the power-splitting factor of signal received from source node m. The value of ranges between 0 and 1 (i.e.,0<p<1)

Optimization Problem Formulation

The optimization problem aims to minimize the total energy harvesting time from the access point to the users while satisfying the energy requirement of the users, the maximum transmit power and hybrid beamforming constraints of the wireless communication system.

$$\textbf{minimize} \quad \sum_{s=1}^{S} t_s$$

$$\textbf{subject to}$$

$$\sum_{s=1}^{S} \psi \mathbf{w}_s^{\mathbf{H}} \mathbf{H}_n \mathbf{w}_s \geq E_n \quad n \in [1, N]$$

$$\mathbf{w}_s^{\mathbf{H}} \mathbf{w}_s \leq P_A t_s \quad s \in [1, S]$$

$$|\mathbf{w}_s(j)| = |\mathbf{w}_s(i)| \quad i, j \in G_l, \quad l \in [1, L], \quad s \in [1, S]$$

$$\textbf{variables}$$

$$t_s \in \mathbb{R}_+, \ \mathbf{w}_s \in \mathbb{C}^M, \quad s \in [1, S]$$

The variables of the optimization problem are ts, the duration of the s-th time slot, and ws, the time weighted energy beam forming vector of the s-th time slot, defined as ws := vspts for ts > 0 and s 2 [1; S]. The ws definition allows the removal of the coupling of the variables ts and vs at the harvested energy of the users. Equation (1b) represents the energy requirement of the users, where the required energy of each user needs to be satisfied by the total energy transferred from the base station. Equation (1c) gives the maximum transmit power constraint of the base station. states the limitation introduced by the hybrid beam forming structure. This optimization problem is a non-convex quadratically constrained linear program (QCLP). Non-convexity stems from the

constraints in Equations (1b) and (1d). Therefore, we will employ approximation methods next. We will examine the usage of semi definite relaxation and alternating minimization algorithms for the efficient approximation of the non-convex QCLP problem

I) Semidefinite relaxation (SDR)

SDR has been proposed as an efficient approximation technique for problems with non-convex quadratic constraints. In SDR, the non-convex QCLP problem is reformulated by using equivalent positive semi definite (PSD) matrices and additional rank constraints. Then the solution methodology is composed of first solving the resulting semi definite programming from the relaxation of the rank constraint and then using rank reduction methods The reformulation of the non-convex QCLP problem (1) is given by

minimize

$$\sum_{s=1}^{S} t_s$$

subject to

$$\sum_{s=1}^{S} \psi Tr(\mathbf{H_n W_s}) \geq E_n \quad n \in [1, N]$$

$$Tr(\mathbf{W_s}) \leq P_A t_s \quad s \in [1, S]$$

$$\mathbf{W_s}(j, j) = \mathbf{W_s}(i, i) \quad i, j \in G_l, \quad l \in [1, L], \quad s \in [1, S]$$

$$rank(\mathbf{W_s}) = 1 \quad s \in [1, S]$$

$$\mathbf{W_s} \geq 0 \quad s \in [1, S]$$

variables

$$t_s \in \mathbb{R}_+, \ \mathbf{W_s} \in \mathbb{C}^{M \times M}, \quad s \in [1, S]$$

The variables of the optimization problem are ts and Ws, defined as the time weighted beam forming matrix at time slots, rank 1 and positive semi definite, respectively. Problem (1) is equivalent to problem (2) . By relaxing the only non-convex constraint, rank constraint in Equation (2e), we can obtain semi definite relaxation of our problem. Relaxed problem is convex and can easily be solved in a numerically reliable and efficient manner by readily available software packages [11]. However this relaxation bound for scheduled, S > 1, and non-scheduled, S = 1, cases are identical as proven in the next lemma.

Let us denote the relaxed version of the optimization problem (2) with S time slots as _S, its feasible solution as XS = f(Ws)Ss=1; (ts)Ss=1g, where (Ws)Ss=1 denotes the collection of S time weighted beam forming matrices (W1;W2; : : : ;WS) and (ts)Ss=1 represents the collection of S time slot durations, (t1; t2; : : : ; tS), and its objective function as fS(XS). We prove the lemma by demonstrating that an optimal solution X1 of the problem _1 can be constructed from an optimal solution XS of the problem _S with the same value of the objective function, and vice versa. Let XS = f(Ws)Ss=1; (ts)Ss=1g be a feasible solution to the problem _S. Due to linearity of trace function, X1 =f(PSs=1Ws); (PSs=1 ts)g is a feasible solution of the problem with the same optimal value. Similarly, given a feasible solution X1 of the problem _1, XS = f(W1=S)Ss =1; (t1=S)Ss =1g is a feasible solution of the problem _S with the same optimal value. Since a feasible solution with the same objective value to one problem can be constructed from the other problem, then by contradiction it can be proven that an optimal solution to one problem can be constructed from the other problem.

Since the result is valid for any S , SDR bound is independent of the number of available time slots.

Therefore, there is no point in continuing with SDR rank reduction methods. However, the solution of SDR is a good lower bound for the total energy harvesting time.

II) Alternating Minimization (AM) Algorithm

Alternating minimization (AM) algorithm is based on reformulating the rank constraint as an equivalent non-convex constraint and iteratively

solving the convex optimization problem obtained by moving rank constraint to the objective function as a penalty function. The convergence of the objective function of the optimization problem by this iterative algorithm has been proved in The rank constraint given in Equation (2e) is first replaced by Tr(Ws)2 - Tr(Ws2) ; s 2 [1; S], based on the fact that for every non-zero positive semi definite matrix W, Tr(W2) _ Tr(W)2; and Tr(W2) = Tr(W)2 if and only if rank(W)=1. This new constraint is non-convex but can be moved to the objective function as a penalty by including the sum of the amount of the violation of the constraint at each time slot s, i.e. PSs =1 _s(Tr(Ws)Tr(Ws)-Tr(WsTs)), where _s is the weight of the violation at time slot s. Resultant problem can be solved iteratively by AM algorithm. In the q-th iteration of the algorithm, the following problem is solved: The rank constraint given in Equation (2e) is first replaced by Tr(Ws)2 - Tr(Ws2); s 2 [1; S], based on the fact that for every non-zero hermitian positive semi definite matrix W, Tr(W2) _ Tr(W)2; and Tr(W2) = Tr(W)2 if and only if rank(W)=1 [7]. This new constraint is non-convex but can be moved to the objective function as a penalty by including the sum of the amount of the violation of the constraint at each time slot s, i.e. PSs=1ws(Tr(Ws)Tr(Ws)-Tr(WsTs)), where ws is the weight of the violation at time slot s. Resultant problem can be solved iteratively by AM algorithm. In the q-th iteration of the algorithm, the following problem is solved

$$\min \quad \sum_{s=1}^{S} t_s + \sum_{s=1}^{S} \xi_s (Tr(\mathbf{W_s}^{(q-1)}) Tr(\mathbf{W_s}) - Tr(\mathbf{W_s}^{(q-1)} \mathbf{W}$$

where Ws (q-1) is the optimal solution for s 2 [1; S] at the (q -1)-th step of the algorithm.

Algorithm 1: Alternating minimization algorithm [12]

1 Set $\xi_s = 1$, $q = 0$, $\mathbf{W_s}^0$ as zero matrix for $s \in [1, S]$
2 **while** $(q++ \leq q_{max})$ **do**
3 Solve problem (3) with $\mathbf{W_s}^{q-1}, s \in [1, S]$ as input and assign optimal solution to $\mathbf{W_s}^q$, t_s
4 **if** $\exists s$ *such that* $rank(\mathbf{W_s}^{(q)}) \neq 1$ *and* $eig_1(\mathbf{W_s}^{(q)})) - eig_1(\mathbf{W_s}^{(q-1)})) \leq \epsilon_1$ **then**
5 $\xi_s \leftarrow 2\xi_s$
6 **end**
7 **if** $\exists s$ *such that* $rank(\mathbf{W_s}^{(q)}) \neq 1$ *at* q_{trsh} *or* q_{max} **then**
8 Find the rank 1 projection of $\mathbf{W_s}^{(q)}$ from eigenvalue weighted average of eigenvectors
9 **end**
10 **if** *Penalty* $\leq \epsilon_2$ *and convergence* **then**
11 return $\mathbf{W_s}$, t_s $s = 1, \cdots, S$
12 **end**
13 **end**

Fig 4: Alternating minimization algorithm

Algorithm (1) provides the details of the implementation of the AM algorithm. qmax is the maximum number of iterations,qtrsh is the iteration threshold where algorithm projects the solution matrices to rank 1 matrices, eig1 is the function which gives the principal eigenvalue of the input matrix, E1 and E2 are desired accuracies, and penalty is the un weighted cost of the constraint violation. Algorithm starts with the initialization (Line 1). Then, at the q-th iteration, the optimization problem (3) is solved and corresponding optimal solution is recorded (Line 3). Then the violation weight of the non-rank 1 matrix whose principal eigenvalue is not improved within the desired range E1 is doubled to increase its priority (Lines 4 - 6). The solution is guaranteed to have rank 1 solution by rank projection at qtrsh and qmax (Lines 7 - 9). Unlike previous implementations of AM algorithm, this algorithm continues searching around the solution after projection through intelligent configuration of the penalty coefficients and uses weighted sum of eigenvectors instead of primal eigenvector as a solution, after rescaling its elements to satisfy Equation

5. Performance analysis

The goal of this section is to demonstrate the performance gain achieved by the scheduling of

energy harvesting for different network topology and hybrid beam forming architectures.The solution of the optimization problem (1) obtained by the AM algorithm is denoted by scheduled for S = 5 and nonscheduled for S = 1. To demonstrate the closeness of the proposed algorithm to the optimal solution, the semidefinite programming problem obtained by the removal of the rank constraint in Equation (2e) from Equations (2) is included and denoted by SDR bound. based on 120 independent random network topologies, where the users are distributed randomly on a sphere of radius 4 m. Base station contains 16 antennas with maximum allowed power, PA, 40 dBm, complying with FCC base station regulations.

Screen shots

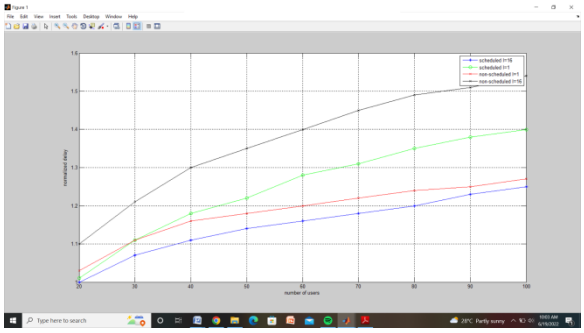

Fig 5.1: Normalized energy harvesting time for different number of users

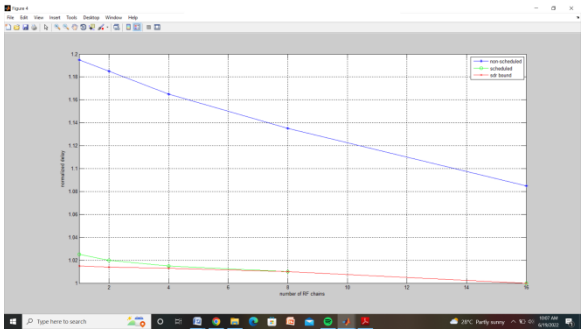

Fig 5.2: Normalized energy harvesting time in a network for different number of RF chains

APPLICATIONS

1) **Antenna communications**
2) **Radar communications**
3) **Tele communications**

6.CONCLUSION

A study on resource allocation algorithms for RF-based wireless communication networks, which are of interest were carried out. A parametric non-linear model was discussed, which facilitated the resource allocation algorithm design to enable efficient wireless powered communication networks. The algorithm designs were formulated as a non convex optimization problem for maximizing the throughput in WPCN systems. The problem formulations took into account the imperfectness of the transmission system and the non-linearity of the in order to ensure robust resource allocation. The proposed resource allocation design optimization problems were optimally solved by advanced signal processing techniques using MATLAB Numerical results showing the potential gains in harvested power that was enabled depends on user by the proposed optimization wireless powered communication networks.

Future scope: Models for predicting the amount of power required for WPCNs as a way of improving the current scheme, for using artificial intelligence Technique's such as neural networks may also be carried out.

REFERENCES

[1] Q. Wu, M. Tao, D.W. Kwan, W. Chen, & R. Schober, "EnergyEfficient Resource Allocation for Wireless Powered Communication Networks". IEEE Transactions on Wireless Communications, 15(3),2312–2327.

[2] M. Ku, W. Li, Y. Chen, & K.J.R. Liu, "Advances in Energy Harvesting Communications : Past , Present , and Future Challenges", 1–23. 2014.

[3] S.B. Zhang, "Placement Optimization of Energy and Information Access Points in Wireless Powered Communication Networks". IEEE Trans. Wireless Commun, 2016

[4] Z. Chang, J. Gong, Y. Li, Z. Zhou, T. Ristaniemi, G. Shi, Z. Niu, "Energy Efficient Resource Allocation for Wireless Power Transfer Enabled Collaborative Mobile Clouds". IEEE Journal on Selected Areas in Communications, 34(12), 3438–3450.https://doi.org/10.1109/JSAC.2016.2611843, 2016.

[5] R. Zhang, "Throughput maximization in wireless powered communication networks with energy saving". IEEE Transactions on Wireless Communications, 2015–April(1), 516–520.

[6] D. Hwang, D.I. Kim, & T.J. Lee, "Throughput Maximization for Multiuser MIMO Wireless Powered Communication Networks". IEEE Transactions on Vehicular Technology, 65(7), 5743–5748. https://doi.org/10.1109/TVT.2015.2453206, 2016

[7] K. Xiong,P. Fan, Y. Lu, & K. Letaief, "Energy efficiency with proportional rate fairness in multirelay OFDM Networks". IEEE Journal on Selected Areas in Communications, 34(5), 1431–1447. https://doi.org/10.1109/JSAC.2016.2545479, 2016

[8] X. Lin, L. Huang, C. Guo,P. Zhang, M. Huang, & J. Zhang, "Energy-Efficient Resource Allocation in TDMS Based Wireless Powered Communication Networks". IEEE Communications Letters, 7798(c), 1–1. https://doi.org/10.1109/LCOMM.2016.2639484, 2016.

[9] S. Yin, Z. Qu, Z. Wang, & L. Li, " Energy-efficient cooperation in cognitive wireless powered networks". IEEE Communications Letters, 21(1), 128–131. https://doi.org/10.1109/LCOMM.2016.2613537, 2017.

[10] B. Khal, B. Hamdaoui, M. Ghorbel, M. M. Guizani, & X. Zhang, " Joint Data and Power Transfer Optimization for Energy Harvesting Wireless Networks". IEEE INFOCOM International Workshop on Mobility Management in the Networks of the Future World Joint, 864–869. https://doi.org/10.1109/INFCOMW.2016.7562175, 2016.

[11] H.J. Zhang, "Throughput Maximization in Wireless Powered Communication Networks". IEEE Trans. Wireless Commun , pp. 418–28, 2014

[12] Z.I.N Hadzi-Velkov, “Wireless networks with energy harvesting and power transfer: Joint power and time allocation". IEEE Signal Process , pp. 50-54, 2016.