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Energy-Efficient Resource Allocation in Wireless Energy Harvesting Sensor Networks

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Abstract – *Increasing the sensor's lifespan is a major barrier to the major spreading use of wireless sensor networks (WSNs). The mentioned problem is fixed by implementing Energy Harvesting (EH) sensors. Their usable lives could 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, in which energy harvest sensors be permitted for broadcasting their output stream if the quantity of energy it has gained exceeds the amount of power it has consumed, under consideration of things such as planning of timer and TX power usage. The closed-form equation of the energy efficiency modification issue is created using the Dinkelbach method, and it is then converted in to the parametric form. The new problem is then solved using Karush-Kuhn-Tucker criteria. The analytical solutions show that the suggested strategy is viable.*

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

1. Introduction

Energy efficiency refers to the use of less energy to perform the same tasks, while resource allocation refers to the efficient use of resources such as network bandwidth, processing power, and storage. These two concepts are often critical in the design and operation of wireless sensor networks (WSNs), as WSNs are typically powered by small, limited-capacity batteries and rely on wireless communication, which can be energy-intensive.

To improve the energy efficiency of a WSN, designers can use low-power sensors and microcontrollers, optimize communication protocols and power management strategies, and use energy-efficient routing algorithms. In addition, energy harvesting techniques can be used to replenish the energy of the sensor nodes, either by converting ambient energy sources such as light or temperature gradients into electricity, or by harvesting energy from the environment through methods such as vibration or radio-frequency (RF) energy scavenging.

Resource allocation in WSNs refers to the effective use of the available resources, such as network bandwidth, processing power, and storage, to meet the needs of the application. Efficient resource allocation can improve the performance of the WSN and extend the lifetime of the sensor nodes. Techniques for improving resource allocation in WSNs include using adaptive or opportunistic routing algorithms and carefully selecting the sensor nodes and their deployment locations to balance the trade-offs between coverage, communication range, and energy consumption.

Overall, energy efficiency, resource allocation, and energy harvesting are important considerations in the design and operation of WSNs, as they can help to improve the performance and extend the lifetime of the sensor nodes.

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 comm. system for modifying the efficiency of the spectrum and resource allocation was discussed by Sultana et al. in. Nobar et al. researched a cognitive Wireless Powered Communication Network (WPCN) consisting of a green power beacon, of them secondary network survives with the collection of energy through beacon for power to simultaneously give an extended as well as spectrum performance.

The authors of this study examined two spectrum access strategies for the implementation method, any of the random spectrum access, and sensing-based spectrum access, to derive the closed-form equations to the working time for Secondary User (SU) as well as Primary User (PU). Additionally, Nobar et al. have suggested a modified approach to satisfy the demands of resource-limited cognitive WSNs as well as 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 [2] attempted to increase the efficiency of energy by decreasing the complete energy spent in a group-based IoT of energy collecting capability, while Ding et al. in [2] examined a repetitive combined allocation of time and management of resources.

Another strategy proposed in [2] by Pei et al. applies an underlying NOMA (Non-Orthogonal Multiple Access technique) for the network while taking into account the cellular users' signal-to-interference-and-noise ratio restriction. This joint resource block and transmission power control technique is employed for energy-harvesting D2D communications (CU). For energy-harvesting D2D communications, this joint resource block and transmission power management technique is used (CU). Wu et al. also looked at [2] how to increase network throughput in Time Division Multiple Access and Non-Orthogonal Multiple Access approaches for wirelessly powered IoT networks in the uplink, where the spectral energy and energy efficiency are limited to circuit energy consumption.

Another strategy proposed in [2] by Pei et al. applies an underlying NOMA (Non-Orthogonal Multiple Access) methods to a cellular network underneath the signal-to-interference-and-noise ratio restriction of the Cellular Users. This combinational block of resources and controlling of TX power is in energy gained D2D comm. (CU). In addition, Wu et al. examined [2] how to maximize the network rate of packet delivering in TDMA and NOMA from user to BS wireless-powered IoT networks, in which efficiency of energy and spectrum will be restricted for energy dissipation of the network.

2. Related Works

[1] J. Huang, C. Xing, and C. Wang, Efficiency of energy be a key component of upcoming communication systems, and 5G radio access networks have made this a top priority in all of their design efforts. They are costly for using and difficult in charging again and using an alternate battery of wireless across many situations, like sensors humans called medical sensors that are connected through wireless, have prompted the development of a new technique that enables wireless devices to take energy through the network by using radio frequency signals of ambient. 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 a brief explanation of the technologies that enable SWIPT and SWIPT-assisted wireless systems before showcasing a brand-new power distribution method that uses SWIPT. To inspire and stimulate additional studies on SWIPT, we highlight a few potential future research directions.

[14] K. Kang, R. Ye, this research examines wireless power transfer, a novel method that can be used in an Internet of Things (IoT) network where a single hybrid access point (H-AP) with a reliable power source links with many IoT devices. It is expected that this H-AP operates in full-duplex mode, which sends and accepts data from and sends the data to the Internet of Things devices at the same time for the duration of the entire frame. H-received AP signals can be used to generate energy by 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 uplink time slot because from user to BS link uses TDMA. Our aim is that the research is for optimizing overall excess energy, described as difference in the energy available as well as the energy consumed in user to BS links, by employing the best time division technique for all devices. Dispersed non-cooperative and negotiating cooperative game-based procedures will be created for addressing the current issue. The popular KKT condition technique is also used to set a benchmark. In terms of the total surplus energy as well as the equality table, implementation solutions demonstrate that the negotiating supporting approach surpasses the distributed non-cooperative algorithm (DNCA) and the KKT procedure (KKTA). Although KKTA will be more equitable than DNCA, it performs better than DNCA in terms of excess energy.

[3] Z. Chu, F. Zhou, Z. Zhu, R. Q. Hu, and P. Xiao, in this research, a wireless power-driven 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 transmission stage, during the wireless data transmission phase, sensor nodes communicate their personal controlling data to a mixture center using the energy they have collected. We aim to improve network throughput when both alternative circumstances, such as PS and sensor nodes belonging to similar or dissimilar facility operators, are taken into account (s). We suggest a total best strategy to simultaneously plan energy beamforming as well as time-sharing in the first scenario. 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, a new paradigm being created in compliance with LTE and WiMAX advanced specifications, will help networks perform better. D2D communication may make use of shared spectrum or dedicated spectrum (overlay) (underlay). While the overlay mode may not fully utilize the specified specific frequency, interference from D2D and cellular users impairs the underlay mode. Can a D2D system's resource allocation be optimized using the cognitive approach, in which users take use of an underutilized radio spectrum? The focus of this essay is on that. Through the optimization of the transmission rate for D2D users,

this study simultaneously satisfies five sets of power, interference, and data rate limitations. D2D users are depicted as supplemental cognitive 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 TX by PB serves as a single basis of energy 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. Algorithms and Methods

We have used the following algorithms and methods

3.1. **Fuzzy c-means (FCM)** is a clustering algorithm that is used to cluster data into a specified number of groups or clusters. This algorithm is similar to the k-means clustering algorithm, but instead of assigning each data point to a single cluster, FCM allows each data point to belong to each cluster to a different degree. This is known as "fuzzy" membership, which means that the degree of membership of a data point in a cluster can range from 0 to 1.

The algorithm then iteratively improves the clusters by minimizing the cost function. This is done by updating the cluster centers and the degree of membership of each data point in each cluster. The algorithm stops when the cluster centers and membership degrees converge to a stable solution. FCM allows for the use of prior knowledge or expert knowledge about the data to be incorporated into the clustering process, which can improve the quality of the clusters.

3.2. **Simultaneous wireless information and power transfer (SWIPT)** uses electromagnetic waves to transmit both data and electrical power wirelessly. The transmitter sends a signal that contains both the information to be transmitted and the power to be delivered to the receiver. The receiver has a device called a power splitter that is able to separate the information and power components of the signal. The information is then processed by the receiver's data receiver, and the power is directed to the device's power management unit. The power management unit stores the power in a battery or other storage device and uses it to power the device.

3.3. **The Dinkelbach algorithm** is a mathematical optimization technique used to solve nonlinear fractional programming problems. A fractional programming problem is a type of optimization problem in which the objective function is a ratio of two functions (i.e., a fraction). The Dinkelbach algorithm is an iterative method that seeks to find the optimal solution to a fractional programming problem by reformulating the problem into a series of simpler optimization subproblems. The Dinkelbach algorithm is based on the idea of dividing the objective function into two parts: the numerator and the denominator. The algorithm then iteratively solves a sequence of subproblems, each of which involves optimizing the numerator while keeping the denominator fixed. As the numerator is optimized, the value of the objective function (the ratio of the numerator to the denominator) is also optimized.

3.4. The Krust-Kahn (KK) algorithm is a mathematical optimization technique used to solve linear programming problems. A linear programming problem is a type of optimization problem in which the objective function and constraints are all linear functions. The KK algorithm is an iterative method that seeks to find the optimal solution to a linear programming problem by reformulating the problem into a series of simpler optimization subproblems. The KK algorithm works by dividing the constraints of the linear programming problem into two sets: the "basis" constraints and the "no basis" constraints. The algorithm then iteratively solves a sequence of subproblems, each of which involves optimizing the objective function while keeping the basis constraints fixed. As the objective function is optimized, the values of the no basis constraints are also optimized.

3.5.

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4. Implementation

4.1. Problem Formulation

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 [2], the "harvest-and-then-transmit" technique is applied. Sensors must first acquire energy from a wireless energy transfer (WET) in a downlink (DL) before communicating data wirelessly (WIT). The term "T_{max}" refers to the longest period that can be used to transmit data and collect energy. We take into consideration a WEHSN with TDMA that gathers energy from every sensor.

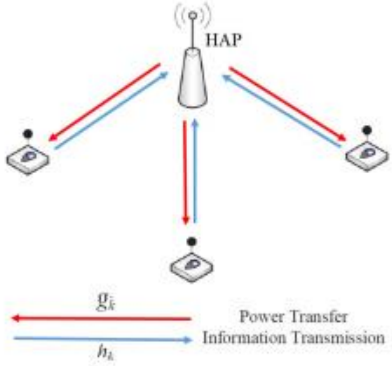

Fig. 1. System Model of Wireless Energy Harvesting Sensor Networks

information is transmitted throughout UL WIT and DL WET. The second interval has M slots, one for each sensor. It is expected that each sensor has the component for a channel information system (CSI) for resource sharing in the best possible condition. DL channel rise amid the Hybrid Access Points with respect to the sensor i and UL channel increase amongst sensor i and the HAP are represented through the letters G_i and h_i correspondingly. Throughout the BS to user phase, HAP shows the energy signal by a continuous power p_0, with τ_0 omnidirectional to all sensors. The quantity of energy collected at the sensor i can therefore state as

$$E_i^h = \left(n_i p_0 G_i - p_{c_r}\right)\tau_0 = f_i \tau_0$$

$$\forall_i \in \{1,2,\dots,M\} \tag{1}$$

Here, p_{c_r} the circuit's power usage through the energy gathering period, and i is the continuous energy alteration factor of the sensor. 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 throughout the user to BS link 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**+** $p_{c_t i}$ **)** i**,** where p_i represents the power supplied to the sensor i in the WIT and $p_{c_t i}$ represents the power used by the circuit. As a result, the throughput for sensor i that can be reached (normalized by bandwidth) can be expressed as

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

where σ^2 is the additive white Gaussian noise power at the HAP.

system throughput would be shown as

$$R = \sum_{i=1}^{M} r_i = \sum_{i=1}^{M} \tau_i \left(1 + \frac{p_i h_i}{\sigma^2}\right) \tag{3}$$

The total energy consumption in the network and the enrgy that is being consumed by each sensor will be shown as

$$E_i^T = \left(p_i - p_{c_t i}\right)\tau_i \tag{4}$$

$$E_T = \sum_{i=1}^{M} E_i^T = \sum_{i=1}^{M} \left(p_i - p_{c_t i}\right)\tau_i \tag{5}$$

Energy Efficiency (EE) is termed and defined as

$$EE = \frac{R}{E_T} \tag{6}$$

Now, we summarize the EE maximization as

$$EE$$

$$s.t. C_1 \;:\; E_i^T \le E_i^h$$

$$C_2 \;:\; \tau_0 \le \sum_{i=1}^{M} \tau_i \le T_{max}$$

$$C_3 \;:\; 0 \le \tau_0, 0 \le \tau_i, 0 \le p_i, \tag{7}$$

where the C1 constraint ensures that less energy was harvested by each sensor than was utilized over the WIT time. In the event that the first constraint, C1, is not met for sensor i no information will be delivered.

The problem (7) is known as fractional programming. Finding the appropriate λ, which is determined using the Dinkelbach Algorithm, is necessary to optimize EE.

4.2. Resource Allocation

τ_0 and $\{\tau_i\}$ are first taken to be constants. Slater's condition [2] is satisfied by the convex optimization problem which involves p_i. The proper application of the Lagrange dual technique enables the rapid discovery of the optimal solution [2]. To do this, we need the answer to the Lagrangian function, which is denoted by

$$L(\{p_i\},\{\gamma_i\}) = \sum_{i=1}^{M} \left[\tau_i\left(1+\frac{p_i h_i}{\sigma^2}\right) - \lambda(p_i + p_{c_t i})\tau_i\right] - \sum_{i=1}^{M} \left[(p_i + p_{c_t i})\,\tau_i - f_i\tau_0\right] \tag{3}$$

the Lagrangian coefficient is γ_i. Since complementary slackness causes the optimal lagrangian multipliers in constraint C3 to be zero, the corresponding lagrangian multipliers in constraint C3 are not included in equation (3). To comply with Karush Kuhn-(KKT) Tucker's [2] specifications, we have

$$\frac{\partial L}{\partial_{p_i}} = \tau_i \frac{h_i(e)}{\sigma^2 + p_i h_i} - \lambda_{\tau_i} - \gamma_i\tau_i = 0 \ \forall_i \ \epsilon \{1,\ldots,M\} \tag{4}$$

$$\gamma_i\left[(p_i + p_{c_t i})\tau_i - f_i\tau_0\right] = 0 \ \forall_i \ \epsilon \{1,2,\ldots,M\} \tag{5}$$

Now, look at the problems (4) and (5) to solve it with three cases:

Case 1) $\gamma_i \neq 0 \quad \forall_i \ \epsilon \{1,2,\ldots,M\}$, with this case, we have

$$p_i = \frac{f_i\tau_0}{\tau_i} - p_{c_t i} \tag{6}$$

$$\gamma_i = \frac{h_i}{\sigma^2 + p_i h_i} - \lambda \tag{7}$$

Both p_i and γ_i must be bigger than zero for KKT to be satisfied ($0 < \{p_i\}$ & $0 < \{\gamma_i\}$).

Case 2) where $\gamma_i = 0 \quad \forall_i \ \epsilon \{1,2,\ldots,M\}$ here we have

$$p_i = \frac{e}{\lambda} - \frac{\sigma^2}{h_i} \tag{8}$$

Case 3) firstly, we separate zero and nonzero γ_i**s** so that $\gamma_i \neq 0 \quad \forall_i \ \epsilon \{1,2,\ldots,K\}$ and $\gamma_i = 0 \quad \forall_i \ \epsilon \{K+1,\ldots,M\}$. With respect to the equations (6) and (8), we obtain the p_i corresponding to each γ_i.

In [2], makes use of the concept of "virtual queues" to dynamically allocate resources based on the current and predicted energy availability at each node in the network.

Here's how the resource allocation method works in [2]:

- The algorithm maintains a virtual queue for each node in the network. The virtual queue represents the amount of data that can be transmitted by the node in the future, given its current energy availability and the energy that is expected to be harvested.
- The algorithm uses the virtual queues to determine the number of resources (such as bandwidth and transmission power) that should be allocated to each node in order to maximize the amount of data transmitted while minimizing energy consumption.
- The algorithm adjusts the resource allocation based on the changing energy availability at each node. For example, if a node is expected to have a higher energy availability in the future, it may be allocated more resources to transmit more data.
- The algorithm repeats this process until all data has been transmitted or the network reaches a steady state.

By dynamically allocating resources based on the current and predicted energy availability of each node, the resource allocation method proposed in this paper aims to improve the energy efficiency of the wireless energy harvesting sensor network.

With the above points given and as in the reference [2] given, we obtained the equation

$$\tau_0 = \frac{T_{max}}{1 + \sum_{i=1}^{M} \frac{1}{\theta_i}} \ \& \ \tau_i = \frac{T_0}{\theta_i} \quad \forall \in \{1,2,\ldots,M\}$$

By using this equation, we can obtain our results.

4.3. Existing and new method protocol of storing harvested Energy

Energy efficient clustering protocols aim to minimize the energy consumption of nodes in a wireless sensor network while maintaining good cluster formation and communication. Some

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strategies for improving the energy efficiency of clustering protocols include:

4.3.1. **Minimizing the number of messages exchanged during the clustering process**: By reducing the overhead of communication, the energy expenditure of each node can be reduced.

4.3.2. **Selecting energy-efficient communication protocols**: Different communication protocols have different energy efficiency characteristics, so selecting a protocol that is well-suited to the specific requirements of the application can help to reduce energy consumption.

4.3.3. **Using sleep scheduling techniques:** Nodes in a wireless sensor network can enter a low-power "sleep" mode when they are not communicating, which can help to save energy. By carefully scheduling when nodes enter and exit sleep mode, it is possible to further improve the energy efficiency of the network.

4.3.4. **Using energy-aware routing protocols**: Routing protocols that take into account the energy levels of nodes can help to reduce energy consumption by routing data along the most energy-efficient path.

Improved energy efficient clustering protocol IEECP

4.3.5. **Optimizing the selection of cluster heads:** Cluster heads are responsible for relaying data from other nodes in the cluster, so it is important to select cluster heads that are energy efficient. This can be done by selecting nodes with strong communication capabilities or by using an energy-aware selection algorithm. This protocol is used to get the efficient results now.

4. Results

We use the "harvest-and-then-transmit" protocol proposed in. At first, sensors harvest energy in downlink (DL) from a Wireless Energy Transferring (WET), then, they transmit information in uplink (UL) towards a Wireless Information Transmission (WIT). This has increased the lifespan of the nodes thus further increasing the lifespan of the wireless energy harvesting sensor network.

Also, research studies on WSN routing prove that clustering offers an effective approach to prolong the lifetime of a WSN, particularly when it is combined with multi-hop communication that can reduce energy costs by minimizing the distance between the transmitter and the receiver. We have included both in our implementation method.

We know in a normal wireless sensor network the plot of the number of nodes alive to the rounds would be a straight line with a negative scope. To increase energy efficiency and network lifetime, the network can be divided into several groups (clusters), with two types of nodes in the cluster: cluster head (CH) and cluster member. The CH is responsible for gathering, aggregating data from its cluster members, and sending the collected data to the BS. The dissipation of energy in CH is higher than the cluster member when data is transmitted to longer distances. The energy consumption must be balanced along with nodes to achieve a maximum network lifetime. Accordingly, all nodes inhomogeneous networks are supposed, to begin with the same initial energy, it is possible to regularly rotate the role of the CH between the sensor nodes to distribute the energy dissipation. Also, clustering can reduce the consumption of energy by eliminating redundant transmissions and merging the collected data into a single packet and then transmitting it to the sink. Using this approach to implement we have successfully increased the network life

After 5000 rounds the number of nodes alive is plotted in the below graph. It can be noted that a 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.

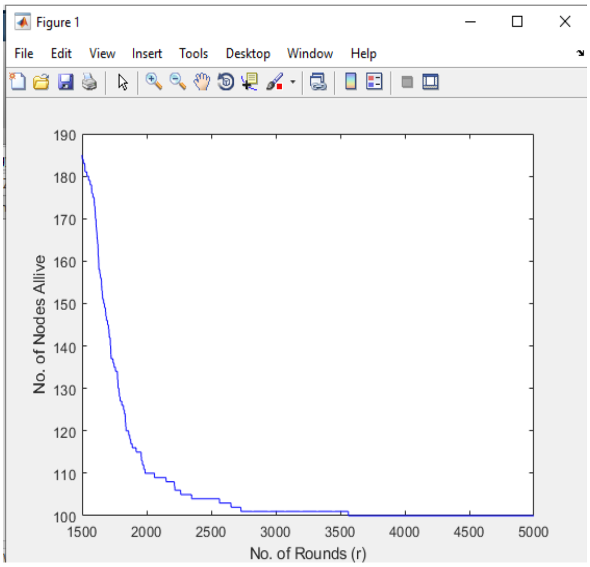

Fig -1: *No of Nodes Alive after 5000 Rounds*

No. of rounds Vs Energy consumption. The describes how the total amount of energy consumption increases with respect to total number of rounds. With the increasing number of rounds the number of packets being sent increases. According to our implemented method, we have realized an approximately linearly increasing graph between energy consumption and rounds. After 5000 rounds,

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the consumption of energy of all the nodes in the network **is** 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.

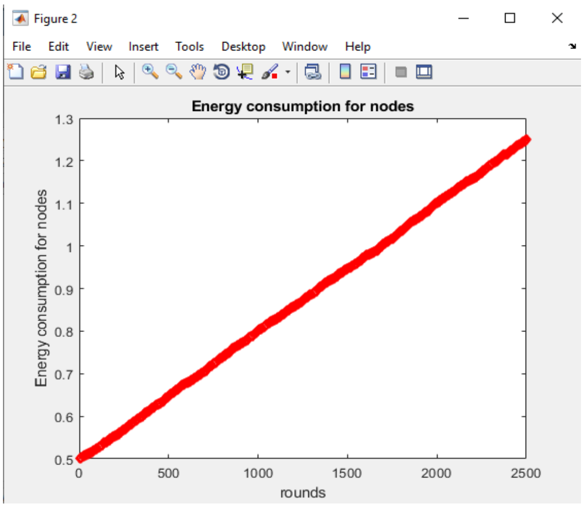

Fig -2: Energy Consumption for Nodes

Throughput is a measure of total units of information a system can process in a given amount of time. Related measures of system output include, the speed with which some specific workload can be completed and response time, the amount of time between a single interactive user request and receipt of the response. Latency is the delay from input into a system to desired result. It is a known fact that WSN is a resource constrained network in which energy efficiency is always the main issue since the operation of WSN depends heavily on the life span of the sensor nodes' battery. The most energy consuming operation in WSN is the data packet routing activity. The characteristics of the WSN are different from the conventional networks. These unique characteristics are often taken into account for addressing the issues and challenges related to network coverage, runtime topologies management, node distribution, node administration, node mobility, energy efficiency/consumption, network deployment, application areas/environment, and so forth.

Energy efficiency vs HAP transmit power is plotted in the below graph, which shows a greater usage of transmit power for making the nodes live to some longer rounds than the typical limit. It shows that the current protocol can maximize the power usage with minimal power.

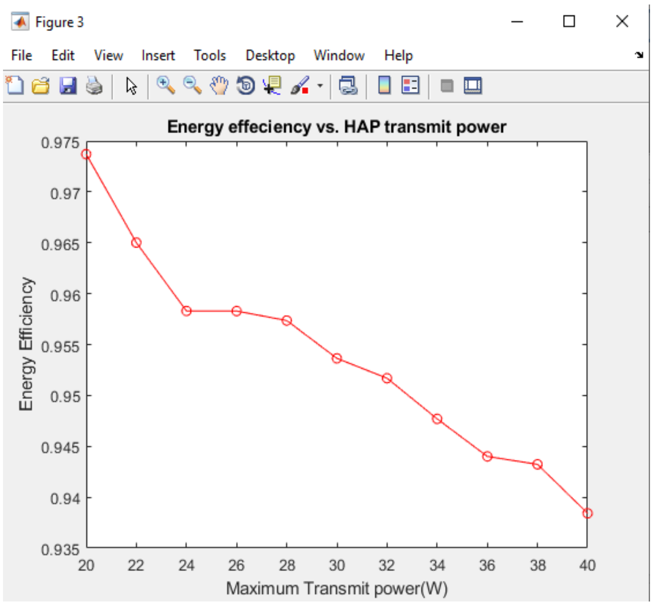

Fig -3: HAP TX power Vs Energy efficiency

Hybrid access point (HAP) is a node in wireless powered communication networks (WPCN) that can distribute energy to each wireless device and also can receive information from these devices. Recently, mobile HAPs have emerged for efficient network use, and the throughput of the network depends on their location. There are two kinds of metrics for throughput,

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

As mentioned before, throughput is the term used to refer to the quantity of data being sent that a system can process within a specific time period. Throughput is a good way to measure the performance of the network connection because it tells you how many messages are arriving at their destination successfully. If the majority of messages are delivered successfully then throughput will be considered high. In contrast, a low rate of successful delivery will result in lower throughput.

The lower the throughput is, the worse the network is performing. Devices rely on successful packet delivery to communicate with each other so if packets aren't reaching their destination the end result is going to be poor service quality. Within the context of a VoIP call, low throughput would cause the callers to have a poor-quality call with audio skips.

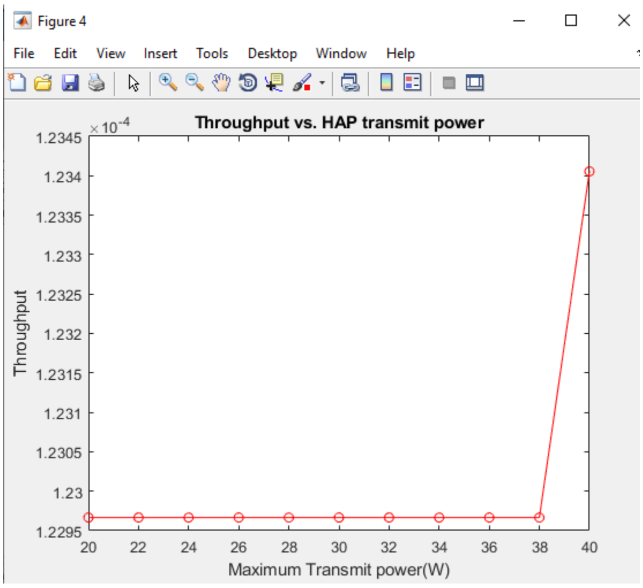

Fig -4: Hap TX power Vs throughput

Overall significant performance improvement is seen based on several factors such as enhancement in the network life time, energy efficiency, and utilizing maximum possible energy of each individual sensor network node; with the increase in rounds, the network throughput even increases more.

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 of 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 parameters and TX pow of every sensor to the system performance. Using the Dinkelbach algorithm, the issue is resolved, and the expression of a form of closed is obtained. The analytical findings demonstrate that throughput could slightly fall in comparison to the other ways, and the energy usage would decrease significantly more, leading to maximization of the efficiency of the network's energy.

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