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Energy Efficient Resource Allocation in Wireless Energy Harvesting Sensor Networks

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Abstract - Extending the sensor life is one of the most significant obstacles to the broad adoption of Wireless Sensor Networks (WSNs). Energy Harvesting (EH) sensors have been proposed as a remedy for the aforementioned problem in recent years. These sensors' usable lives can be increased by finding the energy they require from their surroundings in a number of different ways. We take into account a Wireless Energy Harvesting Sensor Network (WEHSN) based on TDMA where the time slot consists of two time intervals, the first of which is utilized for sensor data transmission and the second of which is utilized for energy absorption. We analyze the effective resource allocation in WEHSN, where an EH sensor is allowed to broadcast its data if the quantity of energy it has harvested exceeds the amount of power it has consumed, under constraints on time scheduling parameters and transmission power usage. The closed form equation for the energy efficiency optimization problem is created using the Dinkelbach method, and it is then converted into a parametric form. The new problem is then solved using Karush-Kuhn-Tucker (KKT) criteria. The numerical results show that the suggested strategy is viable.

Key Words: Energy Efficiency, Resource Allocation, Energy Harvesting, Wireless Sensor Networks.

1. Introduction

The rapidly evolving fields of Wireless Sensor Networks (WSN) and Internet of Things (IoT) applications, including the smart home, smart factory, and others, have attracted a lot of interest in recent years. The lifespan of the sensors would be extended and system performance would be greatly enhanced by the efficient use of resources like power and energy harvesting technology.

The usage of a cognitive D2D communication system to improve the efficiency of spectrum and resource allocation was discussed by Sultana et al. in. Nobar et al. researched a cognitive Wireless Powered Communication Networks (WPCN) with green power beacon, in which the secondary network is wirelessly powered by an energy collecting power beacon, in order to simultaneously give an efficient energy and spectrum performance.

In order to derive the closed form equations for the service rate of the Secondary User (SU) and the Primary User, the authors of the research studied two spectrum access techniques for the proposed model, namely a random spectrum access and a spectrum-sensing based spectrum access (PU). Additionally,

Nobar et al. have suggested a modified approach to satisfy the demands of resource-limited cognitive WSNs and to improve the performance of the secondary network while adhering to specific QoS restrictions. For PU, they implemented an endless battery status, but they limited the battery life for wireless sensor nodes. Similarly, Yang et al. in [8] attempted to maximize energy efficiency by minimizing the total energy spent in a cluster-based IoT network with energy collecting capability, while Ding et al. in [7] examined an iterative combined resource management and time allocation.

Another strategy proposed in [9] by Pei et al. applies an underlying Non-Orthogonal Multiple Access (NOMA) scheme to a cellular network under the signal-to-interference-and-noise ratio constraint of the Cellular Users. This joint resource block and transmission power control scheme is for the energy harvesting D2D communications (CU). Additionally, Wu et al. examined [10] how to maximize network throughput in TDMA and NOMA for uplink wireless-powered IoT networks, where the spectral and energy efficiency are restricted to circuit energy consumption.

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2. Related Works

[1] J. Huang, C. Xing, and C. Wang, Energy efficiency will be a key component of future communication systems, and 5G radio access networks have made this a top priority in all of their design efforts. The high operational costs and difficulty of replacing or recharging wireless device batteries in many situations, such as wireless medical sensors inside the human body, have prompted the development of a new technology that enables wireless devices to harvest energy from the environment by capturing ambient RF signals. SWIPT has become a potent tool for tackling this problem. In this article, we examine the available SWIPT designs and supporting technologies and list the technical difficulties in implementing SWIPT. To highlight the significance of using SWIPT, we first give

an overview of the technologies that enable SWIPT and SWIPT-assisted wireless systems before showcasing a brand-new power distribution method that uses SWIPT. In order to inspire and stimulate additional study on SWIPT, we highlight a few potential future research directions.

[2] K. Kang, R. Ye, In the Internet of Things (IoT) network, where a single hybrid access point (H-AP) with a consistent power source communicates with a variety of IoT devices, wireless power transfer is a new technology that is being studied in this research. It is expected that this H-AP operates in full-duplex mode, which sends and receives signals to and from these Internet of Things devices simultaneously during the entire frame. The H-received AP's signals can be used to generate energy by the IoT devices. Additionally, the uplink transmission is supported by the energy that was captured. One Internet of Things device continues to collect energy until its own uplink time slot because uplink transmission uses time-division multiple access. The objective of this research is to optimize the overall surplus energy, which is defined as the difference between the energy available and the energy consumed for uplink transmissions, by employing the optimal time allocation technique for each device. Distributed non-cooperative and bargaining cooperative game-based algorithms are created to address this problem. Additionally, a benchmark is created using the well-known KKT condition technique. The numerical results show that the negotiating cooperative algorithm outperforms the distributed non-cooperative algorithm (DNCA) and the KKT algorithm in terms of total surplus energy and the fairness index (KKTA). KKTA outperforms DNCA in terms of total excess energy, although KKTA is more equitable than DNCA.

[3] Z. Chu, F. Zhou, Z. Zhu, R. Q. Hu, and P. Xiao, In this research, a wireless powered sensor network with many sensor nodes placed to track a specific external environment is investigated. These sensor nodes are fueled by a multi-antenna power station (PS) during the wireless energy transfer phase, and during the wireless information transfer phase (WIT), the sensor nodes communicate their own monitoring data to a fusion center using the energy they have collected. The goal is to maximize the system sum throughput of the sensor network when two alternative circumstances, such as PS and sensor nodes belonging to the same or distinct service operators, are taken into account (s). We propose a global optimal strategy to simultaneously design the energy beamforming and time allocation in the first scenario. In order to respond in closed form to the proposed sum throughput, we continue.

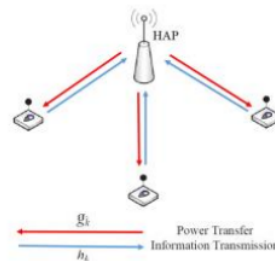
[4] A. Sultana, L. Zhao, and X. Fernando, Device-to-device (D2D) communication is being developed as a new paradigm to enhance network performance, according to LTE and WiMAX advanced specifications. D2D communication may use dedicated spectrum (overlay) or shared spectrum (underlay). While the designated specialized frequency may not be

adequately utilized in the overlay mode, interference between cellular users and D2D users degrades the underlay mode. Can a D2D system's resource allocation be optimized using the cognitive approach, in which users opportunistically use the radio spectrum that isn't being used as much? The focus of this essay is on that. This work optimizes the transmission rate of the D2D users while simultaneously satisfying five sets of power, interference, and data rate limits. It models D2D users as cognitive secondary users.

[5] S. K. Nobar, K. A. Mehr, and J. M. Niya, In this letter, we'll examine an RF-powered green cognitive radio network (RF-GCRN), where a power beacon (PB) serves as the hub and collects green energy from local sources before wirelessly distributing it to cognitive users. Random in-band energy transmission by PB serves as the only energy source for cognitive users. The effectiveness of this network is tested for both random access and spectrum sensing-based access strategies with just one set of secondary users. The results show that the RF-GCRN paradigm is viable if the energy transmission rate is below a particular threshold. This threshold is determined by the requirements of the spectrum access technique and the maximum delay that the primary user will endure.

3. Implementation

We look at a WEHSN that has one hybrid access point (HAP) and M energy-harvesting sensors coupled to an unlimited power source (see Fig. 1). As indicated in [11], the "harvest-and-then-transmit" technique is applied. Sensors first gather energy in a downlink (DL) from a wireless energy transferring (WET) in order to transmit information to a wireless information transmission (WIT). T_{max} stands for the maximum time interval for data transmission and energy harvesting. We take into consideration a WEHSN with TDMA that gathers energy from every



sensor.

information is transmitted throughout UL WIT and DL WET. The second interval has M slots, one for each sensor. It is assumed that each sensor has the component in the optimal state for a channel information system (CSI) for resource allocation. DL channel gain between the HAP and sensor i and UL channel gain between sensor i and the HAP are denoted by the letters g_i and h_i , respectively. During the downlink phase, HAP broadcasts the energy signal with a constant power P_0 and in an omnidirectional

1 fashion to all sensors. The amount of energy collected at sensor i can therefore be expressed as

$$E_i^h = (\eta_i P_{0g_i} - P_{c,i})\tau_0 = f_i\tau_0 \quad \forall i \in \{1, 2, \dots, M\},$$

1 Here, $P_{c,i}$ is the circuit's power usage during the energy harvesting period, and I is the constant energy conversion coefficient of the sensor (0, 1). Each sensor is thought to have positive levels of accumulated energy ($f_i > 0$). The appropriate sensor cannot participate in transmission if $f_i = 0$ due to a lack of energy.

Each sensor transmits data in the assigned time slot I during the uplink period thanks to TDMA-based WEHSN. Because of this, the energy consumed by each sensor while the information is being transmitted will be equal to $(p_i + P_{c,i})\tau_i$, where p_i is the amount of power given for sensor i in the WIT and $P_{c,i}$ is the amount of power consumed by the circuit. As a result, the throughput for sensor i that can be reached (normalized by bandwidth) can be expressed as

$$r_i = \tau_i \log_2 \left(1 + \frac{p_i h_i}{\sigma^2} \right)$$

I and 0 are first taken to be constants. Slater's condition [13] is satisfied by the convex optimization problem (8) in this case, which involves p_i . The proper application of the Lagrange dual technique enables the rapid discovery of the optimal solution [13]. To do this, we need the answer to the Lagrangian function of issue (8), which is denoted by

$$\mathcal{L}(\{p_i\}, \{\gamma_i\}) = \sum_{i=1}^M [\tau_i \log_2 \left(1 + \frac{p_i h_i}{\sigma^2} \right) - \lambda(p_i + P_{c,i})\tau_i] - \sum_{i=1}^M \gamma_i [(p_i + P_{c,i})\tau_i - f_i\tau_0] \quad (9)$$

the Lagrangian coefficient, i . Since complementary slackness causes the optimal lagrangian multipliers in constraints C3 to be zero, the corresponding lagrangian multipliers in constraints C3 are not included in equation (9). To comply with Karush Kuhn-(KKT) Tucker's [13] specifications, we have

$$\frac{\partial \mathcal{L}}{\partial p_i} = \tau_i \frac{h_i \log_2(e)}{\sigma^2 + p_i h_i} - \lambda \tau_i - \gamma_i \tau_i = 0 \quad \forall i \in \{1, \dots, M\}$$

$$\gamma_i [(p_i + P_{c,i})\tau_i - f_i\tau_0] = 0 \quad \forall i \in \{1, 2, \dots, M\}$$

We look at three situations in order to solve (10) and (11).

Case 1) In this case, $I = 6 = 0 \quad I = 1, 2, \dots$

$$p_i = \frac{f_i \tau_0}{\tau_i} - P_{c,i}$$

$$\gamma_i = \frac{h_i}{\sigma^2 + p_i h_i} - \lambda$$

Both p_i and I must be bigger than zero in order for KKT to be satisfied ($0 < p_i$ & $0 < I$).

Case 2) where $\gamma_i = 0 \quad \forall i \in \{1, 2, \dots, M\}$, in this case we have

$$p_i = \frac{\log_2(e)}{\lambda} - \frac{\sigma^2}{h_i}$$

Case 3) To get the pair (0, I), we substitute (12) in the maximizing issue (8). As a result, the problem is modified to each value.

1 Case 1) To obtain the pair $(\tau_0, \{\tau_i\})$, we substitute (12) in maximization problem (8). Thus, the problem is converted to

$$\max_{(\tau_0, \{\tau_i\})} \sum_{i=1}^M [\tau_i \log_2 \left(1 + \frac{f_i h_i \tau_0}{\sigma^2 \tau_i} - P_{c,i} \frac{h_i}{\sigma^2} \right) - \lambda \tau_0 (f_i + P_{c,i})]$$

$$s.t \quad C_4 : 0 < \tau_i(A_i) - \lambda f_i \tau_0 \quad \forall i \in \{1, 2, \dots, M\}$$

$$C_2, C_3 \quad (15)$$

where $A_i = (1 - \lambda \sigma^2 h_i + \lambda P_{c,i})$ and constraint C4 comes from substituting (12) in (13) to satisfy $0 < \{\gamma_i\}$ constraint C2, C3, C4 are linear, then the object function in (8) could be rewritten as

$$- \{R - \lambda E_T\} = \sum_{i=1}^M [L_i + K_i]$$

$$L_i = -\tau_i \log_2 \left(1 + \frac{f_i h_i \tau_0}{\sigma^2 \tau_i} - P_{c,i} \frac{h_i}{\sigma^2} \right)$$

$$K_i = \lambda \tau_0 (f_i + P_{c,i})$$

2 Whereas, $2(L_i) > 0$ demonstrates the convexity of L_i and suggests that K_i is a linear function according to equation (17).

The maximization problem (15) thus meets both Slater's condition and is a concave optimization problem. The Lagrangian function of issue (15) takes the following form to produce the best solution:

$$\mathcal{L}(\tau_0, \{\tau_i\}, \{\alpha_i\}, \beta) = \sum_{i=1}^M [\tau_i \log_2(t_i) - \lambda \tau_0 (f_i + P_{c,i})]$$

$$+ \sum_{i=1}^M \alpha_i [\tau_i(A_i) - \lambda f_i \tau_0] + \beta(T_{max} - \tau_0 - \sum_{i=1}^M \tau_i) \quad (16)$$

where $t_i = (1 + f_i h_i \tau_0 / \sigma^2 \tau_i - P_{c,i} h_i / \sigma^2)$ and $\{\alpha_i\}$ and β consist of Lagrangian coefficients. T_i will be positive because $P_{c,i}$ is thought to be quite small. Following are the KKT conditions.

$$\frac{\partial \mathcal{L}}{\partial \tau_0} = \sum_{i=1}^M [\frac{f_i h_i}{t_i \sigma^2} \log_2(e) - \lambda(f_i + P_{c,i})] - \sum_{i=1}^M \alpha_i \lambda f_i - \beta = 0 \quad (19)$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \tau_i} &= \log_2(t_i) - \frac{f_i h_i \tau_0}{t_i \sigma^2 \tau_i} \log_2(e) + \alpha_i(A_i) - \beta = 0 \\ \alpha_i[\tau_i(A_i) - \lambda f_i \tau_0] &= 0 \\ \beta(T_{max} - \tau_0 - \sum_{i=1}^M \tau_i) &= 0 \end{aligned}$$

Due to constraint C4 and the fact that $I = 0$, the parameter I is equal to zero (21). By replacing (19) with (20), we get the following equation.

$$\begin{aligned} \sum_{i=1}^M [\frac{f_i h_i}{t_i \sigma^2} \log_2(e) - \lambda(f_i + P_{c,i})] \\ - \log_2(t_i) + \frac{f_i h_i \tau_0}{t_i \sigma^2 \tau_i} \log_2(e) = 0 \quad \forall i \in \{1, 2, \dots, M\} \end{aligned}$$

When $I = 0$ is defined, all is $I = 1, 2, \dots, M$ can be discovered from (23). Additionally, in order to meet (22), we need to have $(0 + \sum_{i=1}^M I = T_{max})$, therefore we may deduce 0 and $I = 1, 2, \dots, M$ as follows

$$\tau_0 = \frac{T_{max}}{1 + \sum_{i=1}^M \frac{1}{\theta_i}} \quad \& \quad \tau_i = \frac{\tau_0}{\theta_i} \quad \forall i \in \{1, 2, \dots, M\}$$

Case 2) We replace (14) in problem to get relevant (τ_0, I) in case two (8). Consequently, the issue mentioned in (8) is changed to

$$\begin{aligned} \max_{(\tau_0, \tau_i)} \quad & \sum_{i=1}^M [\tau_i B_i - \tau_0 \lambda P_{c,i}] \\ \text{s.t. } C_5: \quad & (\frac{\log_2(e)}{\lambda} - \frac{\sigma^2}{h_i} + P_{c,i}) \tau_i \leq f_i \tau_0 \quad \forall i \in \{1, 2, \dots, M\} \end{aligned}$$

C_2, C_3

where $B_i = (\log_2(\log_2(e) h_i \sigma^2 \lambda) - \log_2(e) + \sigma^2 \lambda h_i - \lambda P_{c,i})$. An example of a linear optimization issue is the maximum problem in (25) Therefore, it is simple to calculate (0, 1).

Case 3) Problem (8) is changed to Problem (26), a combination of problems, by entering the estimated π from Case 3 into the problem (15) and (25)

$$\begin{aligned} \max_{(\tau_0, \tau_i)} \quad & \sum_{i=1}^k [\tau_i \log_2(1 + \frac{f_i h_i \tau_0}{\sigma^2 \tau_i} - P_{c,i} \frac{h_i}{\sigma^2}) - \lambda \tau_0 (f_i + P_{c,i})] \\ & + \sum_{i=k+1}^M [\tau_i B_i - \tau_0 \lambda P_{c,i}] \\ \text{s.t. } C_6: \quad & 0 < \tau_i(A_i) - \lambda f_i \tau_0 \quad \forall i \in \{1, 2, \dots, k\} \\ C_7: \quad & (\frac{\log_2(e)}{\lambda} - \frac{\sigma^2}{h_i} + P_{c,i}) \tau_i \leq f_i \tau_0 \quad \forall i \in \{k+1, \dots, M\} \end{aligned}$$

C_2, C_3

Using the equation, the solution to problem (26) to acquire 0 and I might be reached similarly to case (1). (24).

4. Results

After 5000 rounds the number of nodes alive are plotted in the below graph. It can be noted that total number of nodes started to die after some 3500 or more rounds which is the maximum capacity we have achieved with this type of protocol.

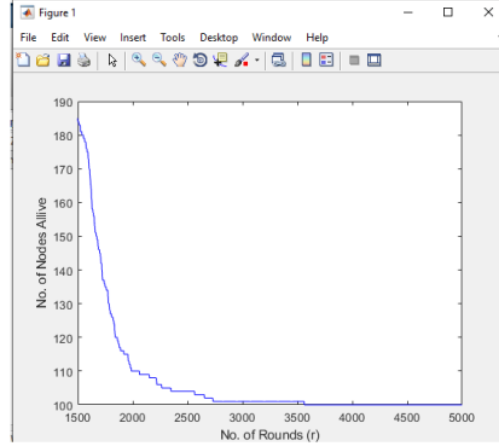


Fig -1: No of Nodes Alive after 5000 Rounds

After 5000 rounds, the consumption of energy of all the nodes in the network are plotted in the below graph. It can be noted that, the energy consumption is stretched to more than 2500 rounds which is possible because of our proposed protocol.

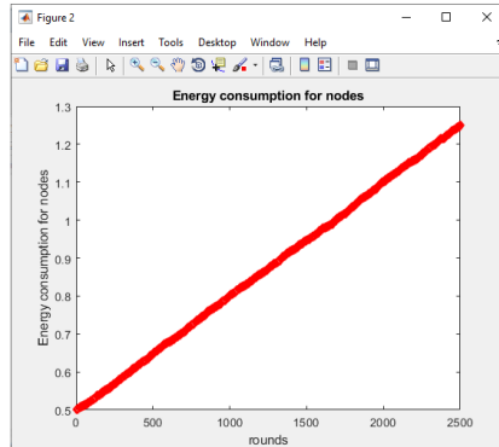


Fig -2: Energy Consumption for Nodes

Energy efficiency vs HAP transmit power are plotted in the below graph, which shows a greater usage of transmit power for making the nodes alive to some longer rounds than typical limit. It shows that, the

current protocol can maximize the power usage minimal power.

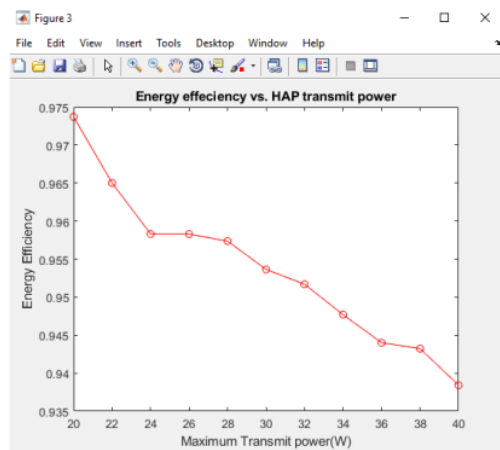


Fig -3: HAP TX power Vs Energy efficiency

Hap TX power Vs throughput are plotted in the below graph which shows the increase of transmit power when the throughput minimizes shows that the proposed protocol maximized the throughput of the network.

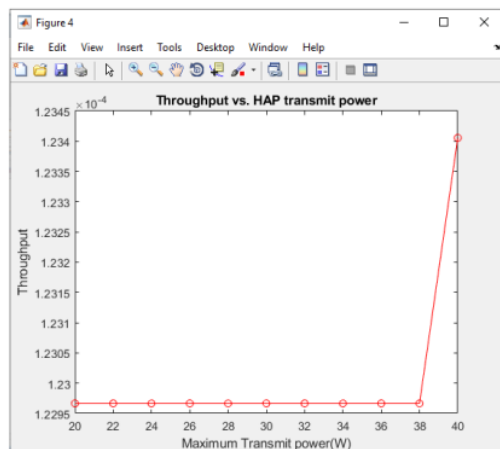


Fig -4: Hap TX power Vs throughput

5. CONCLUSION

In this article, we provide a brand-new system design where wireless sensors gather the energy needed for data transmission, then transmit using the harvest with transmit protocol. Additionally, the sensors interact consisting an access point of hybrid during the remaining time span using TDMA. We get at the energy efficiency optimization problem by putting limits to the time scheduling parametre and TX pow of every sensor to the system performance. Using the Dinkelbach algorithm, the issue is resolved, and expression of form of closed are obtained. The analytical findings demonstrate that throughput could slightly fall in comparison to the other ways, the energy usage would decrease significantly more, leading to maximize of efficiency of network's energy.

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PAGE 4

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