Implementation of Distributed Energy Efficient Clustering for Wireless Sensor Network using Simultaneous Wireless Information and Power Transfer (SWIPT)

Nagaraju Sonti, Lakshmi Padmavathi Banka, Venkata Divya Lakshmi Garlapati, Bala Snigdha Gaddamadugu, Asha Anaparthi

[1]Assistant Professor, [2,3,4,5]UG Students
[1,2,3,4,5]Department of ECE
[1,2,3,4,5] Vasireddy Venkatadri Institute of Technology, Andhra Pradesh 522508, India.

Abstract - The idea of embedding a wireless sensor network (WSN) in a wireless-powered communication network is to achieve energy-neutral operation (ENO) of WSNs. However, if sensor nodes have high harvesting energies and reasonable connection budgets, the cluster head (CH) may need help to obtain sufficient energy for its operations. To overcome this issue, we propose implementing simultaneous wireless information and power transfer (SWIPT), allowing sensor nodes to transfer excess energy to the CH while transmitting data. Our proposed approach uses a SWIPT with DEEC protocol. It introduces structural changes to the ENO framework, providing a frame structure for the SWIPT process, the rate increase in performance subject to ENO, SWIPT ratio enhancement, clustering, and CH selection algorithm. We aim to determine the most appropriate approach to maximize the sensing data rate while ensuring ENO. We show through extensive simulations that our SWIPT-based scheme significantly enhances the achievable rate while providing ENO, in contrast to traditional methods that do not use SWIPT.

Keywords - Wireless Sensor Networks (WSN), Simultaneous wireless transformation and power transform (SWIPT), Cluster Head Node (CH Node), energy-neutral operation (ENO).

I. Introduction

Wireless Sensor Networks (WSNs) typically comprise hundreds or thousands of sensor nodes with sensing, processing, and communication capabilities [1]. Each node is capable of detecting activity and conducting basic calculations. A sensor node can transmit or receive data from a base station or its peers. Base stations link sensor networks, and sensor network protocols must be energy-aware to extend network lifespan due to the difficulty of replacing sensor batteries. WSNs should efficiently use network energy to monitor the environment for longer.

A sensor node comprises sensing, processing, transceiver, and power units [2]. Additionally, it may feature application-specific components such as a locator, power generator, and mobilizer. Sensing units, which include sensors and analog-to-digital converters (ADCs), transform analog signals from sensors based on observable phenomena into digital signals for processing. The processing unit, typically paired with a small storage unit, controls events that make the sensor node work with other nodes to perform sensing duties. Transceivers link nodes to networks. Power units and power scavenging units are crucial to sensor nodes. Most sensor network routing and sensing methods require accurate location, so sensor nodes often have location-finding systems. When needed, a mobilizer may shift sensor nodes.

Deterministic or random deployment of wireless network nodes is possible [3–6]. In physically accessible deployment areas, deterministic deployments are preferred, where sensor nodes are manually set at specific sites. Examples include a line in the sand for target tracking, city sense for urban monitoring, soil monitoring, etc. However, random sensor node deployment is employed when the deployment location is inaccessible, such as bird observation on Great Duck Island, Mines, etc. Sensor nodes are dropped from aeroplanes in such circumstances.

WSN lifetime is directly or indirectly affected by network energy. By clustering sensors, network energy may be used more efficiently. The cluster head, or master node, and numerous sensor nodes make up each cluster. The cluster leader does fusion and aggregation. Energy is essential for network longevity. Adding sensors to the monitoring region boosts network energy. The number of sensor nodes increases network energy, but the cost is considerable since each sensor costs ten times more than the batteries. Therefore, it's better and cheaper to put specific high-battery sensors to extend the network lifespan. Heterogeneous wireless sensor networks contain sensor nodes with varied energy levels [7].

However, meeting real-time requirements in WSNs is still a challenge. Very few results exist to date regarding meeting real-time requirements in WSNs, and most protocols either ignore real-time or attempt to process as fast as possible and hope that this speed is sufficient to meet deadlines. Some initial results exist for real-time routing. However, many other functions must meet real-time constraints, including data fusion, data transmission, target and event detection and classification, query processing, and security [8].

In this context, the paper presents SWIPT and LEACH algorithms that indicate different features with hybrid protocols. The overall system model has been implemented with and without SWIPT, and results have been concluded with the implemented formulations based on the SWIPT algorithms with DEEC and LEACH. Finally, the paper concludes by implementing effective bitrate and other energy features [8].

II. LITERATURE SURVEY

Researchers have proposed several optimization techniques to enhance the performance and lifetime of wireless sensor networks over the past few years. In 2008, Wang et al. [9] developed a multi-charge routing scheme for Distributed Source coding (DSC) to optimize routing. They proposed energy scheduling to improve network performance and energy utilization scheduling for efficient power optimization. Since then, several studies have been conducted to address the challenges wireless sensor networks face regarding energy consumption and network lifetime.

Phan et al. [10] focused on joint cross-layer optimization for energy distribution and green routing to meet Quality of Service (QoS) requirements in 2020. In 2021, Habibi et al. [11] proposed an optimization technique to evaluate direct and cooperative transmission preferences in a given node configuration. Long et al. [12] developed a tree-based diversionary routing scheme in 2022 to increase network lifetime. In 2007, Baek and Veciana [13] focused on trade-off optimization to achieve power efficiency in ad hoc network structures. In 2023, researchers will continue to explore new optimization techniques to improve the performance of wireless sensor networks.

For instance, Luo and Hubaux [14] addressed the durability problem of Wi-Fi sensor networks and proposed a primal-twin algorithm for joint optimization of routing and sink mobility. Guha et al. [15] studied energy-conscious routing schemes in wireless networks and proposed a coalition routing algorithm in 2020. Li et al. [16] addressed the dual optimization problem of lifetime and distortion to develop a generalized energy consumption model in 2021. Kim et al. [17] proposed a distributed joint routing and medium access control algorithm to maximize wireless sensor networks in 2022. Yang et al. [18] optimized routing and detection in fusion centres using three routing metrics and the Neyman-Pearson concept for joint optimization in 2023.

Chamam and Pierre [19] optimized sensor states in cluster-based sensor networks for increased network lifetime and less energy dissipation using an integer linear programming model, and Tabu searched heuristic in 2020. Shah and Lozano [20] developed fixed tree Relaxation-based and Iterative distributed algorithms to solve power distribution issues in 2021. In 2022, Chen and colleagues proposed a low-complexity online solution and distributed algorithm to maximize system application with power allocation in routing. This approach improved the network performance and energy efficiency. Valentini et al. [22] used dynamic multi-objective routing algorithms to frame a hybrid protocol for energy-efficient routing in 2023.

Hamadi and Chen [23] applied trade-off optimization between timeliness and power consumption to manage redundancy in heterogeneous wireless sensor networks in 2020. In recent years, Maddali [24] proposed the multi-cast routing protocol to maximize network performance, while Alanis et al. [25] developed a quantum-assisted algorithm for wireless multi-hop networks in 2021.

Zhang et al. [26] proposed a multi-objective optimization problem to balance load and power efficiency in 2022; Gupta and Bose [27] developed dual minimum total energy strategies to reduce power consumption in wireless sensor networks in 2023. In 2020, Luo et al. implemented an opportunistic routing algorithm to save energy, while in 2021, Tang et al. developed a cost-aware secure routing algorithm. In 2022, Ghaderi et al. proposed a solution for the minimum power routing problem in Wi-Fi networks. In 2023, Gupta et al. introduced an energy-efficient homogeneous clustering method for Wi-Fi sensor networks. Rahat et al. [32] proposed a multi-objective routing optimization technique in the current year.

III. SYSTEM MODEL DESIGN

The Simultaneous Wireless Information and Power Transfer (SWIPT) technique is a model proposed to address the energy limitations of Wireless Sensor Networks (WSNs). This technique is applied in various ways to reduce the total recharging cost and prolong the lifespan of the WSN while maximizing the rate of sensing data. Additionally, a dynamic routing algorithm has been proposed for a renewable WSN using SWIPT, increasing the sensing data's achievable rate. Figure 1 describes the model architecture.

- The DEEC protocol is designed based on the following assumptions about the wireless sensor network:
- All sensor nodes and base stations are deployed stationary and uniquely identified by an ID.
- The nodes are not equipped with GPS-capable antennae and hence are location unaware.
- Although the nodes have similar processing and communication capabilities, they may differ in terms of their energy levels, thus leading to heterogeneity.
- Once deployed, the nodes are left unattended, and recharging the batteries is impossible.
- Only one base station in the network has a constant power supply and hence no energy, memory, and computation constraints.
- Each node can aggregate data, and multiple packets can be compressed into one packet.
- The distance among the nodes can be estimated based on the received signal strength.
- Nodes can control their transmission power based on the distance of the receiving nodes. The node failure is considered only due to energy depletion.
- The radio link is symmetric, which means the energy consumption of data transmission from node A to node B is the same as that from node B to node A.
- The nodes in the network can be either homogeneous or heterogeneous but are not rechargeable.

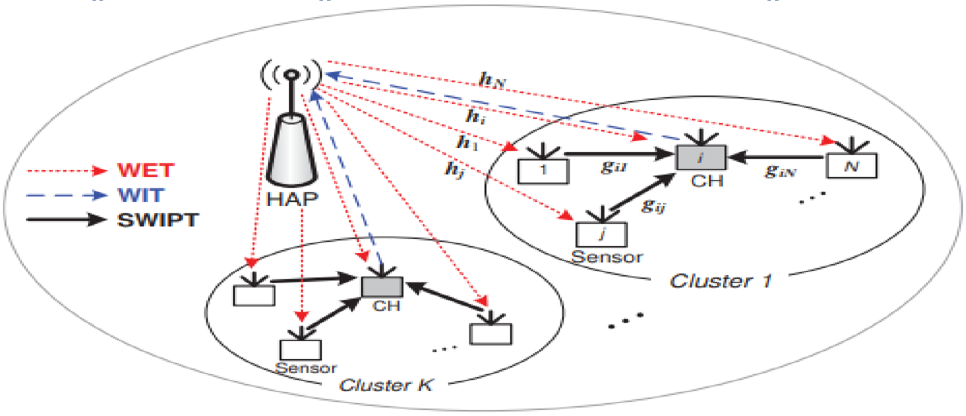

Figure 1: Architecture of Wireless Sensor Network

In this protocol, the wireless sensor network consists of three types of sensor nodes, each with different energy levels. The nodes with higher energy levels are assumed to be costlier and thus deployed in minimum numbers. On the other hand, the nodes with the lowest energy levels are the cheapest and hence can be deployed abundantly. This heterogeneity in the network helps optimise energy utilisation and extend the network's lifetime.

a. Design procedure

The proposed method's design procedure is illustrated in Figure 2.

A random sensor network is created, consisting of nodes. The network is then divided into clusters using the DEEC protocol, an energy-efficient protocol designed to minimize the energy consumption of nodes within each group. The DEEC protocol uses a probability-based method to choose cluster heads based on the ratio of each node's residual energy to the average energy of the network. Dead nodes in the network are identified by checking if their energy level is zero or below. A dynamic routing algorithm is used to transfer data from nodes to the cluster head and then from the cluster head to the base station. The simulation results include the following:

- The energy dissipation of each node.
- The number of dead nodes in the network.
- The achievable data transfer rate.

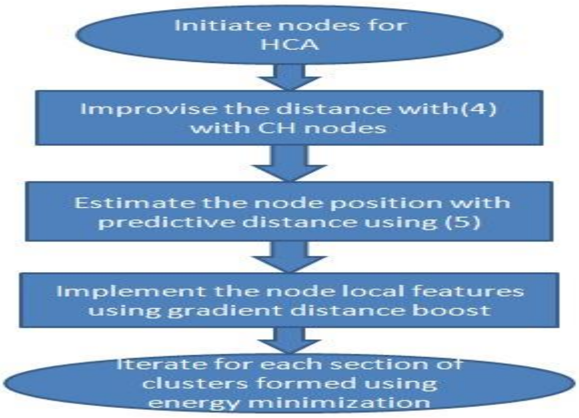

Figure 2: Step by Step Design of SWIPT

The Table 1 provides the values for various parameters used in the proposed method's design procedure. The number of nodes in the field is 100, and the number of clusters can be chosen from 2 to 4. The optimal election probability of a node to become a cluster head is 0.05. The packet length is 6400 bits, and the Ctr Packet length is 200 bits. The initial energy of each node is 0.5 Joules, and the energy consumed for transmission and reception is $50*10^{-9}$ Joules. The free space loss is $10*10^{-12}$ Joules, and the energy spent by the amplifier to transmit is $0.0013*10^{-12}$ Joules. The data aggregation energy is $5*10^{-9}$ Joules. These parameters are essential for evaluating the performance of the proposed method and optimizing its energy efficiency.

Table 1: Parameter Setup

Parameter	Value
Number of Nodes in the field (n)	100
Number of Clusters (k)	2 to 4
Optimal Election Probability of a node to become cluster head (p)	0.05
Packet Length	6400
Ctr Packet Length	200
Initial Energy (Eo)	0.5 Joules
Energy of Transmission, Reception	50*10-9 Joules
Free Space Loss (Efs)	10*10-12 Joules
Amount of energy spent by the amplifier to transmit (Emp)	0.0013*10-12 Joules
Data Aggregation Energy (EDA)	5*10-9 Joules

b. Energy minimization formulations

We improvise a Decision threshold for each set of nodes and selected clusters as:
This design for energy equation is measure with the square root of the sigmoid function as in equation (1):

$$S(i) = \sum_{j=1}^{N}\sum_{i=1}^{N} \boldsymbol{\mu} * \boldsymbol{Fx(i,j)} + \boldsymbol{\varphi} * \boldsymbol{Fz(i,j)}) \quad (1)$$

The $\boldsymbol{\mu}, \boldsymbol{\varphi}$ The functionality of the S represents the design solution of which nodes appear at a given timing aspect where each set of the design parametric are considered with active and dead cell from the equation(1).

$$\boldsymbol{F(i > k)} = \sum_{i=1}^{N}(\boldsymbol{n_i} * \boldsymbol{Dmin(i)} + \boldsymbol{\sigma} * \boldsymbol{S(i)}) \quad (2)$$

In equation (2), F representing the solution model for where all the active and alive nodes in cell regions are established with equation (1). n_i representing the no of active nodes and $\boldsymbol{\sigma}$ being the best predicted based on DEEC protocol for all iterations as mentioned in algorithms above.

$$\boldsymbol{PE_{MPR's}} = \boldsymbol{F(i > k)} \quad (3)$$

$$\boldsymbol{PE_{Head\_cluster}} = \boldsymbol{\gamma} * \boldsymbol{W_i} * \boldsymbol{D_{min}} + \boldsymbol{\mu MPr(i)} + \boldsymbol{E(i)} \quad (4)$$

In equation (4), $E(i)$ represents the entropy of each selected feature on node localization selected.
Hence the total Network energy estimated as in equation (5):

$$\boldsymbol{PE_T} = \boldsymbol{PE_{Head\_cluster}} + \boldsymbol{PE_{cluster\_LCM}} \quad (5)$$

Here γ, μ, σ, estimated probabilities for the optimized values for the best solution in modified.

a. Heterogeneous Network Model:

In our model, we assume that there are N sensor nodes, which are evenly scattered within a M×M square region and organized into clusters hierarchy for aggregate data by cluster heads to base station. That is located at the center of this region. Nodes have low mobility or stationery as being assumed at [15, 16]. In the two-level heterogeneous networks advanced nodes fraction m with a time more energy than the others which have an initial energy E0. The total energy is assumed as in equation (6):

$$E_{total} = N(1-m)E_o + NmE_o(1+a) = NE_o(1+am) \quad (6)$$

In multi-level heterogeneous networks, the clustering algorithm should consider the discrepancy of initial energy, Etotal is expressed by equation (7):

$$E_{total} = \sum_{i=1}^{N} E_o(1+a_i) = E_0(N + \sum_{i=0}^{N} a_i) \quad (7)$$

ni denotes the number of rounds to be a cluster-head for the node si, and we refer to it as the rotating epoch. In DEEC protocol, we choose different $n_i = \frac{1}{p_i}$is based on the residual energy of Ei(r) node si at round r. If nodes have different amounts of energy, pi of the nodes with more energy should be larger than p opt. Let Ē(r) denotes the average energy at round r of the network, which can be obtained by equation (8):

$$\bar{E}(r) = \frac{1}{N}\sum_{i=1}^{N} E_i(r) \quad (8)$$

To calculate Ē(r) we have equation (9):

$$p_i = p_{opt} * \left(\frac{E_i(r)}{\bar{E}(r)}\right) \quad (9)$$

Where G is the set of nodes that are eligible to be cluster-heads at round r, ni is chosen based on the residual energy Ei(r) at round r of node si as follows in equation (10):

$$n_i = \frac{1}{p_i} = n_{opt} = \frac{E(r)}{E_i(i)} \quad (10)$$

When the networks are heterogeneous, the reference value of each node should be different according to the initial energy. In the model of multi-level heterogeneous networks, the weighted probability shown as in equation (11):

$$p(s_i) = p_{opt} * N\,(1+a_i) * \frac{E_i(r)}{N + \sum_{i=1}^{N} a_i}\bar{E}(r) if\ s_i \in G$$

$$\bar{E}(r) = \frac{1}{N}(E_{total})\left(1 - \frac{r}{R}\right) \quad (11)$$

$$\bar{E}(r) = \frac{E_{total}}{E_{round}}$$

The total Energy dissipated in the network during a round is as shown in equation (12):

$$E_{round} = L(2 * NE_{cluster} + NE_{dt} + k\varepsilon_{np}d_{toBS}^4 + N\varepsilon_{fi}d_{toCH}^2)$$

$$d_{toBS} = \frac{M}{\sqrt{2\pi k}}, d_{toCH} = 0.765 * \frac{M}{2} \quad (12)$$

Where k is the number of clusters, EDA is the data aggregation cost expended in the cluster heads evolving. The lost energy is proportional to the number of cluster heads noted by s in this area. Thus the probability threshold (5), which each node si uses to determine a cluster-head in each round, becomes in our proposed approach as in equation (13):

$$\begin{Bmatrix} T_i(s_i) = \dfrac{p_i}{1 - p_i * \left(rmod\left(\frac{1}{p_i} - \frac{a}{N * p_i}\right)\right)} \\ 0 \end{Bmatrix} if\ s_i \in G \quad (13)$$

Where α is the number of nodes that are excluded from the cluster head threshold selection due to their location and distribution density reason, with an initial value of 0. When s increases, T(si) increases as well, therefore the chances of nodes, that are eligible to be cluster heads, decreases. Indeed, with this algorithm we can save the lost energy caused by the election of these cluster heads excluded and extend the lifetime of the network. The analytical method to calculate the number s is a perspective of this work.

IV. RESULTS AND DISCUSSION

Implementation:

Step 1: The clustering begins by dividing the network into k non-empty subsets or clusters. The seed points are computed as the centroids, with j=1 to k denoting the index of centroids and i=1 to mc indicating the nodes, where mc is the number of the nearest nodes. The remaining nodes select their CH based on Euclidean distance to the closest centroid.
Step 2: The re-clustering process begins by calculating the centroid of each cluster. This operation is recursively executed with the new CH in each cluster until the CH is no longer changed.
Step 3: Once the clusters are formed, each node is assigned an ID number based on its distance from the centroid, with smaller numbers assigned to nodes closer to the centroid. Figure 2 shows the sensor nodes distributed with their ID numbers. The ID number is used to select the CH, with the node having the lowest number chosen as the CH. The connectivity of the network is maintained by checking the residual energy of the CH every round. If the energy falls below a threshold, the node with the following lowest ID number is selected as the new CH. The newly elected CH informs other nodes of the change.

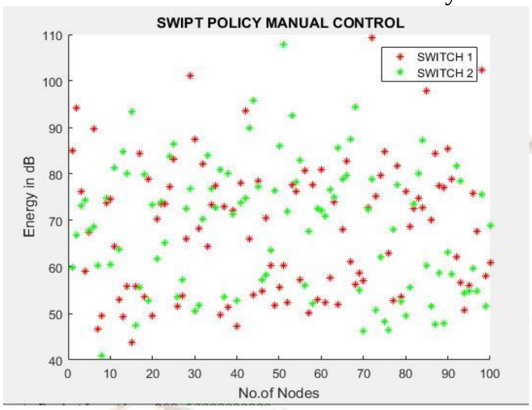

Figure 3: Energy in dB for Cluster 1 - 2

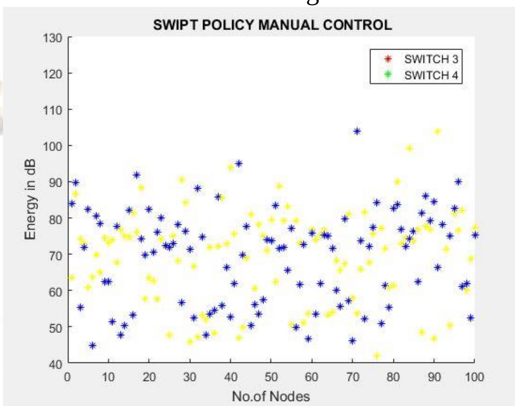

Figure 4: Energy in dB for Cluster 3 - 4

Figures 3 and 4 improvising the overall cluster representation based on the operational changes of the design with SWIPT model on 1-4 clusters.

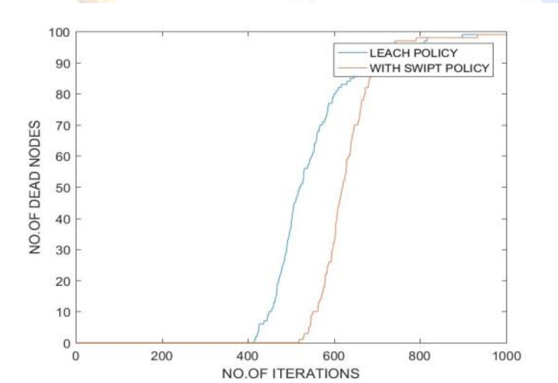

Figure 5: Estimation of Number of Dead Nodes both in SWIPT Policy and LEACH Policy

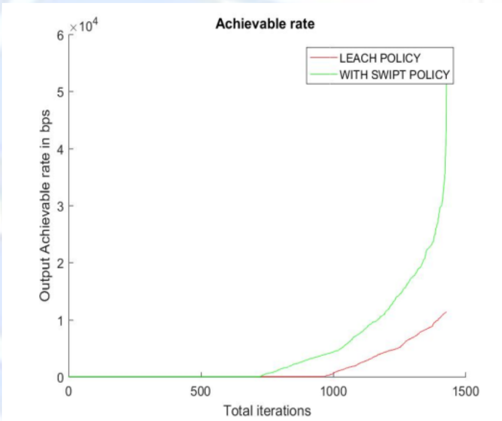

Figure 6: Achievable rate of SWIPT Policy and LEACH Policy

After implementing the proposed changes in the design, we observed a significant improvement in the overall bit rate, which increased to four times that of the existing LEACH model. This is demonstrated in figures 5 and 6, which provide a more accurate representation of the design.
In figure 5, we can see the overall dead cluster time for each iteration, which indicates the passive states. This state helps to activate higher frequency of active nodes for the DEEC protocol with SWIPT, ultimately improving the network's performance.
The overall parametric representation of the proposed design can be found in Table 2.

Table 2: Comparative values for the existing and proposed model

Parameters	LEACH	Proposed method (DEEC + SWIPT)
Achievable Rate	1.2	5.8
Energy (dB)	23.09	1.1
Dead clusters iteration	400	600

V. CONCLUSION

This study demonstrated that selecting cluster heads closest to others can lead to significant energy dissipation, ultimately reducing the network's performance. We proposed using the SWIPT model with the DEEC protocol to address this issue, which improved bit rates and energy optimizations.

Although previous studies have only utilized LEACH and DEEC protocols without optimization using hybrid or natural selective algorithms, we observed that machine learning algorithms could be more efficient and improve performance.

Moving forward, our proposed approach involves utilizing MDE concepts, UML/MARTE profiles, and design patterns to support the high-level specification and automatic analysis of WSNs. By employing this approach, we aim to develop an energy-aware reconfigurable WSN that can meet the demands of modern applications.

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