Utility-Driven Joint Time-and-Power Allocation in Energy-Harvesting Cognitive Radio Relay Networks

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Abstract. The increasing number of wireless devices has raised significant global concerns regarding energy efficiency and spectrum scarcity. To address this, wireless energy harvesting technology has emerged as a potential solution. By utilizing conventional radio frequency transmissions, this technology can extend the battery life of mobile devices and improve the operational period of energy-constrained wireless networks. This study focuses on a wireless energy harvesting and information transfer protocol within cognitive radio relay networks. In this setup, an energy-constrained secondary user shares the spectrum and simultaneously harvests energy while assisting with the primary transmission. To optimize the allocation of transmission time and harvested power, a challenging computational problem is formulated. The goal is to enhance the utility of the secondary user. To tackle this computationally hard problem, a heuristic solution based on a joint time-and-power allocation strategy is proposed. This approach achieves an impressive 98.5% accuracy while comparing the utility of the secondary users to the optimal benchmark results.

Keywords: Primary users · Secondary users · Energy Harvesting · Optimal Allocation · Utility

1 Introduction

Due to growing environmental concerns and the rising demand for wireless services, energy efficiency and spectral efficiency are two crucial design criteria in wireless communications [11]. Energy harvesting (EH) has recently gained popularity as a way to extend the lifespan of wireless networks with limited energy source. When compared to conventional energy sources like batteries, which have limited operating times, energy harvesting from the environment could offer wireless networks an endless source of power [20]. Radio frequency (RF) signals hold a promising future for wireless energy harvesting (WEH) in addition to other widely used energy sources like solar and wind, because it can also be used to simultaneously transmit wireless information. Recently, it is shown that

simultaneous wireless information and power transfer (SWIPT) becomes appealing since it realizes both useful utilization of RF signals at the same time, and thus potentially offers great convenience to mobile users [12,21]. On the other hand, cognitive radio (CR) is a promising solution concept to improve spectrum utilization by allowing spectrum sharing, where unlicensed or secondary users (SUs) can use the unused portion of licensed spectrum resources of licensed or primary users (PUs) [1,2]. Thus, merging of CR technology with energy harvesting provides an efficient way of utilizing both spectrum and energy to prolong the operational time of SUs.

Many of the recent works have studied energy efficient communication in Cognitive Radio Network (CRN) using either the popular Time Switching (TS) based or Power Splitting (PS) based SWIPT technology. In [21], TS as well as PS based SWIPT techniques were separately applied on SU receiver side, and the rate-energy trade-off analysis in both techniques was investigated. Another work based on PS and TS receiver architectures at the relay node was studied in [19], and proposed a PS-based relaying protocol and a TS-based relaying protocol separately to enable wireless information transferring and EH at the battery-free relay node. Here, the end-to-end error performance and throughput of the proposed protocol during secondary transmission were investigated. In [18], an optimal power allocation problem using a PS-based approach within an energy-constrained CRN was proposed. This investigation encompassed several key aspects, including assessing outage probabilities for both PUs and SUs, evaluating system energy efficiency, and examining the trade-off between data rate and energy consumption. Another work addressed in [9], a PS-based SWIPT technology was implemented within a cooperative CRN. In this scenario, energy-constrained SUs harnessed energy not only from the primary transmitter's (PT) received signal but also from interfering sources. The research delved into the performance of two relay cooperation schemes, examining the tradeoff between the PU's and SU's performance, particularly concerning outage probabilities. In [17], author addressed an optimization problem involving transmitting time and transmission power of SU within an underlay RF energy-harvesting CRN. Their objective was to maximize the energy efficiency of the secondary network by enabling the SUs to reserve the residual energy after previous slots for upcoming transmissions. A rapid iterative algorithm based on Dinkelbach's method was proposed to achieve optimal resource allocation as well the QoS of SUs. In [6], a hybrid TS-PS model was established for EH in a bidirectional relay assisted communication and explored an end-to-end outage probability of the network. Primarily, this work solved an optimization problem of outage probability with respect to relay placement and time allocation factor. Another work [8] explored techniques for simultaneous EH and information transfer within an EH-based CRN model. This approach combined both TS and PS receiver architectures to derived and analyzed optimal expressions for transmission power and energy harvesting power to attain maximum energy efficiency within the secondary network. Finally, in the work [14], a radio-frequency (RF) energy harvesting enabled CRN adopts a PS-based SWIPT architecture. The study addresses two significant challenges: prolonging network lifetime and enhancing link reliability by accounting for transceiver hardware impairments.

The majority of the works cited above focus on either TS or PS SWIPT technology separately during the optimization of harvested energy and primary information decoding rates at SU. To the best of our knowledge, there is limited research, such as [6] and [8], where integration of TS and PS techniques is used in the CRN framework to harvest energy from RF signal. However, these studies do not tackle the vital issue of optimizing the utility and operational duration of energy-constrained SUs. By simultaneously employing both of these techniques during energy harvesting phase, SUs can accumulate a greater amount of energy compared to their separate uses, which in turn contributes to extending the lifespan of the secondary network. Therefore, this research introduces a unified model that integrates TS and PS SWIPT technology for EH in energy-constrained SUs within a cognitive radio relay network. Subsequently, it optimizes the allocation of harvested power to enhance the effectiveness of the secondary network. Each SU harvests maximum energy from the received primary signal and successfully forwards primary and secondary information to the intended receivers. Accordingly, we formulate an optimization problem to achieve the optimal allocation of TS-PS factors and harvested power. Heuristic approach is applied to obtain a near-optimal solution for this problem. Simulation-based results demonstrate that the heuristic solution succeeds in attaining the maximum possible utility for both the energy-constrained SUs and PUs.

The rest of the paper is organized as follows. Section 2 outlines the system model and the formulated optimization problem. The solution concept for the proposed optimization problem is discussed in Sect. 3. In Sect. 4, numerical results are analyzed, and finally, the paper is concluded in Sect. 5.

2 System Model and Assumptions

We consider a cognitive radio network framework with a set of M PU transceiver pairs, denoted as $\mathcal{M} = \{(PT_1, PR_1), .., (PT_i, PR_i), .., (PT_M, PR_M)\}$ and a set of N SU transceiver pairs, denoted as $\mathcal{N} = \{(ST_1, SR_1), .., (ST_j, SR_j), .., (ST_N, SR_N)\}$. The assumption is that the physical distance between PT (transmitter) and PR (receiver) exceeds the effective transmission range. Consequently, a relay node (ST) is needed to forward primary information to PR in order to attain at least the target rate R_{pt}^{tar}. At the same time, ST accepts the offer from the PU, exchanging the rendered relay service for a spectrum opportunity to enable secondary communication towards SR. It is important to note that STs are energy-constrained nodes, operating in an energy-harvesting data-transmission mode with a minimum target rate requirement of R_{st}^{tar}. Moreover, STs are equipped with rechargeable batteries and feature a non-linear energy harvester [4,7,14], which allows them to harvest energy from the received primary signal. In this paper, the terms SU and ST, and PU and PT, are used interchangeably.

The proposed work considers information transmission between PT and PR as illustrated in Fig. 1. In this scenario, a single PU transmits primary information to PR with the assistance of a suitable ST acting as a relay node. The entire
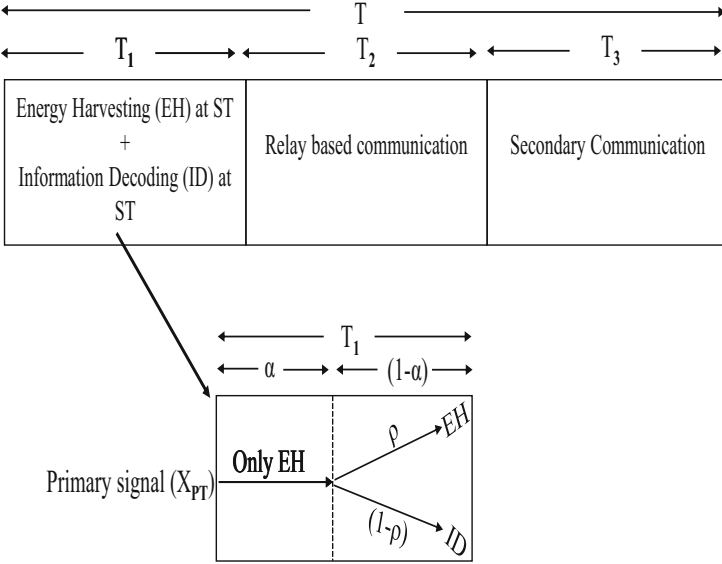
Fig. 1. Time-slot division of a PU band for EH and ID

time duration T of the PU band is subdivided into three sub-slots: T_1, T_2, and T_3. In the T_1 sub-slot (referred to as Phase 1), PT transmits its information towards the appropriate ST. Upon receiving the primary signal, ST harvests energy from it while simultaneously decoding it for further processing. During the T_2 time (termed as Phase 2), ST uses a portion of its harvested energy to forward the primary signal to PR through the Decode and Forward (DF) relaying technique. Finally, in the T_3 time (termed as Phase 3), ST performs secondary transmission using the remaining harvested energy.

Drawing on the principles of SWIPT and Dynamic Power Splitting (DPS) technology [13,21] a joint TS-PS technique is applied during the T_1 time slot, as depicted in Fig. 1. The T_1 time is further subdivided into two parts to serve the purposes of energy harvesting and information decoding. The time-switching factor α $(0 < \alpha < 1)$ determines the duration αT_1 allocated for energy harvesting, during which ST utilizes the entire signal power solely for this purpose. The remaining time $(1-\alpha)T_1$, is divided into two power streams with a power ratio of $\rho : (1-\rho)$. Here, ρ $(0 < \rho < 1)$ is used for energy harvesting, and $(1-\rho)$ is used to decode the primary information at ST. Therefore, in the proposed technique, ST can harvest energy during both αT_1 and $(1-\alpha)T_1$ time fractions, utilizing two different power values. However, information can only be decoded during the $(1-\alpha)T_1$ time fraction.

2.1 Utility of PUs and SUs

During the T_1 time, when PT transmits its information to ST, the received signal at ST, denoted as $Y_{pt,st}^I$, can be expressed as shown in Eq. (1) [17].

$$Y_{pt,st}^I = \sqrt{P_{pt}}h_{pt,st}X_{pt}^I + n_a + n_{cov} \tag{1}$$

Here, P_{pt} represents the transmit power of PT, and $h_{pt,st}$ is the channel gain between PT and ST. The channel gain is calculated as $h_{pt,st} = |d_{pt,st}|^{-2}$, where 2 corresponds to the pathloss index [15]. Additionally, X_{pt}^I represents the transmitted signal from PT intended for PR. The term $n_a \sim \mathcal{CN}(0, \sigma_1^2)$ denotes the narrowband Gaussian noise introduced by the antenna at ST, while $n_{cov} \sim \mathcal{CN}(0, \sigma_{cov}^2)$ refers to the RF band to baseband signal conversion noise at ST. Taking inspiration from [21] and [18], we model the maximum possible harvested energy (EH_{st}^{max}) at ST (in Joule) and the maximum achievable instantaneous decoding rate ($R_{T_1}^{max}$) at ST (in bps) during the T_1 time using Eqs. (2) and (3).

$$EH_{st}^{max} = T_1 \eta P_{pt} |h_{pt,st}|^2 \tag{2}$$

where η is the energy conversion efficiency ($0 < \eta < 1$) at ST.

$$\begin{aligned}
R_{T_1}^{max} &= B * T_1 * \log_2(1 + SNR_{pt,st}) \\
&= B * T_1 * \log_2(1 + \frac{P_{pt}|h_{pt,st}|^2}{n_a^2 + n_{cov}^2})
\end{aligned} \tag{3}$$

where B is the available bandwidth in PU band.

Now, building upon the proposed joint TS-PS technique shown in Fig. 1, the harvested energy at ST (Eq. (2)) can be reformulated for this work as given in Eq. (4) below.

$$\begin{aligned}
EH_{st}^{prop} &= \alpha T_1 \eta P_{pt} |h_{pt,st}|^2 + (1-\alpha)T_1 \eta \rho P_{pu} |h_{pt,st}|^2 \\
&= (\alpha + (1-\alpha)\rho)T_1 \eta P_{pt} |h_{pt,st}|^2
\end{aligned} \tag{4}$$

Likewise, the information decoding rate at ST (Eq. (3)) can be reformulated for this work as given in Eq. (5) below.

$$\begin{aligned}
R_{T_1}^{prop} &= B * T_1 * \log_2(1 + SNR_{pt,st}) \\
&= B * (1-\alpha)T_1 * \log_2(1 + \frac{(1-\rho)P_{pt}|h_{pt,st}|^2}{(1-\rho)n_a^2 + n_{cov}^2})
\end{aligned} \tag{5}$$

Drawing inspiration from [14] and [4], the harvested power at ST (HP_{st}^{prop}) can be derived from the harvested energy, as expressed in Eq. 4. This harvested power is then utilized by ST for relaying primary information and transmitting secondary information.

During the T_2 time, ST forwards $(1-\rho)Y_{pt,st}^I$ towards PR using a portion of the harvested power, specifically $x.HP_{st}^{prop}$, and reserves $y.HP_{st}^{prop}$ power for secondary transmission during Phase 3. Here, $0 < x, y < 1$. Consequently, the

received signal-to-noise ratio (SNR) at PR can be modeled as given in Eq. (6) below.

$$\text{SNR}_{st,pr} = \frac{x.HP_{st}^{prop}\,|h_{st,pr}|^2}{x.n_a^2 + n_{cov}^2} \tag{6}$$

Likewise, the instantaneous achievable rate at PR for the proposed work during T_2 time ($R_{T_2}^{prop}$) can be formulated as given in Eq. (7).

$$R_{T_2}^{prop} = B * T_2 * \log_2(1 + \text{SNR}_{st,pr}) \tag{7}$$

At this juncture, we can analyze the cooperative capacity (C_{pu}^{coop}) achieved by PT through DF relaying assistance from ST over the duration of $T_1 + T_2$. Building on insights from [16], the attained cooperative capacity (C_{pu}^{coop}) over bandwidth B and the time duration of T_1+T_2 can be modeled using the Shannon-Hartley theorem [10,13] as shown in Eq. (8).

$$C_{pu}^{coop} = B * (T_1 + T_2) * log\,(1 + \text{SNR}_{pt,st} + \text{SNR}_{st,pr}) \tag{8}$$

Therefore, the utility of PU (U_{pu} in bps/Joule) can be represented as a fraction of the achieved C_{pu}^{coop}, relative to the energy consumption of PU during T_1 time, as defined in Eq. (9) below.

$$U_{pu} = \frac{C_{pu}^{coop} * a}{EC_{pu_{T_1}}} \tag{9}$$

where a is the gain per unit of cooperative capacity achieved at the Maximal Ratio Combining output.

Lastly, in the duration of T_3 time, ST engages in secondary communication by transmitting its signal towards SR with a power of $y.HP_{st}^{prop}$. Consequently, the received SNR at SR is formulated as presented in Eq. (10) below.

$$\text{SNR}_{st,sr} = \frac{y.HP_{st}^{prop}\,|h_{st,sr}|^2}{x.n_a^2 + n_{cov}^2} \tag{10}$$

Likewise, the instantaneous achievable rate at SR for the proposed work during T_3 time ($R_{T_3}^{prop}$) can be formulated as shown in Eq. (11).

$$R_{T_3}^{prop} = B * T_3 * \log_2(1 + \text{SNR}_{st,sr}) \tag{11}$$

The utility of SU (U_{su} in bps/Joule) is now expressed as a fraction of the achieved instantaneous achievable rate of ST during Phase 3, relative to the total energy consumption (EC) of ST throughout T_2 and T_3 time. This model is formulated as shown in Eq. (12) below.

$$U_{su} = \frac{R_{T_3}^{prop}}{\underbrace{x.HP_{st}^{prop}}_{\text{EC during } T_2} + \underbrace{y.HP_{st}^{prop}}_{\text{EC during } T_3}} \tag{12}$$

2.2   Formulation of Optimization Problem

In this context, we present the optimization problem aimed at optimizing the allocation of transmission time and harvested power to enhance the utility of the secondary user. The objective of this optimization is to maximize U_{su}, achieved by maximizing $R_{T_3}^{prop}$, while minimizing the total energy consumption by ST. This optimal allocation is determined by the decision variables α, ρ, x, and y.

The key to achieving the maximum $R_{T_3}^{prop}$ lies in increasing $\text{SNR}_{st,sr}$ (as shown in Eq. (11)), which can be attained through three primary factors: (i) increasing HP_{st}^{prop}, (ii) optimizing $|h_{st,pr}|$, and (iii) finding the optimal allocation for power allocation factors x and y. By effectively managing these variables, we can significantly enhance the utility of the secondary user and optimize the resource consumption by ST. To achieve factor (i), we can maximize EH_{st}^{prop} at ST by allocating larger values of α and ρ as given in Eq. (4). However, while maximizing EH_{st}^{prop}, ST must simultaneously monitor the obtained R_{T1}^{prop} to meet R_{pt}^{tar}. Hence, optimal allocation of α and ρ is crucial at this stage. In contrast, factor (ii) depends solely on the distance between PT and ST and remains independent of any decision variables discussed in this paper. For factor (iii), ST naturally prefers to allocate the maximum possible y during T_3 time by assigning the minimum possible x for T_2 time. However, in the process of reducing x, ST must be attentive to the gradual reduction of $R_{T_2}^{prop}$ (Eq. (7)) while ensuring it satisfies R_{pt}^{tar}. Additionally, allocating a larger y increases the energy consumption of ST during T_3 time, which consequently reduces U_{su} (Eq. (12)). As a result, trade-offs arise that necessitate the optimal allocation of decision variables α, ρ, x, and y, satisfying PU constraints while maximizing U_{su}. Hence, we formulate the optimization problem for the same, as depicted in Eq. (13) below.

$$
\textbf{OP:} \quad \max_{\alpha,\rho,x,y} \quad U_{su}
$$

$$
\begin{aligned}
\text{s.t.} \quad & (a)\, 0 < \alpha, \rho\ < 1 \\
& (b)\, 0 < x, y < 1 \\
& (c)\, (1 - (x + y)).HP_{st}^{prop} \leq P_{st}^{min} \qquad (13) \\
& (d)\, R_{pt}^{tar} \leq R_{T_1}^{prop} \\
& (e)\, R_{pt}^{tar} \leq R_{T_2}^{prop} \\
& (f)\, R_{st}^{tar} < R_{T_3}^{prop}
\end{aligned}
$$

where P_{st}^{min} represents the minimum required power for an ST to remain active in the network.

However, it should be noted that the proposed optimization problem (Eq. (13)), exhibits a non-linear nature, and solving nonlinear systems is well-known to be an NP-hard problem [3]. In a related study [5], Gaganov demonstrated that nonlinear systems with polynomial equations having rational coefficients also fall under the NP-hard category. The proposed objective function (Eq. (13)) has polynomial equations, and the decision variables, viz. α, ρ, x, and y all

act as coefficients with rational boundaries (each of them within the range (0, 1)). Therefore, inspired by [3,5] it can be stated that the proposed problem is also a hard problem that is intractable and difficult to solve in polynomial time. Such a non-linear and NP-hard nature of the optimization problem calls for advanced optimization techniques to find approximate or optimal solutions efficiently. Heuristic approaches are found widely used to address such problems. Therefore, a numerical analysis-based quick iterative heuristic approach can be applied to decide the near optimal solution of α, ρ, x and y with the aim of maximizing U_{su} as well as U_{pu} in polynomial time.

3 Proposed Heuristic Solutions

To tackle the formulated optimization problem involving decision variables α, ρ, x, and y, we propose two iterative heuristic solutions based on conventional numerical methods. These solutions aim to achieve near-optimal resource allocation points α^*, ρ^*, followed by x^* and y^*. For simplicity, we divide the entire optimization problem into two phases. In the first phase, we focus on analyzing the maximum harvested energy at ST by optimally allocating α and ρ values based on Eq. (4) and (5). Subsequently, in the second phase, we achieve optimal allocation of x and y, effectively utilizing the harvested energy to maximize U_{su} while adhering to all the associated constraints given in Eq. (13). The basic steps involved in both heuristic solutions are illustrated through flowcharts, as provided in Subsects. 3.1 and 3.2. These heuristic approaches offer quick iterative solutions to efficiently tackle the optimization problem, providing practical, near-optimal solutions for the resource allocation variables.

3.1 Flowchart for Allocation of α^* and ρ^*

The range of α and ρ is confined within the interval $(0,1)$. The underlying principle of the proposed strategy revolves around iteratively narrowing down this $(0,1)$ range towards the optimal α^* and ρ^* points, where the maximum EH_{st}^{prop} can be attained. The step-wise flow of the proposed allocation scheme for α^* and ρ^* is presented as shown in Fig. 2.

3.2 Flowchart for Allocation of x^* and y^*

The ranges of both x and y are constrained within $(0,1)$. The fundamental concept behind the proposed strategy entails partitioning the given $(0,1)$ range into two sub-ranges for x and y dynamically. As the sub-range of x narrows towards the left (i.e., towards 0) in the quest for x^*, the sub-range of y simultaneously expands in search of y^* that maximizes U_{su}. The step-wise flow of the proposed allocation scheme for x^* and y^* is presented as shown in Fig. 3.
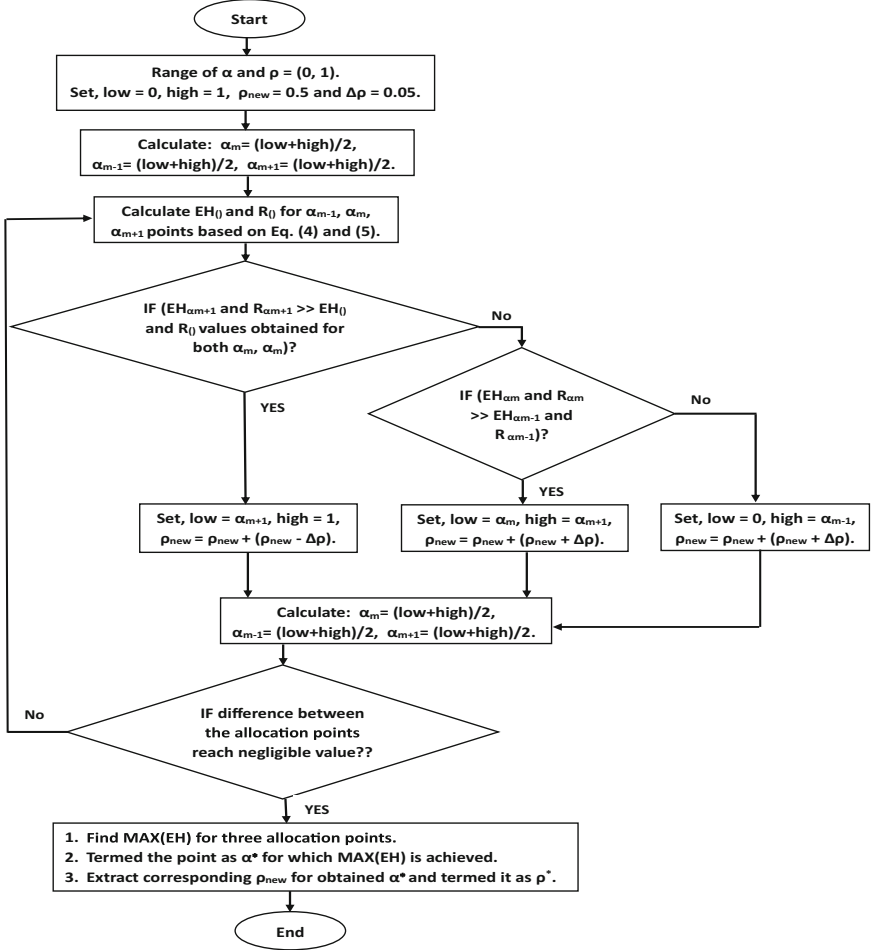
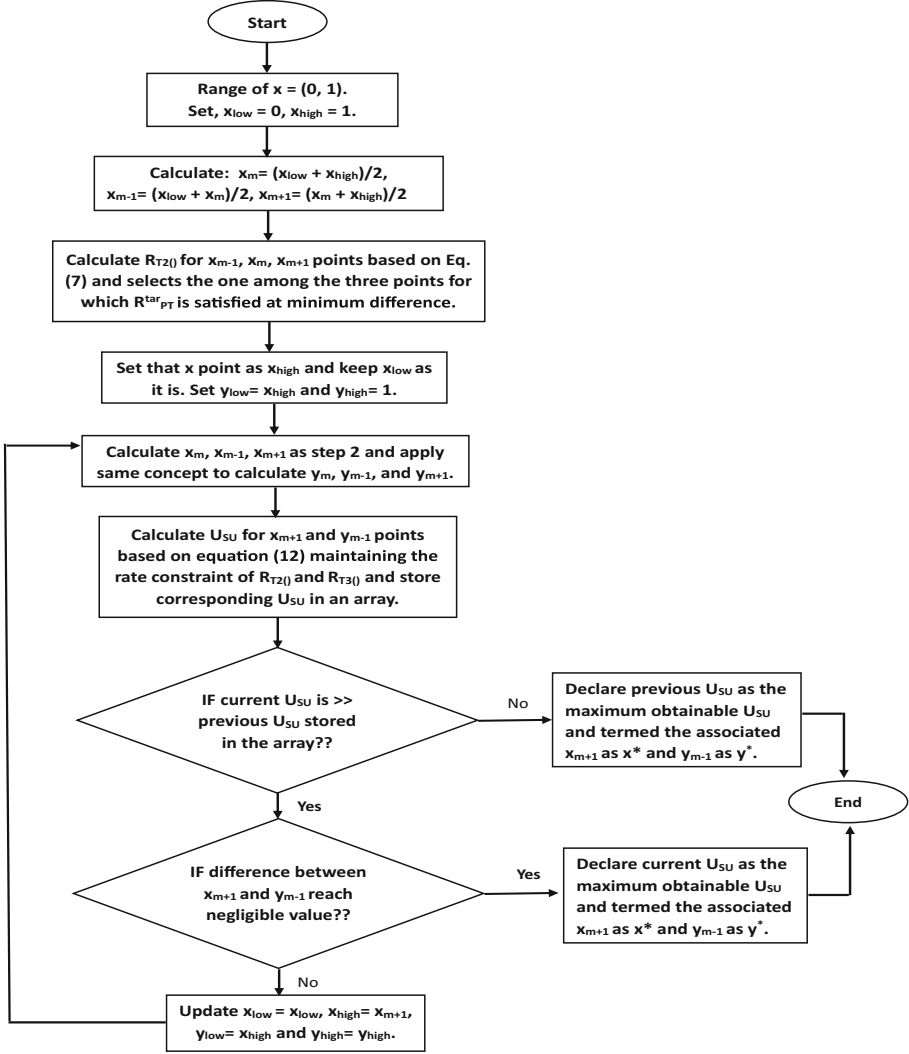**Fig. 2.** Flowchart for the allocation of α^* and ρ^*

Fig. 3. Flowchart for the allocation of x^* and y^*

3.3 Proof of Convergence of the Proposed Solutions

In the formulated optimization problem, all decision variables are confined within the range $(0, 1)$. The proposed heuristic solutions aim to determine optimal points for each decision variable within this range. In the first solution, the search for α^* and ρ^* is designed such that as the number of iterations increases, the range $(0, 1)$ progressively narrows towards the optimal α and ρ values. These values enable ST to achieve maximum EH_{st}^{prop}.

In the second solution, the ranges of x and y are managed within a single $(0, 1)$ range. As the number of iterations increases, the new range of $x \in (0, 1)$ starts to contract in search of x^*, while the new range of $y \in (0, 1)$ begins to expand in pursuit of the optimal y^* point. This iterative process continues until the x and y values of the current iteration yield a higher U_{su} than the values obtained in the previous iteration. This approach allows the solution to converge towards the optimal allocation of x and y that maximizes the utility U_{su} within the given range constraints.

At each iteration, ST calculates EH_{st}^{prop} and U_{su} for the corresponding allocation points α_{m-1}, α_m, α_{m+1}, x_{m+1}, and y_{m-1}. It then verifies their intervals on a per iteration basis. The process continues until the difference between the allocation points reaches a negligible value, approaching zero. As the proposed solutions reach this negligible difference, they terminate, yielding the maximum achievable EH_{st}^{prop} and U_{su} for their respective allocation points. Thus, we can conclude that the proposed heuristic solutions terminate when the difference between α_{m-1}, α_m, α_{m+1}, and x_{m+1}, y_{m-1} approaches almost zero or becomes zero.

4   Simulation Results and Comparison Analysis

The proposed solutions are evaluated through a simulation study conducted using MATLAB 7 (R2017a) on a 64-bit PC powered by a core i5 processor and 8 GB of RAM. The simulation is based on a Cognitive Radio (CR) network comprising M PUs and N SUs. Both the PUs and SUs are randomly distributed in a square area measuring 1000×1000 m^2. In the simulation setup, the transmission power of PT is fixed at 1 W, and each time slot's duration is set to $T_1 = T_2 = T_3 = 10$ s. Also the PU band's bandwidth is maintained at 1 MHz [16]. Moreover, the PU transceiver pairs are set at an average distance of approximately 30 m, while the SU transceiver pairs are spaced at an average distance of about 20 m. Furthermore, PU channels are modeled as Additive White Gaussian Noise (AWGN) channels, with the noise variance set to 1 mW. These parameters and settings provide the basis for the comprehensive evaluation of the proposed solutions in the context of the CR network under study..

The proposed solution technique, as discussed in Subsect. 3.1, is employed to obtain the graph for maximum energy harvesting at ST through appropriate allocation of α^* and ρ^*. The corresponding results are presented in Fig. 4, achieving an accuracy of 97.7% compared to the optimal (benchmark) result. Furthermore, when considering the individual values of α^* and ρ^*, the proposed solution demonstrates 96% and 95% correctness, respectively, in comparison to the benchmark α^* and ρ^*. These findings highlight the effectiveness and reliability of the proposed solution technique in obtaining near-optimal allocation points for α and ρ, thus leading to significant improvements in the energy harvesting at ST.

Once more, the graph depicting the maximum U_{su}, attained by suitably allocating x^* and y^* utilizing the solution technique discussed in Subsect. 3.2,
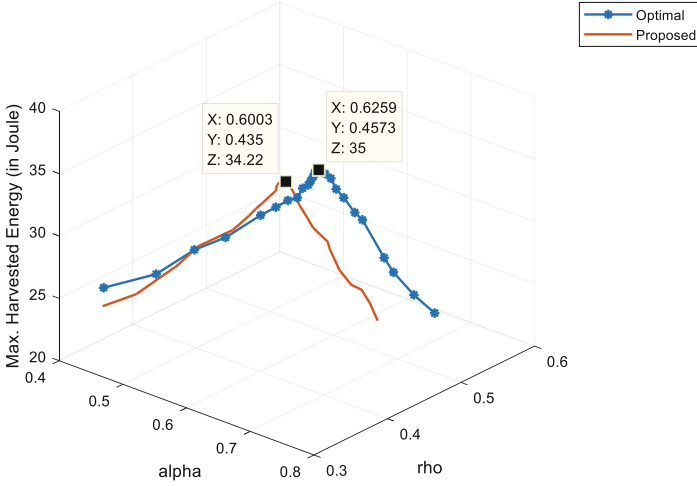
Fig. 4. Max. Harvested Energy vs. optimal allocation of α^* and ρ^* with $\eta = 1$
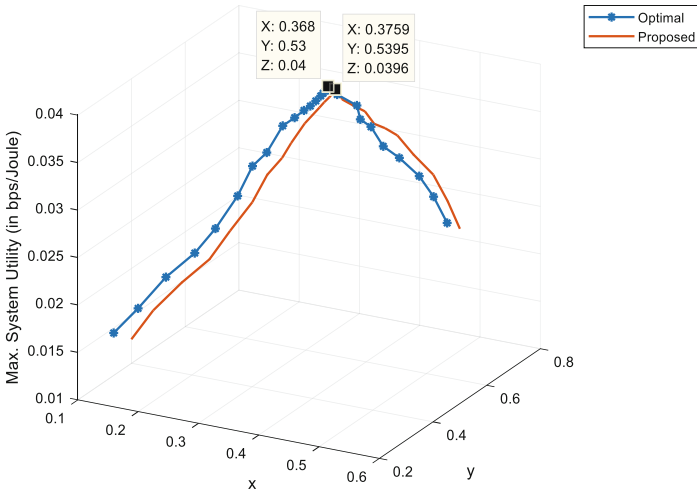

Fig. 5. Max. Utility of SU vs. optimal allocation of x^* and y^*

is presented in Fig. 5. This approach achieved a high accuracy of 98.5% when compared to the optimal result. Furthermore, in the case of x^* and y^* allocation, the proposed technique demonstrated 97.8% and 98% correctness, respectively, when compared to the optimal x and y. These results affirm the efficacy of the proposed solution technique, showcasing its ability to efficiently allocate near-optimal points for x and y, thereby significantly enhancing the U_{su} performance.

Finally, we analyze the impact of the distance between PT and ST on the allocation of x^* and y^* to achieve U_{su} and U_{pu}, as illustrated in Fig. 6. The figure
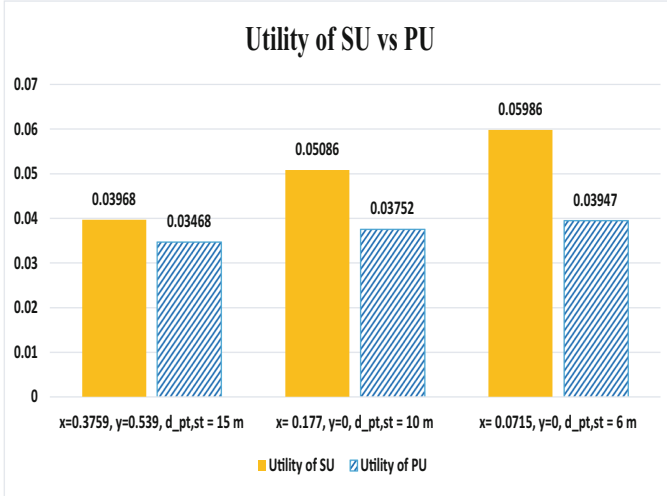
Fig. 6. Utility of SU vs. Utility of PU at obtained x^* and y^* for different distances between PT and ST

reveals that when the distance between PT and ST is very small (say 6 m in the figure) or when ST is in close proximity to PT, the $h_{pt,st}$ value is significantly favorable. Consequently, allocating a small fraction of total power ($x = 0.0715$) during T_2 time allows R_{pt}^{prop} to be easily satisfied in this phase. As a result, ST can allocate a large fraction of total power ($y = 0.53$) during Phase 3, achieving the maximum possible $Usu = 0.05986$.

On the other hand, as the distance between ST and PT gradually increases (say 15 m in the figure), the quality of $h_{st,pr}$ begins to deteriorate. Consequently, ST needs to invest more power during T_2 time by increasing the value of x, as depicted in Fig. 6, to meet R_{pt}^{tar}. However, this increase in x leads to higher energy consumption by ST during T_2 time, consequently reducing the achievable Usu.

Similarly, the gradual decrease in distance between PT and ST results in a gradual increment of U_{pu}. However, the rate of increment in U_{pu} is found to be less than that of U_{su}. This is due to the smart strategy adopted by ST, which allocates the minimum required fraction (x) of total power during T_2 only to meet R_{pt}^{tar}. This strategic approach ensures efficient power utilization by ST while optimizing the performance of both U_{su} and U_{pu}.

5   Conclusion

This paper presents an energy harvesting technique for energy-constrained Cognitive Radio Relay Networks, aimed at improving the utility of SUs. The study formulates an optimization problem to maximize the achieved utility of SUs through optimal allocation of time-switching and power-splitting factors. Given the computationally challenging nature of the problem, a heuristic approach is

proposed, which provides a near-optimal solution by optimally allocating all the decision variables. Simulation results demonstrate that the proposed solution achieves high accuracy, with approximately 97.7% and 98.5% accuracy in terms of harvested energy and utility of SUs, respectively, compared to the benchmark result.

Additional simulation research, taking into account various parameter configurations to simulate different real-world deployment scenarios, is planned for future work. These findings will be incorporated into an expanded version of this study.

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