Optimal Resource Allocation for Energy Harvesting Two–way Relay Systems with Channel Uncertainty

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***Abstract*—In this paper, we consider two–way decode–and–forward (DF) multiple access and time division broadcasting relaying protocols with energy harvesting (EH) nodes. We propose optimal offline joint energy and transmission time allocation schemes for the considered relaying protocols taking into account channel state uncertainty. The proposed joint energy and transmission time allocation schemes are obtained based on convex optimization problems and maximize the aggregate system throughput over a finite number of transmission intervals. We compare the optimal throughputs obtained for the multiple access and time division broadcasting protocols via simulations. Our results reveal that the proposed schemes are robust to imperfect channel state information and that multiple access broadcasting is less affected by low harvesting rate at the relay than time division broadcasting.**

I. Introduction

Recently, energy harvesting (EH) has been considered as a promising approach for powering the nodes in cooperative communication systems [1]–[4]. Harvesting energy from renewable sources, e.g., wind, solar, thermoelectric or motion effects, ensures a perpetual and environmentally friendly supply of energy. The use of EH relays in cooperative communication was introduced in [1], whereas a deterministic EH model (assuming a priori knowledge of the energy arrival times and the amount of harvested energy) for the Gaussian relay channel was considered in [2] for delay and non–delay constrained traffic. In [3], [4], two–way relay channels with EH nodes were considered, and power allocation algorithms for solving short–term sum rate maximization problems were proposed.

The above works on EH–assisted communication [1]–[4] assume that the channel state information (CSI) of all links are perfectly known at a central node, which executes the resource allocation algorithm. In practice, the CSI of all links has to be estimated via pilot/training symbols and fed back to the central node through feedback channels. Therefore, the CSI may not be perfectly known at the central node due to different sources of error in the estimation process such as noise, quantization errors, and outdated estimates [5]. To address this problem, in [6], a single source–relay–destination link was considered with channel and energy state uncertainty and robust offline and online power allocation schemes were proposed. Recently, in [7], a robust beamforming scheme was proposed for two–way relaying with channel state uncertainty, where two source nodes exchange information via a set of relay nodes and harvest energy from the relay nodes.

In this paper, we consider channel state uncertainty in two–way relaying systems, where two transceivers transmit and receive messages via a half–duplex decode–and–forward (DF) relay and the transceivers and the relay are EH nodes. In the literature, there are two prevalent methods to incorporate the effect of channel uncertainty: worst case optimization and probabilistically constrained optimization [8]. In this paper, we adopt the worst case optimization framework by assuming a bounded uncertainty for the CSI as this approach does not require any statistical information to model the uncertainty. Moreover, unlike probabilistic optimization, worst case optimization with bounded CSI uncertainty ensures that channel outages do not occur when the channel uncertainty model is valid in practice, e.g., in case of quantization errors [8]. We consider the time division broadcasting (TDBC) and multiple access broadcasting (MABC) protocols and propose robust optimal offline joint energy and transmission time allocation schemes by maximizing the sum data rate of the transceiver nodes for the considered protocols over a finite number of transmission time intervals. Offline schemes are of interest when the amounts of harvested energy and the estimated channel signal–to–noise ratios (SNRs) are known a priori for all transmission intervals. Considering offline schemes is important since they provide performance upper bounds for more practical online schemes. Moreover, offline schemes also provide valuable insight for the design of efficient online algorithms, which is an interesting topic for future research.

II. System Model

We consider a two–way EH relay system, where two transceiver nodes, A and B, communicate with each other via a half–duplex DF relay, R, using the TDBC and MABC protocols. A, B, and R are EH devices and their participation in signal transmission and processing depends on their harvested energies. We assume that R, which is the central node of the considered system, acquires the information about the channel SNRs, calculates the optimal transmit energy and transmission time for A, B, and R, and informs A and B about the energy and time allocation. For both TDBC and MABC, we assume that the transmissions are organized in time intervals of duration 1 sec. The total transmission time for each protocol is equal to K sec.

Signal Model for TDBC: In TDBC, each time interval $k \in \{1, 2, \cdots, K\}$ is comprised of three time slots of variable durations. The durations of the first, second, and third time slots, namely the time sharing factors in interval k, are denoted as $d_{1,k}^T$, $d_{2,k}^T$, and $d_{3,k}^T$ sec, respectively. We assume no direct link between A and B due to heavy blockage. During the first time slot, A transmits and R receives and decodes the signal transmitted from A. During the second time slot, B transmits and R receives and decodes the signal transmitted from B. During the third time slot, R combines the signals detected in the first and second time slots and broadcasts the composite signal to A and B. A and B then cancel the self–interference terms and decode the information transmitted by the other node [9].

Signal Model for MABC: In MABC, each time interval $k \in \{1, 2, \cdots, K\}$ is comprised of two time slots of variable durations. The durations of the first and second time slots, namely the time sharing factors of an interval k, are denoted as $d^M_{1,k}$ and $d^M_{2,k}$ sec, respectively. During the first time slot, A and B transmit simultaneously and R receives the combined signal. R performs joint multiuser detection, e.g., via successive decoding [9], and detects the signals transmitted from A and B. During the second time slot, R combines the signals detected in the first time slot and broadcasts the composite signal to A and B [9]. Like for TDBC, A and B cancel the self–interference terms and decode the information transmitted by the other node.

Channel Model: We assume that the channels are quasi–static within each interval and the estimated complex valued channel gains of the A–R and the R–B links are denoted by $\hat{h}_{A,k}$ and $\hat{h}_{B,k}$, respectively. We assume $\hat{h}_{A,k}$ and $\hat{h}_{B,k}$ are independent of each other and independent and identically distributed (i.i.d.) over the time intervals. $\hat{h}_{A,k}$ and $\hat{h}_{B,k}$ can follow any distribution, e.g., Rayleigh, Rician, Nakagami–m, and Nakagami–q. We assume that the channel gains are reciprocal and the signals received at A, B, and R are impaired by additive white Gaussian noise (AWGN) with zero mean and unit variance. Next, we model the uncertainty originating from estimating the channel gains. Thereby, the channel estimation errors are confined to some uncertainty region. The size and the shape of the uncertainty region depends on the physical phenomena causing the errors [5]. The actual channel gains of the A–R and R–B links can be expressed as

$$h_{A,k} = \hat{h}_{A,k} + e_{A,k}, \tag{1}$$

$$h_{B,k} = \hat{h}_{B,k} + e_{B,k}, \tag{2}$$

where $e_{A,k}$ and $e_{B,k}$ are the random estimation errors and are unknown to R. The actual channel SNRs of the A–R and R–B links are denoted as $\gamma_{A,k} = |h_{A,k}|^2$ and $\gamma_{B,k} = |h_{B,k}|^2$, respectively. By exploiting (1) and (2), $\gamma_{A,k}$ and $\gamma_{B,k}$ can be expressed as

$$\gamma_{A,k} = \hat{\gamma}_{A,k} + |e_{A,k}|^2 + 2\Re\{\hat{h}_{A,k}e^*_{A,k}\} \tag{3}$$

$$\gamma_{B,k} = \hat{\gamma}_{B,k} + |e_{B,k}|^2 + 2\Re\{\hat{h}_{B,k}e^*_{B,k}\}, \tag{4}$$

respectively, where $\hat{\gamma}_{A,k} = |\hat{h}_{A,k}|^2$ and $\hat{\gamma}_{B,k} = |\hat{h}_{B,k}|^2$. Here, $\Re(\cdot)$ and $(\cdot)^*$ represent the real part and the conjugate of the argument, respectively, and $|\cdot|$ denotes the magnitude of the argument. Our goal is to optimize the system for the worst case scenario to avoid outages due to the transmission rate exceeding the channel capacity. Therefore, we adopt the worst case channel SNRs of the A–R and R–B links for system design. We follow the channel uncertainty model described in [6] and represent $\gamma_{A,k}$ and $\gamma_{B,k}$ as

$$\gamma_{A,k} \geq \gamma^W_{A,k} = [\hat{\gamma}_{A,k} - 2|\sqrt{\hat{\gamma}_{A,k}}||\epsilon_A|]^+ \tag{5}$$

$$\gamma_{B,k} \geq \gamma^W_{B,k} = [\hat{\gamma}_{B,k} - 2|\sqrt{\hat{\gamma}_{B,k}}||\epsilon_B|]^+, \tag{6}$$

where $[x]^+ = \max\{x, 0\}$, and $\gamma^W_{A,k}$ and $\gamma^W_{B,k}$ represent the worst case SNRs of the A–R and R–B links, respectively. Here, as the exact channel estimation errors are not known to R, we only assume that the errors are bounded as $|e_{A,k}| \leq |\epsilon_A|$ and $|e_{B,k}| \leq |\epsilon_B|$, where ϵ_A and ϵ_B are the maximum channel estimation errors of the A–R and R–B links, respectively [8]. Note that ϵ_A and ϵ_B determine how far $h_{A,k}$ and $h_{B,k}$, respectively, can deviate in both real and imaginary parts from the estimated values $\hat{h}_{A,k}$ and $\hat{h}_{B,k}$. For future reference, we introduce the estimated average SNRs of the A–R and the R–B links as $\hat{\bar{\gamma}}_A = \mathcal{E}\{\hat{\gamma}_{A,k}\}$ and $\hat{\bar{\gamma}}_B = \mathcal{E}\{\hat{\gamma}_{B,k}\}$, respectively, where $\mathcal{E}\{\cdot\}$ denotes statistical expectation.

System Throughput: We denote the transmit powers of node $\mathcal{N} \in \{A, B, R\}$ for each transmission interval, $k \in \{1, 2, \cdots, K\}$ as $\tilde{P}^T_{\mathcal{N},k}$ and $\tilde{P}^M_{\mathcal{N},k}$ for TDBC and MABC, respectively. Since the power amplifier used for transmission is not ideal, the power drawn from the battery of node $\mathcal{N}$ for TDBC (MABC) is given by $\rho_{\mathcal{N}}\tilde{P}^T_{\mathcal{N},k}$ ($\rho_{\mathcal{N}}\tilde{P}^M_{\mathcal{N},k}$). Here, $\rho_{\mathcal{N}} \geq 1$ is a constant that accounts for the power amplifier inefficiency. Note that we assume the energy consumed by the internal circuitry of node $\mathcal{N}$ is negligible compared to the transmit power [2]. In TDBC (MABC), the transmit energies from A, B, and R in interval k are denoted as $P^T_{A,k} = d^T_{1,k}\tilde{P}^T_{A,k}$ ($P^M_{A,k} = d^M_{1,k}\tilde{P}^M_{A,k}$), $P^T_{B,k} = d^T_{2,k}\tilde{P}^T_{B,k}$ ($P^M_{B,k} = d^M_{1,k}\tilde{P}^M_{B,k}$), and $P^T_{R,k} = d^T_{3,k}\tilde{P}^T_{R,k}$ ($P^M_{R,k} = d^M_{2,k}\tilde{P}^M_{R,k}$), respectively. We denote the achievable data rates in TDBC (MABC) from A to B ($A \to R \to B$) and from B to A ($B \to R \to A$) as $\xi^T_{A,k}$ ($\xi^M_{A,k}$) and $\xi^T_{B,k}$ ($\xi^M_{B,k}$), respectively. Therefore, the achievable rate region for TDBC in each time interval k is defined by [9]

$$\xi^T_{A,k} \leq \min\Big\{d^T_{1,k}\log_2\Big(1 + \frac{\gamma^W_{A,k}P^T_{A,k}}{d^T_{1,k}}\Big), d^T_{3,k}\log_2\Big(1 + \frac{\gamma^W_{B,k}P^T_{R,k}}{d^T_{3,k}}\Big)\Big\}, \tag{7}$$

$$\xi^T_{B,k} \leq \min\Big\{d^T_{2,k}\log_2\Big(1 + \frac{\gamma^W_{B,k}P^T_{B,k}}{d^T_{2,k}}\Big), d^T_{3,k}\log_2\Big(1 + \frac{\gamma^W_{A,k}P^T_{R,k}}{d^T_{3,k}}\Big)\Big\}. \tag{8}$$

Similarly, the achievable rate region for MABC in each time interval k is defined by [9]

$$\xi^M_{A,k} \leq \min\Big\{d^M_{1,k}\log_2\Big(1 + \frac{\gamma^W_{A,k}P^M_{A,k}}{d^M_{1,k}}\Big), d^M_{2,k}\log_2\Big(1 + \frac{\gamma^W_{B,k}P^M_{R,k}}{d^M_{2,k}}\Big)\Big\}, \tag{9}$$

$$\xi^M_{B,k} \leq \min\Big\{d^M_{1,k}\log_2\Big(1 + \frac{\gamma^W_{B,k}P^M_{B,k}}{d^M_{1,k}}\Big), d^M_{2,k}\log_2\Big(1 + \frac{\gamma^W_{A,k}P^M_{R,k}}{d^M_{2,k}}\Big)\Big\}, \tag{10}$$

$$\xi^M_{A,k}+\xi^M_{B,k} \leq d^M_{1,k}\log_2\Big(1+\frac{\gamma^W_{A,k}P^M_{A,k}}{d^M_{1,k}}+\frac{\gamma^W_{B,k}P^M_{B,k}}{d^M_{1,k}}\Big). \tag{11}$$

Battery Dynamics: Each node $\mathcal{N} \in \{A, B, R\}$ is equipped with a battery and can store at most $S_{\mathcal{N},max}$ Joules of energy. The battery energy of $\mathcal{N}$ in interval k for TDBC (MABC) is $S^T_{\mathcal{N},k}$ ($S^M_{\mathcal{N},k}$). In TDBC (MABC), during transmission interval k, the consumed energy of $\mathcal{N}$ is bounded by its battery energy, i.e., $0 \leq \rho_{\mathcal{N}}P^T_{\mathcal{N},k} \leq S^T_{\mathcal{N},k}$ ($0 \leq \rho_{\mathcal{N}}P^M_{\mathcal{N},k} \leq S^M_{\mathcal{N},k}$). In time interval k, the energy harvester at node $\mathcal{N}$ collects $H_{\mathcal{N},k} \leq S_{\mathcal{N},max}$ Joules of energy. $H_{\mathcal{N},k}$ is modelled as an ergodic random process with mean $H_{\mathcal{N}} \triangleq \mathcal{E}\{H_{\mathcal{N},k}\}$. Due to the inefficiency of the battery, a fraction of the stored harvested energy may be lost. We adopt the energy loss model from [10], [11] to incorporate the imperfections of the battery which stores the harvested energy. We assume that a fraction of $1-\mu_{\mathcal{N}}$ of the stored harvested energy is leaked at node $\mathcal{N}$ per time interval, where $0 \leq \mu_{\mathcal{N}} \leq 1$ represents the efficiency of the battery at node $\mathcal{N}$ per time interval. We assume that the stored energy at $\mathcal{N}$ increases and decreases linearly provided the maximum storage capacity, $S_{\mathcal{N},max}$, is not exceeded, i.e.,

$$S^T_{\mathcal{N},k+1}=\min\{\mu_{\mathcal{N}}(S^T_{\mathcal{N},k}-\rho_{\mathcal{N}}P^T_{\mathcal{N},k})+H_{\mathcal{N},k}, S_{\mathcal{N},max}\},\ \forall k, \quad (12)$$

$$S^M_{\mathcal{N},k+1}=\min\{\mu_{\mathcal{N}}(S^M_{\mathcal{N},k}-\rho_{\mathcal{N}}P^M_{\mathcal{N},k})+H_{\mathcal{N},k}, S_{\mathcal{N},max}\},\ \forall k. \quad (13)$$

$S^T_{\mathcal{N},1} = H_{\mathcal{N},0} \geq 0$ and $S^M_{\mathcal{N},1} = H_{\mathcal{N},0} \geq 0$ denote the available energy at $\mathcal{N}$ before the transmission starts in TDBC and MABC, respectively.

III. Offline Resource Allocation Schemes

In this section, we propose joint offline energy and transmit time allocation schemes for both TDBC and MABC. We consider maximizing the sum throughput of the two transceivers by a deadline of K intervals over fading channels assuming offline (prior) knowledge of the estimated channel SNRs and the energy arrivals at A, B, and R in each time interval.

A. TDBC

The offline optimization problem for maximizing the throughput for TDBC over K time intervals can be formulated as follows:

$$\max_{\mathcal{V}^T\succeq 0,\xi^T_{A,k},\xi^T_{B,k}} \sum_{k=1}^{K} \xi^T_{A,k}+\xi^T_{B,k} \quad (14)$$

$$\text{s.t.} \quad \xi^T_{A,k} \leq d^T_{1,k}\log_2\left(1+\frac{\gamma^W_{A,k}P^T_{A,k}}{d^T_{1,k}}\right),\ \forall k, \quad (15)$$

$$\xi^T_{A,k} \leq d^T_{3,k}\log_2\left(1+\frac{\gamma^W_{B,k}P^T_{R,k}}{d^T_{3,k}}\right),\ \forall k, \quad (16)$$

$$\xi^T_{B,k} \leq d^T_{2,k}\log_2\left(1+\frac{\gamma^W_{B,k}P^T_{B,k}}{d^T_{2,k}}\right),\ \forall k, \quad (17)$$

$$\xi^T_{B,k} \leq d^T_{3,k}\log_2\left(1+\frac{\gamma^W_{A,k}P^T_{R,k}}{d^T_{3,k}}\right),\ \forall k, \quad (18)$$

$$\sum_{k=1}^{l}\rho_{\mathcal{N}}\mu_{\mathcal{N}}^{l-k}P^T_{\mathcal{N},k} \leq \sum_{k=0}^{l-1}\mu_{\mathcal{N}}^{l-k-1}H_{\mathcal{N},k},\ \forall l,\ \forall \mathcal{N}, \quad (19)$$

$$\sum_{k=0}^{q}\mu_{\mathcal{N}}^{q-k}H_{\mathcal{N},k}-\sum_{k=1}^{q}\rho_{\mathcal{N}}\mu_{\mathcal{N}}^{q-k+1}P^T_{\mathcal{N},k} \leq S_{\mathcal{N},max}, \forall q, \forall \mathcal{N}, \quad (20)$$

$$d^T_{1,k} \leq 1,\ d^T_{2,k} \leq 1,\ d^T_{3,k} \leq 1,\ \forall k, \quad (21)$$

$$d^T_{1,k}+d^T_{2,k}+d^T_{3,k}=1,\ \forall k, \quad (22)$$

where $\mathcal{V}^T \triangleq [P^T_{A,k}\ P^T_{B,k}\ P^T_{R,k}\ d^T_{1,k}\ d^T_{2,k}\ d^T_{3,k}]$, $k \in \{1,2,\cdots,K\}$, $l \in \{1,2,\cdots,K\}$, $q \in \{1,2,\cdots,K-1\}$, and $\mathcal{N} = \{A,B,R\}$. Constraints (15) and (16) ((17) and (18)) satisfy the data rate requirement in (7) ((8)). Constraints (19) stem from the causality requirement on the energy harvested at each node $\mathcal{N}$. Moreover, (20) ensures that the harvested energy does not exceed the limited storage capacity of the batteries at each node $\mathcal{N}$. The upper limits of the time sharing factors for the three time slots in each time interval for TDBC are represented by (21). Constraint (22) ensures that the sum of the time sharing factors in an interval is equal to the duration of the time interval (1 sec). Problem (14)-(22) is a convex optimization problem and the optimum solution can be obtained by using standard techniques for solving convex optimization problems [12], [13]. It can be shown that at optimality, (15)–(18) are met with equality.

B. MABC

The offline optimization problem for maximizing the throughput for MABC over K time intervals can be formulated as follows:

$$\max_{\mathcal{V}^M\succeq 0,\xi^M_{A,k},\xi^M_{B,k}} \sum_{k=1}^{K} \xi^M_{A,k}+\xi^M_{B,k} \quad (23)$$

$$\text{s.t.} \quad \xi^M_{A,k} \leq d^M_{1,k}\log_2\left(1+\frac{\gamma^W_{A,k}P^M_{A,k}}{d^M_{1,k}}\right),\ \forall k, \quad (24)$$

$$\xi^M_{A,k} \leq d^M_{2,k}\log_2\left(1+\frac{\gamma^W_{B,k}P^M_{R,k}}{d^M_{2,k}}\right),\ \forall k, \quad (25)$$

$$\xi^M_{B,k} \leq d^M_{1,k}\log_2\left(1+\frac{\gamma^W_{B,k}P^M_{B,k}}{d^M_{1,k}}\right),\ \forall k \quad (26)$$

$$\xi^M_{B,k} \leq d^M_{2,k}\log_2\left(1+\frac{\gamma^W_{A,k}P^M_{R,k}}{d^M_{2,k}}\right),\ \forall k. \quad (27)$$

$$\text{Inequality (11)},\ \forall k, \quad (28)$$

$$\sum_{k=1}^{l}\rho_{\mathcal{N}}\mu_{\mathcal{N}}^{l-k}P^M_{\mathcal{N},k} \leq \sum_{k=0}^{l-1}\mu_{\mathcal{N}}^{l-k-1}H_{\mathcal{N},k},\ \forall l,\ \forall \mathcal{N}, \quad (29)$$

$$\sum_{k=0}^{q}\mu_{\mathcal{N}}^{q-k}H_{\mathcal{N},k}-\sum_{k=1}^{q}\rho_{\mathcal{N}}\mu_{\mathcal{N}}^{q-k+1}P^M_{\mathcal{N},k} \leq S_{\mathcal{N},max}, \forall q, \forall \mathcal{N}, \quad (30)$$

$$d^M_{1,k} \leq 1,\ d^M_{2,k} \leq 1,\ \forall k, \quad (31)$$

$$d^M_{1,k}+d^M_{2,k}=1,\ \forall k, \quad (32)$$

where $\mathcal{V}^M \triangleq [P^M_{A,k}\ P^M_{B,k}\ P^M_{R,k}\ d^M_{1,k}\ d^M_{2,k}\ d^M_{3,k}]$, $k \in \{1,2,\cdots,K\}$, $l \in \{1,2,\cdots,K\}$, $q \in \{1,2,\cdots,K-1\}$, and $\mathcal{N} = \{A,B,R\}$. Constraints (24)–(27) represent the MABC data rate requirements in (9) and (10). Similar to TDBC, constraints (29) and (30) are required for energy causality and limitedness of the battery, respectively, at each node $\mathcal{N}$. Moreover, the constraints for the time sharing factors for MABC are represented by (31) and (32). Problem (23)-(32) is a convex optimization problem and can be solved optimally and efficiently by using standard convex optimization techniques [12], [13]. Like for TDBC, it can be shown that (24)–(27) are met with equality at the optimal point.

IV. Simulation Results and Discussion

In this section, we evaluate the performance of the proposed offline power allocation schemes for TDBC and MABC by simulations. We assume that in each time interval, $H_{\mathcal{N},k}$, $\mathcal{N} \in \{A,B,R\}$, independently take a value from the set $\{0, H_{\mathcal{N}}, 2H_{\mathcal{N}}\}$, where all elements of the set are equiprobable. For all presented simulation results, we assume that $\hat{\gamma}_{A,k}$ and $\hat{\gamma}_{B,k}$ follow an exponential distribution with mean $\bar{\hat{\gamma}}_A = \bar{\hat{\gamma}}_B = \bar{\hat{\gamma}} = 20$ dB. We also assume that $e_{A,k}$ and $e_{B,k}$ are uniformly distributed in discs of radii $|\epsilon_A|$ and $|\epsilon_B|$, respectively. We adopt $K = 40$, $S_{A,max} = S_{B,max} = S_{R,max} = 200$ Joules, $\mu_A = \mu_B = \mu_R = 0.99$, and $\rho_A = \rho_B = \rho_R = 2.5$. For all simulation results, 10^4 randomly generated realizations of the channel SNRs and the harvested energies are evaluated to obtain the average throughput.

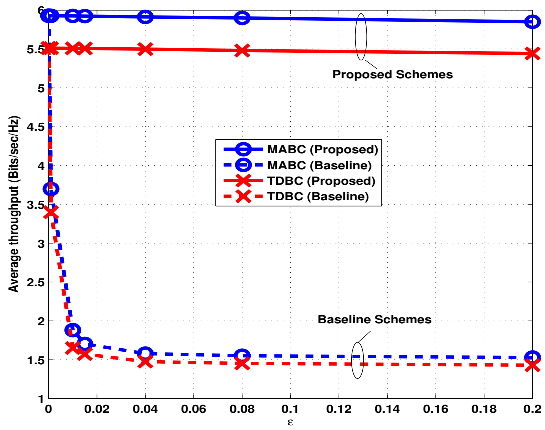

Fig. 1. Average throughput (bits/sec/Hz) vs. $|\epsilon_A| = |\epsilon_B| = \epsilon$ for the proposed and baseline energy and time allocation schemes.

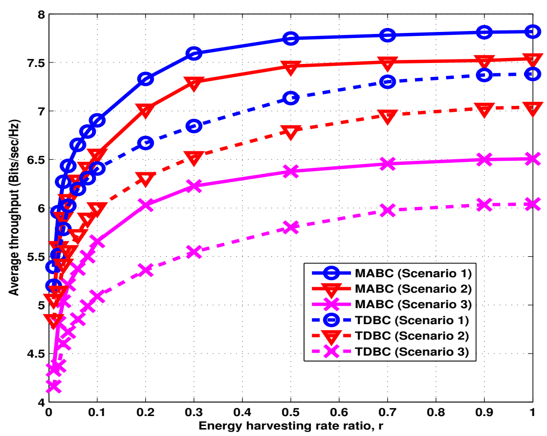

Fig. 2. Average throughput (bits/sec/Hz) vs. energy harvesting rate ratio, r for 3 different scenarios for $|\epsilon_A| = |\epsilon_B| = \epsilon$ for MABC and TDBC.

In Fig. 1, we show the average throughput (bits/sec/Hz) vs. the maximum error of the channel gain, $|\epsilon_A| = |\epsilon_B| = \epsilon$, for both TDBC and MABC. We assume $H_{\mathcal{N}} = 10$ Joules/sec, $\mathcal{N} \in \{A, B, R\}$. We observe from Fig. 1 that the throughput decreases with increasing ϵ for the proposed offline resource allocation schemes for both TDBC and MABC. To show the robustness of the proposed resource allocation schemes, we also consider baseline resource allocation schemes for both TDBC and MABC. In the considered baseline resource allocation schemes, the uncertainty of the CSI is not considered and instead the transmit energy and time are optimized for the estimated channel SNRs. Thus, an outage occurs if the actual channel SNR is lower than the estimated channel SNR. In our simulations, when a link is in outage, we set the throughput for the corresponding time slot to zero. It is worth noting that when $\epsilon = 0$, the proposed and the baseline resource allocation schemes have the same performance for both TDBC and MABC as expected. However, the performance of the baseline schemes degrades rapidly with increasing ϵ. On the other hand, the performance of the proposed scheme degrades gradually, i.e., the proposed resource allocation schemes are much more robust to uncertainty in comparison with the baseline schemes.

In Fig. 2, we show the average throughput (bits/sec/Hz) vs. harvesting rate ratio, $r = \frac{H_R}{H}$, where $H = H_A = H_B = 100$ Joules/sec. Three different scenarios for $|\epsilon_A| = |\epsilon_B| = \epsilon$ are considered. In Scenario 1, we assume $\epsilon = 0$, i.e., the channel states are perfectly known, whereas in Scenarios 2 and 3, $\epsilon = 0.5$ and $\epsilon = 1.5$ are assumed, respectively. We observe that the throughput performance degrades with increasing channel state uncertainty for both TDBC and MABC. Furthermore, the throughputs of TDBC and MABC saturate for large r . This is mainly due to the fact that for large r, i.e., for large H_R, the extra amount of harvested energy at R cannot improve the system throughput as the harvested energies at A and B remain constant. Interestingly, the increase in throughput with respect to r for MABC is faster than that for TDBC, i.e., a low H_R has more impact on the throughput of TDBC than on that of MABC.

V. Conclusions

In this paper, we have considered the problem of joint energy and transmit time allocation for a two–way EH relay network employing TDBC and MABC protocols with channel state uncertainty. We have proposed robust optimal offline resource allocation schemes employing worst case optimization by incorporating a bounded uncertainty for the CSI. We have shown the robustness of the proposed resource allocation schemes and studied the impact of imperfect channel knowledge on the performance of the MABC and TDBC protocols.

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