A novel model to eliminate the doubly near-far problem in wireless powered communication network

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Abstract

In this paper, the newly emerging wireless powered communication network is studied. In doing so, the performance of the global controller (GC) is evaluated, which coordinates the wireless energy transmissions between two sensor nodes. Both the sensors have the same harvested energy for uplink (UL) transmission of information through time-division-multiple-access. Afterwards, the information transmission time is optimised to maximise the common throughput of both the sensors with a total time constraint based on the user's UL channels along with the same harvested energy value. Further, due to the “doubly near-far” phenomenon, a remote sensor from the GC, which has poor channel conditions than a nearer user, has to transmit more time in the UL for maximum common throughput. To overcome this problem, the energy exchange (EEx) model is proposed where both sensors first harvest the same amount of wireless energy and then exchange energy to nullify the different channel conditions between sensors and GC to send their independent information in the UL. Simulation results demonstrate the EEx Model’s effectiveness over without energy exchange (WEEx) model in eliminating the doubly near-far problem in wireless powered communication network but at the cost of maximum sum-throughput. The maximum sum-throughput of the proposed EEx model is 35% lower than the WEEx model. However, the average BER in the proposed EEx model is 74.6% lower than the WEEx model, which increases the reliability of the model.

1 | INTRODUCTION

Wireless sensor networks (WSNs) consist of many nodes that perform powered and information sensing, data acquisition, node localisation, and transmission simultaneously [1]. However, these sensor nodes have a restricted battery life, and the battery’s replacement is not a feasible solution in hard to reach areas such as sensors implanted in the human body. Therefore, optimal network coverage [2], and energy harvesting (EH) could be a solution to create WSNs autonomous and provide widespread use of these systems in various applications such as military, health, environment, and security [3–8].

EH refers to harnessing and converting energy from the surroundings or alternative sources into electrical energy. The harnessed electrical energy strengthens the sensor node. Different sources like solar, mechanical, heat, vibration, temperature differences, and wind can harvest this energy. These sources provide a vast amount of energy but fail to provide a predictable amount of energy and could not be available anytime. The wireless power available from the electromagnetic sources provides the predictable, demand-based energy to the sensor nodes [9, 10].

This paper uses radio frequency (RF) EH technique (wireless information and power transfer (WIPT) to provide wireless power, which takes input from the radio environment and provides a continuous and predictable amount of energy. RF signals provide the delivery of power at a more considerable distance and hence, better than the conventional resonant inductive coupling and magnetic resonance coupling, which delivers power only at a shorter distance. RF EH allows the sensor nodes to harvest energy from the source to which it transmits its sensed data. Hence, WIPT system is more suitable in applications like implementation of sensors in human body [11–13].
The RF sources for RF EH can be classified into two categories: dedicated RF sources and ambient RF sources. Dedicated RF sources provide a predictable amount of energy and use the license-free ISM band for the power transfer [14]. Ambient RF sources are WiFi transceivers, cellular base stations, AM/FM radio transmitters, and TV broadcast transmitters, which provides a low and inconsistent amount of power [15, 16]. In this paper, we have used a dedicated type of RF source, power cast transmitter, operating on 915 MHz with transmitted power of 1 or 3 W.

There exist three types of receiver architecture for RF EH: separated, time switching, and power splitting. In separated architecture, separate antennas are used for EH and information decoding. In time switching, the EH and information decoding takes place through the same antenna at the same time but with varying levels of power [17, 18]. Time switching receiver with a helical antenna is used in this paper due to its comparatively compact form factor of 0.5, and effectively high EH efficiency [16, 19].

Previous work on EH uses simultaneous wireless, and information power transmission (SWIPT) [20–23], has drawn significant attention in which both energy and information transmission takes place simultaneously. In this paper, both sensor and GC works on the harvest-then-transmit protocol, in which sensor nodes harvest energy in the DL from the surroundings RF sources and use the harvested energy for information transmission in the UL [24, 25].

A majority of the existing research in WIPT focuses either on the sum-throughput maximisation or the common throughput maximisation technique. In the sum-throughput maximisation technique, wireless information transmission (WIT) time is allocated based on their distance from the source (WIT is inversely proportional to distance), due to which throughput unfairness problem arises. To solve throughput unfairness problem, the authors propose common throughput maximisation, where WIT is independent of distance from the source. It minimises the throughput unfairness between the sensor nodes at the cost of decreased sum-throughput [26].

The author in [27] focused on the sum-throughput maximisation of the sensors using three scenarios named as mirroring scenario, likely scenario and superior source scenario, which leads to the throughput unfairness in a wireless powered communication network (WPCN). In mirroring scenario and likely scenario, all sensors harvest equal amount energy (EH fairness at sensors). But due to different channel conditions between sensors and GC, there is throughput unfairness even after EH fairness at sensors. To solve this problem of throughput unfairness, the authors proposed the source selection algorithm, which can improve fairness up to 50%. In contrast, by using common throughput maximisation technique, the fairness of the sensors improves significantly and results in equal throughput of the sensors. It also increases the lifetime of the network. This paper considers the mirroring scenario and likely scenario to study throughput unfairness even after EH fairness at sensors and compare sum throughput, using WEEx and EEx model.

The author in [28] maximised the sum-throughput of sensor node through their proposed scheme secondary sum-throughput optimal resource allocation (STORA). The proposed STORA scheme results in low fairness among the sensor nodes. To further enhance fairness, authors have investigated various schemes like equal time allocation (ETA), minimum sum-throughput maximisation (MTM), and proportional time allocation (PTA) which improves the fairness of the system at the cost of decreased sum-throughput. In all these schemes, the MTM scheme provides the best fairness among the sensors, whereas PTA scheme offers the best compromise between the sum-throughput and fairness.

Authors studied relay selection schemes in multiple relays, single source and destination network with objective of minimum outage probability (OP) [29]. OP analysis is done in energy harvesting based NOMA networks [30, 31]. This paper drive OP expressions and compare network lifetime for both WEEx and EEx model.

Transmission completion time (TCT) minimisation problem for a fixed number of bits per node is studied in [32] for unmanned-aerial-vehicle-enabled wireless powered communication networks (UAV-enabled WPCN). Authors have considered a system model containing one UAV as a hybrid mobile sink that acts as both EH and WIT sink nodes for other static nodes. Area discretisation technique is used to convert intractability problem into tractable, where each node in a sub-region harvested the same amount of RF energy under a given error tolerance.

Our major contributions are summarized as follows:

- We propose a novel EEx model which solves the problem of throughput unfairness due to different channel conditions even in EH fairness scenarios (mirroring scenario and likely scenario [27]) and thus achieve equal throughput, BERs and wireless information transmissions (WITs) of the sensors simultaneously and provide the advantage of increased network lifetime and load balancing in the network.
- Our proposed model focus on a common throughput maximisation technique in which sensor node allocated with an equal duration of time in UL WITs, which results in the same time slot for information transmission that synchronises information at GC.
- This paper considers the same system model in [27] with two EH fairness sensors. Sum throughput of our WEEx model is derived using common-throughput maximisation algorithm [25]. WEEx model results in an equal throughput of sensors and addresses the probable cause of unequal BERs and WITs of the sensors. This problem of unequal BERs and WITs is solved by transferring energy from one sensor to others (EEx model) and thus obtained an equal throughput, BERs, and WITs simultaneously.
- We derived the analytical expressions of OP for both models, which shows that our proposed model EEx has better network lifetime than WEEx model.
2 | SYSTEM MODEL

This work considers WIT in the UL, as shown in Figure 1. The network consists of one GC and two sensors (with EH fairness) represented as $S_i$ where $i = 1, 2$. In our work, the following assumptions have been made:

1. GC is the information receiver.
2. GC and both the sensors operate at the same frequency and equipped with a single antenna [19].
3. Further, we assume the time division duplexing (TDD) system because it only needs a single frequency channel of the frequency spectrum for information transmission.
4. Initially, both the sensor nodes have harvest an equal amount of energy (EH fairness at sensor nodes [27]).

Here, GC estimates the channel and broadcast so that both sensor nodes know the channel state at each block's transmission. The UL channel from GC to $S_i$ sensor is denoted by $h_i$, with channel power gains $\beta_i$. The UL channel assumed as quasi-static flat fading where channel remains constant during each block transmission but changes from block to block.

2.1 | WEEx model

This subsection's focus is to determine the common throughput and average BER of both sensors accounting for mirroring and likely scenario as described in [27]. The network works on TDMA, as shown in Figure 2, in which each sensor transmits their sensed data to the GC in their independent time slot. Here $T_1$ and $T_2$ represent the time portion allocated to sensor 1 and sensor 2 for UL WITs respectively. Without loss of generality, we assume the unit block size. So we have,

$$\sum_{i=1}^{i=2} T_i \leq 1$$

![Timing diagram for information transmission](image)

During the UL phase, the sensor’s harvested energy is used for information transmission to the GC. Here, $x_i$ denotes the transmitted signal by the sensor $S_i$, and we assume it to be an arbitrary complex random signal satisfying $E[|x_i|^2] = P_i$, where $P_i$ is the average transmitted power at $S_i$. The received signal at GC from the sensor $S_i$ is expressed as:

$$y_i = h_i x_i + n_i, \quad i = 1, 2$$

Where $y_i$ and $n_i$ denotes the received signal and background noise at GC from $S_i$ respectively; $h_i$ is the Rayleigh fading channel between the sensor $S_i$ and GC. The nature of the noise is Gaussian with zero mean and variance $\sigma^2$. We have assumed that both sensor nodes have harvested enough amount of energy for information transmission. The average transmits power at the $S_i$ is given by:

$$E[|x_i|^2] = P_i = \frac{\eta E}{T_i} \quad i = 1, 2$$

Where $\eta$ is the portion of harvested energy used for information transmission by sensors $0 < \eta < 1$, $E$ is the total energy harvested by the sensors, $T_i$ is the information transmission time of $S_i$.

The achievable UL common throughput of both the sensors in bits/second/Hz at the GC is calculated using the Shannon—Hartley theorem. The throughput of $S_i$ is expressed as:

$$R_{WEEx}^i = T_i \log_2 \left( 1 + \frac{\beta_i \eta E}{\Gamma T_i \sigma^2} \right), \quad i = 1, 2$$

Where $\beta_i$ is the channel power gain between GC and $S_i$, $\Gamma$ is the SNR gap from the additive white Gaussian noise (AWGN)
channel capacity due to practical modulation and coding scheme used, \( \sigma^2 \) is the thermal noise power.

The received SNR at GC due to data transmission by \( S_i \) is calculated by:

\[
\gamma_i = \frac{|b_i|^2 P}{\Gamma \sigma^2} = \frac{\beta_i \eta E}{\Gamma T_i \sigma^2}, \quad i = 1, 2
\]  

(5)

Now, the BER of \( S_i \) can be expressed by using the SNR of the sensors. So, for M-QAM modulation BER of \( S_i \) is given by:

\[
BER_i = \frac{4}{\log_2 M} \left( \sqrt{\frac{3 \beta_i \eta E \log_2 M}{\Gamma T_i \sigma^2 (M - 1)}} \right), \quad i = 1, 2
\]  

(6)

The average BER of both the sensors for equiprobable events can be calculated as:

\[
\text{Avg. BER}_{\text{WEEx}} = \frac{1}{2} \text{BER}_1 + \frac{1}{2} \text{BER}_2
\]  

(7)

Maximum sum-throughput of sensors at GC is given by:

\[
C_{\text{sum}}^{\text{WEEx}}(T) = \sum_{i=1}^{2} R_i(T)
\]  

(8)

From Equation (4), throughput is a function of channel condition between the GC and sensors and time allocated for UL information transmission to the sensors. Here, the equal throughput of the sensors for considering the channel condition as \( \beta_1 > \beta_2 \) is achieved by optimal time allocation to sensors as \( T_2 > T_1 \). It is worthy to note from Equations (5) and (6) that unequal channel conditions and unequal time allocated for UL information transmission will result in unequal BERs of the sensors and asynchronous of sensed UL information at GC. Hence, the main focus here is to achieve equal throughput, BERs with equal WITs simultaneously for the sensors.

### 2.2 EEx model

In this subsection, we have discussed the proposed EEx model, whose primary focus is to achieve equal throughput, BER with equal WITs for both the sensors. This model solves the problem of unequal channel conditions by exchanging a certain amount of energy between the sensors. So, the exchange of energy between the sensors helps in cancelling the effect of different channel conditions. In this model, the problem of unequal time allocated to the sensors is solved by providing the same time to both the sensors for information transmission.

This subsection is divided into two parts. First, we have calculated the amount of energy exchange between the sensors, and second, we derived the expression for the equal time allocated for information transmission.

In the EEx model, a specific duration of time is assigned for the energy exchange between the sensors, which is denoted by \( \tau \) while remaining time is equally divided among sensors for information transmission denoted by \( \zeta \).

All the equations discussed in the previous subsection are expressed using the EEx model in which both the sensors have an equal duration of time for the information transmission.

Further, we assume that \( \beta_1 > \beta_2 \) than SNR \( S_1 > SNR_2 \) & \( BER_1 > BER_2 \), in the WEEx model. Hence, energy exchanges from sensor 1 (strong node) to sensor 2 (weak node) nullify the sensors’ different channel conditions. Let us assume that \( \Delta E \) is the amount of energy exchanged from sensor 1 to sensor 2. In order to nullify the different channel conditions of the sensors, one can derive the expression of throughput [24]. The received SNR of sensor 1 at the GC after the exchange of energy is expressed as:

\[
\text{SNR}_1 = \gamma_1^{\text{en-ex}} = \frac{|h_1|^2 P}{\Gamma \sigma^2 \zeta} = \frac{\beta_1 \eta (E - \Delta E)}{\Gamma \sigma^2 \zeta}
\]  

(9)

The signal transmitted from sensor 1 to sensor 2 is expressed as:

\[
z = h_3 x + n
\]  

(10)

Where \( \zeta \) is the signal received at sensor 2 from sensor 1, \( b_3 \) is the Rayleigh faded channel coefficient between sensor 1 and sensor 2, \( x \) is the arbitrary complex random signal transmitted by sensor 1 to sensor 2 satisfying \( E[|x|^2] = \Delta P \), \( n \) is the background noise at sensor 2 and nature of the noise is Gaussian with zero mean and \( \sigma^2 \) variance.

The average transmit power by sensor 1 to sensor 2 is expressed as:

\[
\Delta P = \frac{\Delta E \eta}{\tau}
\]  

(11)

The received power at sensor 2 from sensor 1 by ignoring noise power given in Equation (10) is calculated as:

\[
P_z = |b_3|^2 \Delta P = \beta_3 \Delta P
\]  

(12)

The energy of the signal exchanged from sensor 1 to sensor 2 is given by:

\[
E_z = \beta_3 \Delta P \tau
\]  

(13)

Where \( \beta_3 \) is the channel power gain between sensor 1 and sensor 2.

The total energy at sensor 2 after receiving energy from sensor 1 is:

\[
E_{S2}^{\text{total}} = E + E_z
\]  

(14)

The total power at sensor 2 after receiving energy from sensor 1 is:

\[
P_{S2}^{\text{total}} = \frac{\eta (E + E_z)}{\zeta} = \frac{\eta (E + \beta_3 \Delta P)}{\zeta}
\]  

(15)
The SNR of sensor 2 at the GC after receiving energy from sensor 1 is calculated as:

\[ \text{SNR}_2 = \gamma EEx \frac{\eta(E + \beta_3 \Delta E \eta) \beta_2}{\Gamma \sigma^2 \zeta} \]  

The amount of energy exchanged from sensor 1 to sensor 2 is calculated by equating the sensor’s SNRs.

\[ \text{SNR}_1 = \text{SNR}_2 \]

\[ \frac{\beta_1 \eta(E - \Delta E)}{\Gamma \sigma^2 \zeta} = \frac{\eta(E + \beta_3 \Delta E \eta) \beta_2}{\Gamma \sigma^2 \zeta} \]

\[ \Delta E = E \frac{\beta_2 - \beta_1}{\beta_2 + \beta_3 \beta_2 \eta} \]  

Similarly, for the case of \( \beta_2 > \beta_1 \). The amount of energy exchange from sensor 2 to sensor 1 is expressed as:

\[ \Delta E = E \frac{\beta_2 - \beta_1}{\beta_2 + \beta_3 \beta_1 \eta} \]  

As, \( \text{SNR}_1 = \text{SNR}_2 \) then \( \text{BER}_1 = \text{BER}_2 \). The BERs of both sensor for M-QAM modulation is expressed as:

\[ \text{BER}_1 = \text{BER}_2 = \frac{4}{\log_2 M} \left( \sqrt{\frac{3\beta_1 \eta(E - \Delta E) \log_2 M}{\Gamma \sigma^2 \zeta (M - 1)}} \right) \]  

The throughput for both the sensors is calculated as:

\[ R_1^{\text{EEx}} = R_2^{\text{EEx}} = \zeta \log_2 \left( 1 + \frac{\beta_1 \eta(E - \Delta E)}{\Gamma \sigma^2 \zeta} \right) \]  

while the maximum sum-throughput can be expressed as:

\[ C_\text{sum}^{\text{EEx}} = 2\zeta \log_2 \left( 1 + \frac{\beta_1 \eta(E - \Delta E)}{\Gamma \sigma^2 \zeta} \right) \]

\[ = 2\zeta \log_2 \left( 1 + \frac{\beta_1 \eta(E - \beta_1 \Delta E \eta)}{\Gamma \sigma^2 \zeta} \right) \]  

The average BER after energy exchange for M-QAM modulation is given by:

\[ \text{Avg. BER}^{\text{EEx}} = \frac{4}{\log_2 M} \left( \sqrt{\frac{3\beta_1 \eta(E - \Delta E) \log_2 M}{\Gamma \sigma^2 \zeta (M - 1)}} \right) \]  

Further, we derive the expression for \( \zeta \), which is the same duration of time slot allocated to both sensor 1 and sensor 2 for the information transmission to the GC.

We assumed that sensor 1 transmits a fraction of power to the sensor 2. So, Equation (10) can be expressed as:

\[ z = \sqrt{a Ph_3 x + n} \]

such that \( E[|x|^2] = 1 \). The amount of power \( \Delta P \) transfer from sensor 1 to sensor 2 can be written as \( \Delta P = aP \). Now, the power received at sensor 2 can be calculated using the signal transfer from sensor 1 to sensor 2. The power received at sensor 2 is given by:

\[ P_2 = \beta_3 \Delta P = \beta_3 aP \]

The energy received at sensor 2 is calculated as:

\[ E_z = P_2 \tau = \beta_3 aP \tau \]  

The total energy at sensor 2 after receiving the energy from sensor 1 is expressed as:

\[ E_{z, \text{total}}^S = E_z + E_z \]

The total power at sensor 2 is given by:

\[ P_{\text{total}}^S = \frac{\eta(E + \beta_3 aP \tau) \beta_2}{\zeta} \]  

The amount of power transfer from sensor 1 to sensor 2 can be calculated by equating the SNRs of both the sensors.

\[ \frac{\beta_1 (1 - a) P}{\beta_1 P + \eta \beta_3 P \tau \beta_2} \]

by cancelling the equal terms and rearranging the equations

\[ \beta_1 P - \beta_1 aP = \eta E \beta_2 + \eta \beta_3 aP \tau \beta_2 \]  

So, the fraction of power transfer from sensor 1 to sensor 2 is given by:

\[ a = \frac{\beta_1 P - \eta E \beta_2}{\beta_1 P + \eta \beta_3 P \tau \beta_2} \]  

The power transfer from sensor 1 to sensor 2 is given by:

\[ \Delta P = aP = \frac{\beta_1 P - \eta E \beta_2}{\beta_1 P + \eta \beta_3 P \tau \beta_2} \]  

After calculating the value of \( \zeta \) by using the amount of energy \( \Delta E \) transfer from sensor 1 to sensor 2 we get:

\[ \Delta E = \Delta P \tau \]
Substituting the value of $\Delta E$ and $\Delta P$ from the Equations (18) and (30) respectively

$$E(\beta_1 - \beta_2) = \frac{\beta_1 P - \eta E\beta_2}{\beta_1 + \eta \beta_3 \tau \beta_2}$$

Obtaining the value of $P$ by the expression of average power transmitted by the sensor as $P = \frac{\eta E}{\zeta}$ and substituting it in Equation (32), we get

$$E(\beta_1 - \beta_2) = \frac{\beta_1 \frac{\eta E}{\zeta} - \eta E\beta_2}{\beta_1 + \eta \beta_3 \tau \beta_2}$$

by cancelling the equal terms in previous expression

$$\frac{\beta_1 - \beta_2}{\beta_1 + \beta_3 \beta_2 \eta} = \frac{\beta_1 - \beta_2}{\beta_1 + \beta_3 \beta_2 \eta}$$

by rearranging the terms of previous expression

$$\frac{\beta_1 - \beta_2}{\beta_1 + \beta_3 \beta_2 \eta} = \frac{\beta_1 - \beta_2}{\beta_1 + \beta_3 \beta_2 \eta(1 - 2\zeta)}$$

On rearranging the expression, we get $\zeta$ as

$$2\zeta^2 [\beta_2 (\beta_1 + \beta_3 \beta_2 \eta) + (\beta_1 - \beta_2) \beta_3 \beta_2] -$$

$$\zeta(\beta_1 + \beta_3 \beta_2 \eta)(\beta_2 + 2\beta_1) + (\beta_1 - \beta_2) \beta_3 \beta_2 +$$

$$(\beta_1 - \beta_2) \beta_1 + \beta_1 (\beta_1 + \beta_3 \beta_2 \eta) = 0$$

We recalculated the $\zeta$ through using Equation (33) by considering only positive root.

### 2.3 Outage probability

In this section, we derive the analytical expressions for the outage probability (OP) \[29\] of the sensor nodes for both the models. In the considered system model, the information outage of a sensor node at GC can occur due to weak channel conditions between sensor nodes and GC. Due to which the SNR of the received signal at GC is below the threshold SNR.

#### 2.3.1 WEEx OP

In WEEx model, the information outage at GC occurs due to channel conditions between sensors and GC. Channel links between weak node and GC are poor, and harvested energy at both sensors is the same. Hence, weak node OP is calculated as

$$OP(i) = P_i(R_i \leq R_th)$$

where $R_th$(bit/s/Hz) is a predata transmission rate. From Equation (4), OP of the considered system is given as

$$OP(i) = P_i\left(\beta_i \leq \frac{\frac{\Gamma T \sigma^2}{\eta E} R_th}{\frac{\tau_i}{\delta^2}}\right)$$

where $\beta_i$ is the exponential random variable (RV) with mean $\delta^2$.

PDF of $\beta_i$ is given as

$$f_{\beta_i} = \frac{1}{\delta^2} e^{-\frac{\beta_i}{\delta^2}}$$

The OP can be calculated as:

$$OP(i) = P_i\left(\beta_i \leq \frac{\frac{\Gamma T \sigma^2}{\eta E} R_th}{\frac{\tau_i}{\delta^2}}\right)$$

$$OP(i) = \int_{\frac{\beta_i}{\delta^2}}^{\frac{\beta_i}{\delta^2}} e^{-\frac{\beta_i}{\delta^2}} d\beta_i$$

$$OP(i) = 1 - e^{-\left(\frac{\Gamma T \sigma^2}{\eta E} R_th\right)^\frac{\tau_i}{\delta^2}}$$

#### 2.3.2 EEx OP

In EEx model, SNRs of both sensors at GC are the same. Hence, OP becomes the same for both the sensor nodes.

$$R_i \leq R_th$$

From Equation (20)

$$\beta_1 \leq \frac{T \sigma^2 \zeta}{\eta (E - \Delta E)} \frac{R_th}{\delta^2}$$

$$P_{out}(1) = P_{out}(2) = \int_{\frac{T \sigma^2 \zeta}{\eta (E - \Delta E)} \frac{R_th}{\delta^2}}^{\frac{T \sigma^2 \zeta}{\eta (E - \Delta E)} \frac{R_th}{\delta^2}} 1 - e^{-\left(\frac{T \sigma^2 \zeta}{\eta (E - \Delta E)} \frac{R_th}{\delta^2}\right)^\frac{\tau_i}{\delta^2}} d\beta_i$$

$$P_{out}(1) = P_{out}(2) = 1 - e^{-\left(\frac{T \sigma^2 \zeta}{\eta (E - \Delta E)} \frac{R_th}{\delta^2}\right)^\frac{\tau_i}{\delta^2}}$$

### 3 RESULT AND DISCUSSION

In this section, we consider the WPCN to compare the maximum sum-throughput, average BER and OP of the EEx and WEEx model. We assumed that the GC has the complete knowledge of channel gains $h_1$ and $h_2$, and it broadcast these values so that sensor node 1 and sensor node 2 also have
the complete knowledge of $h_1$ and $h_2$. Further, we assumed that the sensors also have the complete knowledge of channel gain $h_3$ between them. Channel power gains are modelled as $\beta_i = 10^{-3}\rho_i^2D_i^{-\alpha_i}, \ i = 1, 2, 3$, where $\rho_i$ is Rayleigh distributed additional short term fading channel and so $\rho_i^2$ represents the exponentially distributed RV with unit mean. The average signal power attenuation is set to 30 dB (with respect to 1m). Assumed parameters used in the simulation are summarized in Table 1.

Assuming that the sensors have the complete knowledge of $h_1$ and $h_2$. Further, we assumed that the sensors also have the complete knowledge of channel gain $h_3$ between them. Channel power gains are modelled as $\beta_i = 10^{-3}\rho_i^2D_i^{-\alpha_i}, \ i = 1, 2, 3$, where $\rho_i$ is Rayleigh distributed additional short term fading channel and so $\rho_i^2$ represents the exponentially distributed RV with unit mean. The average signal power attenuation is set to 30 dB (with respect to 1m). Assumed parameters used in the simulation are summarized in Table 1.

Table 1 Simulation parameters

| Parameter | Definition | Value |
|-----------|------------|-------|
| $\alpha_i$ | Channel path loss exponent | 2 [25] |
| $N_o$ | Noise power spectral density | $-160 \text{ dBm/Hz}$ [25] |
| $\eta$ | Energy efficiency of both sensors | 0.5 [25] |
| $\Gamma$ | SNR gap | 9.8 dB [25] |

As shown in Figure 4, the maximum sum-throughput of WEEEx model dominates over the EEx model. This is due to the loss of energy in the exchange process between the sensors, which decreases the maximum sum-throughput by 34.97% for the EEx model. Also, we found that the loss in maximum sum-throughput for EEx model increases with harvested energy at the nodes.

The average BER is compared at GC for 16-QAM modulation under WEEEx and EEx model for different values of harvested energy at sensor nodes in Figure 5.

Figure 5 shows that the average BER for the EEx model is lower than the WEEEx model by 74.59% as both nodes transmit data for the same amount of time $\zeta$ and having equal common throughput. We observed that when two equiprobable sensor nodes with the same amount of harvested energy send data to GC, the sensor nodes with better channel conditions require less amount of time to transmit than the other nodes to get equal common throughput. Hence, the average BER of WEEEx model is higher than EEx model. There is a loss of energy in the EEx model, which decreases the SNR at sensor nodes and hence the common throughput. Also, BER decreases as harvested energy increases at the sensor nodes. It is because as harvested energy increases the SNR at the sensor nodes increases, which decreases the average BER.

Further, by fixing $\beta_3$, Figure 6 shows the energy exchange between sensor nodes for different values of the harvested energy and channel power gain difference ($\Delta\beta = \beta_1 - \beta_2$). We observed that when there is no channel power gain difference, no energy exchange takes place. However, with the increase in the channel power gain difference, more energy exchange will occur. Also, energy exchange increases with harvested energy at sensor nodes, which indicates that if there is channel power gain difference, then energy exchange will linearly increase with harvested energy.

Figure 7 shows that energy exchange time increases nonlinearly with channel power gain difference ($\Delta\beta$) when fixing
channel power gain between two sensors. As $\Delta \beta$ increases, significant energy exchange takes place, which also increases the energy exchange time. The maximum sum-throughput of the system also decreases with increasing energy exchange time as WIT time decreases for a block. Hence, maximum sum-throughput also decreases with channel power gain difference.

Lastly, Figure 8 compares the OP of WEEx and EEx model when the instantaneous CSI is available. In our system model, sensor nodes are static; hence, sensors-GC channels are influenced by Rayleigh fading. We observed the following points from Figure 8:

1. Both WEEx and EEx model reached outage for data rate greater than 0.23 and 5.43 bps respectively. Since harvested energy of weak node in WEEx model drained earlier than a weak node in EEx model.

2. For required data rate range [0.23, 2.5] bps, OP in the WEEx model touches outage floor while the OP in the case EEx model still goes down.
3. Network lifetime is better in EEx model as energy exchanged from strong node to weak node, which balanced the load among the nodes.

Table 2 compared obtained results of WEEx model which is simulation of setup [27] with algorithm common-throughput maximisation [25] and our proposed EEx model. Results show that our proposed model performance good in avg. BER and OP with drawback reduce sum throughput due to energy exchange time $\tau$. Large channel gain difference between sensors will increase energy exchange time $\tau$, which limits EEx model.

### Table 2  Comparison of result obtained from WEEx and EEx model for $E = 0.6$ J, $\Delta \beta = 0.4$

| Parameter          | WEEx   | EEx   |
|--------------------|--------|-------|
| $\Delta E$         | 0      | 0.3 J |
| $\tau$             | 0      | 0.18 s|
| Avg.BER            | $1.4 \times 10^{-2}$ | $3.5 \times 10^{-3}$ |
| Sum throughput     | 7.07 bps/Hz | 4.27 bps/Hz |

# Conclusion

Due to the doubly near–far problem, an outage problem occurs to the far user, which reduce the network lifetime. To overcome this, we propose a new sum-throughput maximisation approach called EEx model. We considered a WSN with two sensor scenario that harvests equal energy from the RF source. The harvest-then-transmit protocol enables both the sensors to transmit their independent UL WITs to GC through the TDMA process. Further, the doubly near-far problem is
eliminated by exchanging the energy between sensors such that both sensors get equal rates with equal WITs. In doing so, we found that the proposed approach successfully solves the doubly near-far problem with low average BER (reduced by 74.59%) but at the cost of 34.97% maximum sum-throughput degradation. In future, one can take up the problem of degradation of the sum-throughput to enhance the overall performance of the system.

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How to cite this article: Singh J, Chaturvedi A, Sharma S, Singh A. A novel model to eliminate the doubly near-far problem in wireless powered communication network. IET Commun. 2021;15:1539–1547.
https://doi.org/10.1049/cmu2.12167