A Hybrid Two-Tier Energy Efficient Routing Protocol for WSN

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***Abstract*— In many applications, wireless sensor networks (WSNs) provide an easy-to-use monitoring solution. As the idea of the Internet of Things has become more widely accepted, it is expected that the number of applications will increase in the future. A large number of WSN applications rely on the restricted energy provided by the batteries to power the nodes in the network. As a result, research on energy-efficient data routing protocols is essential for the evolution of these protocols. This paper presents LEACH-DE, a hybrid routing protocol that can be used with two-tier WSNs that include the concept of energy harvesting nodes. This protocol combines the low energy adaptive clustering hierarchy (LEACH) protocol with differential evolution (DE) based optimization technique to form the LEACH-DE protocol. The simulation results show that the proposed approach outperforms both the original LEACH algorithm and various metaheuristic optimization techniques in terms of prolonging network lifetime.**

***Keywords*—** *Wireless sensor networks, Energy-efficiency, Routing, Differential evolution*

I. Introduction

Wireless sensor networks (WSNs) are severely limited in operating over long periods due to a lack of available energy and power consumption imbalances caused by the unequal discharge of nodes. As a result, creating energy-efficient innovative routing solutions is essential for extending the life of WSNs. By reducing the amount of energy consumed by each node, energy-efficient routing protocols aim to extend the life of a network [1]. Classical routing algorithms have made significant progress in increasing the life of wireless sensor networks. They do, however, have several disadvantages, such as scalability and resilience [2]. On the other hand, metaheuristic optimization algorithms (MOAs) have demonstrated better performance [3]. In [4] , author presented a Bee Cluster protocol, an efficient energy grouping technique based on an augmented artificial bee colony (ABC) metaheuristic that they developed. They said that ABC is a popular choice among population-based metaheuristic algorithms for tackling WSN optimization issues because of its simplicity of implementation and applicability to various situations. To lengthen the lifespan of a network, [5] employed the quantum ABC variation, using the ABC method amplified with a Cauchy operator, and [6] used the ABC algorithm for solving linear cluster optimization projects. Implementing particle swarm optimization (PSO) in software and hardware is easier than other metaheuristic approaches such as genetic algorithms (GA). The alternative metaheuristic technique is favored over different genetic algorithms (GA) approaches. PSO provides high-end solutions because it can escape local optima and achieve rapid convergence. PSOs have also been mentioned in several papers on the design of WSN routing and clustering protocols. A few examples of PSO applications in recent literature are general two-tier network routing protocols [7], a multi-objective approach to mobile sink path design, an underwater mobile sink application, and PSO in conjunction with Grey Wolf Optimizer. The routing algorithm differential evolution (DE) has also been proven in other research to be a suitable contender for energy-efficient (EE) WSN routing [8]. In [8], the author demonstrates how DE may be used to improve clustering. The author in [9] shows how DE may be used when nodes have 3D directional antennas. Researchers developed a hybrid method that blends the two techniques using DE and fuzzy logic-based clustering. It has been shown that a hybrid mix of DE and Simulated Annealing (SA) improves the clustering performance [10] in clustering. The capacity to tackle optimization issues in broad search spaces is a criterion for selecting DE for further development.

In summary, research has shown that combining DE with another algorithm can result in a procedure that is significantly more energy-efficient. Except for the MOA described above, the low energy adaptive clustering (LEACH) hierarchy has been demonstrated to be a competitive alternative to routing inside a two-tier network [11]. Thus, LEACH and its following enhancements are frequently cited as performance reference procedures in the scientific community. As a result, the performance of DE and SA in establishing energy-efficient WSN networks is evaluated in contrast to the popular ABC, PSO, and classic LEACH protocols in this study. When using wireless sensor networks with energy harvesting capabilities, it is possible to achieve eternal network functioning by keeping sensor nodes in Energy Neutral States (ENSs). The authors of Peng et al. said that to sustain an ENS, the quantity of energy consumed by a sensor node must not exceed the amount of energy harvested by an energy harvesting device during a certain period of time [12]. Within a two-tier WSN, this study presents a new hybrid algorithm for energy-efficient message routing that is both fast and efficient. The proposed method comprises a well-established LEACH and DEFINE (LEACH-DE) mix. When it comes to extending the network's life, this combination of algorithms has been more effective than other widely used MOAs.

The rest of the paper is divided as follows: section 2- routing and energy model, section 3- metaheuristic optimization algorithm, section 4- simulation, analysis, and discussion, section 5- conclusion and future work.

II. Routing and Energy Model

This study aims to propose an algorithm for two-tier network architecture, as shown in Figure 1. Cluster Heads (CHs) gather data from Sensor Nodes (SNs) and send it to the Base Station in this arrangement (BS). Energy is employed in this network for sensing and transmission. The control packets exchanged when network routes are created a negligible energy impact. The network sends messages from each SN to the BS during each messaging cycle.

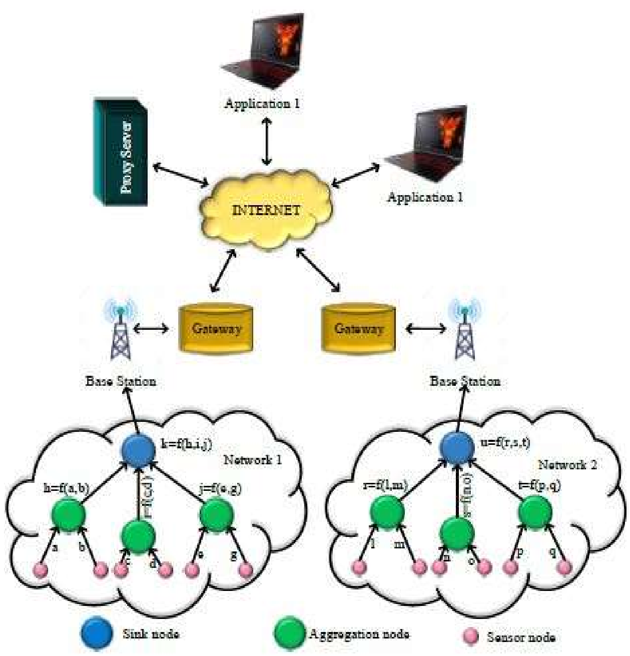

Fig.1: Application-oriented two-tier cluster-based Wireless Sensor Network

Energy model

This study uses a simplified general Euclidean distance coefficient (EDF) energy model like that applied in [13,14]. In this energy model, the receiving energy is represented by equation (1) and the transmission energy by equation (2).

$$E_{Rx(i)} = \epsilon_{r_x} \cdot b_{t_i} \tag{1}$$

$$E_{Tx(i,j)} = \begin{cases} \epsilon_{t_x} \cdot b_{t_i} + \epsilon_{hop} \cdot b_{t_i} \cdot d_{i,j}^2 & \text{if} \quad d < \lambda \\ \epsilon_{t_x} \cdot b_{t_i} + \epsilon_{hop} \cdot b_{t_i} \cdot d_{i,j}^4 & \text{if} \quad d \geq \lambda \end{cases} \tag{2}$$

The energy used by the sensor node circuits to transmit messages is ϵ_{t_x} and ϵ_{r_x} is the energy used for receiving massages. The transmission amplifier coefficient is $\epsilon_{hop} \cdot b_{t_i}$ represents message packet length in bits. $d_{i,j}$ is the Euclidean distance between nodes j and i. The path loss follows the free space loss, $d^2_{i,j}$, or multi-path loss $d^4_{i,j}$, based on its length relative to the cross over distance λ . CH spends a finite amount of energy, E_{DA}, on gathering information from cluster members. It is also essential to determine how much energy remains after a message round. It is assumed that all nodes in an energy harvesting network have energy harvesting features that contribute random amounts of additional energy E_{Rech_i} to the nodes. The node's exposures to the external energy source vary because nodes are not located in the same place. E.g., in the case of solar energy harvesting, exposure to the sun varies with orientation. E_{Next_i} is the remaining energy after a messaging round.

$$E_{Next_i} = E_{\text{init}\,i} - E_{Used_i} + E_{\text{Rech}\,i} \tag{3}$$

In equation (3), node i−'s total energy from the previous round is E_{initi}, and energy consumed in the current round is $E_{Usedi.}$

III. Metaheuristic Optimization Algorithm

This section studies alternatives algorithm for use in both clustering and the steady-state phases. In the literature, there is a large range of energy-efficient routing algorithms [15]. Due to its popularity, LEACH will be studied, as well as DE with other popular meta-heuristic optimization algorithms (MOAs) for benchmarking purposes. The other selected MOAs are ABC, PSO, and SA.

Differential Evolution

Differential Evolution (DE), which is considered to be a stochastic direct search approach, was presented by [16]. It's an Evolutionary Algorithm (EA) that goes through the same mutation, crossover, and selection processes as EA [17]. In order to generate new candidate solutions, mutation and crossover operators are applied (offspring). As a result, when the offspring achieves a higher fitness value, it takes the place of the parents' solution. Basic DE pseudo-code with D decision variables, a population size of N_P, and a generation counter G is summarized in algorithm 1. During each generation G, the algorithm selects from the population distinct individual vectors $X_{r1}^G, X_{r2}^G, X_{r3}^G$ That is distinct from the target vector X_i^G . A mutation computation is implemented using the difference between these vectors [18]. According to equation (4), a mutant vector matching a target vector, X_i^G i = 1, 2, 3,..., N_p, is created for F > 0.

$$V_i^G = X_{r1}^G + F \cdot (X_{r2}^G - X_{r3}^G) \tag{4}$$

To regulate differential variation amplification $(X_{r2}^{G} - X_{r3}^{G})$, the mutation scaling factor F is applied. The crossover technique also makes the perturbed parameter vectors more diverse.

The resulting trial vector is given by,

$$U_{i,j}^{G} = \left(U_{i,1}^{G}, U_{i,2}^{G}, \dots, U_{i,D}^{G}\right) \quad (5)$$

Where,

$$U_{i,j}^{G} = \begin{cases} V_{i,j}^{G} & \text{if } \left(CR > \text{rand}_{i,j}\right) \text{ or } j == j_{\text{rand}} \\ X_{i,j}^{G} & \text{otherwise} \end{cases} \quad (6)$$

j_{rand} guarantees that the trial vector inherits at least one variable from the mutant vector V_i^G.

Algorithm: DE Algorithm

```
Create a random population with a uniform distribution.
    R X^0_{i,j} = X_j^min + rand(0,1) · (X_j^min − X_j^max)
while max iterations are not reached
    do
    for i = 1 : N  do
        Generate V^G_{i,j} using equation (4)
        for i = 1 : D
        do
            Generate U^G_{i,j} using equation (6)
        end for
        Generate X^{G+1}_{i,J} using equation (7)
    end for
end while
```

Using the law of natural evolution as described by Equation 7, the selection operator preserves the better parameter between the trial vector U_i^G and target vector X_i^G preserving the better parameter. There is a good chance that the selected vector will persist and be carried on to the following generations; if we are solving for the minimum of a function, the vector with the highest fitness value is the one with the lowest objective function value.

$$X_{G+1}^{i,j} = \begin{cases} U_{i,j}^{G} & \text{if } f(U_i^G) \le f(X_i^G) \\ X_i^G & \text{otherwise.} \end{cases} \quad (7)$$

IV. Simulation, Analysis, and Discussion

A. Experimental Setup

The experiments are run on a toolbox written in the Matlab/Octave programming language. A network of 50 nodes is run by the toolbox on a two-dimensional square field of 100m. The BS is located at the coordinates (50, 175), 75m away from the nodes. SNs are initialized with E_{init} = 0.5J of energy each. The following parameter values are set: $€_{tx}$ = 50 nJ / bit, hop = 100 PJ/(bit · m2), b_{t_i}=2500 bits and $€_{tx}$ = 50 nJ / bit. The simulations are run until the last node dies. All the MOAs with a population of N_p = 60 individuals executing for Niter = 60 iterations are used. Table 1 lists all the important MOA parameter settings.

Table 1: Parameters and corresponding metaheuristic

Algorithm	Parameters	Value	Description
ABC	L a	1800 0.99	Abandonment limit Acceleration coefficient
DE	F CR	0.5 0.5	Amplification control value Crossover rate
PSO	φ C_{cog} C_{soc}	0.1 0.25 3	Inertia Cognitive acceleration Social acceleration
SA	T_0 α	0.025 0.99	Initial Temperature Temperature reduction rate

B. Hybrid Protocol: Result and Analysis

All of these metaheuristic algorithms performed poorly in clustering operations as compared to LEACH. The metaheuristic technique fails to produce optimum outcomes, despite the fact that the clustering goal function is well-formulated. LEACH-CS outperforms metaheuristic-based clustering algorithms as a consequence. However, when it comes to routing outcomes, DE outperforms all others in terms of network durability.

As a consequence, the novel hybrid routing method for two-tier networks combines LEACH as a clustering method and DE as a routing protocol (LEACH-DE). In an energy-harvesting network, LEACH-DEEH will be the name for LEACH-DE. In order to determine LEACH-energy DE's efficiency, it is initially used for the test without including energy harvesting.

The LEACH-DE efficiently balances average network energy while lowering node death rates until it approaches half of the nodes are dead(HND), as shown in Fig 2.

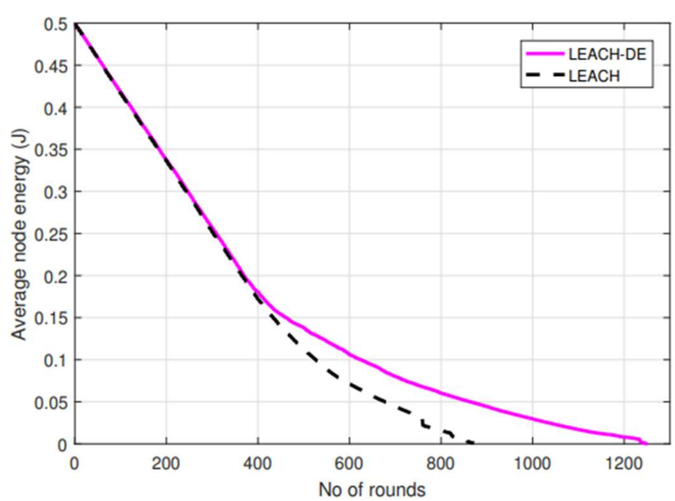

Fig.2. The average energy of the node per messaging round.

As the node's death rate surpasses the HND point, it continues to rise as shown in Fig 3.

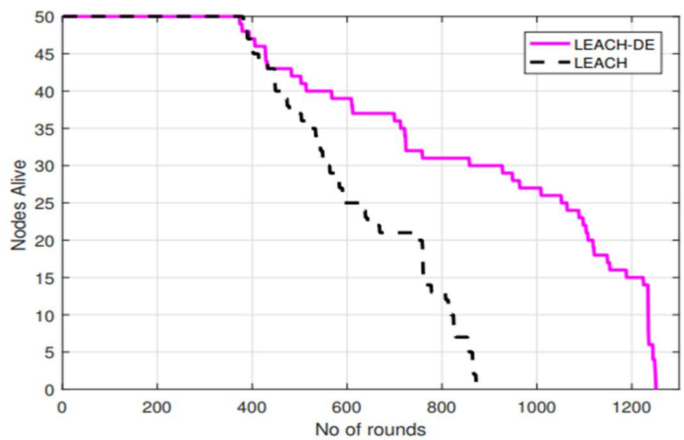

Fig.3. The number of alive nodes per messaging round for LEACH.

Figures 2-4 show how LEACH-DE compares to conventional LEACH-CS, which is used as a reference.

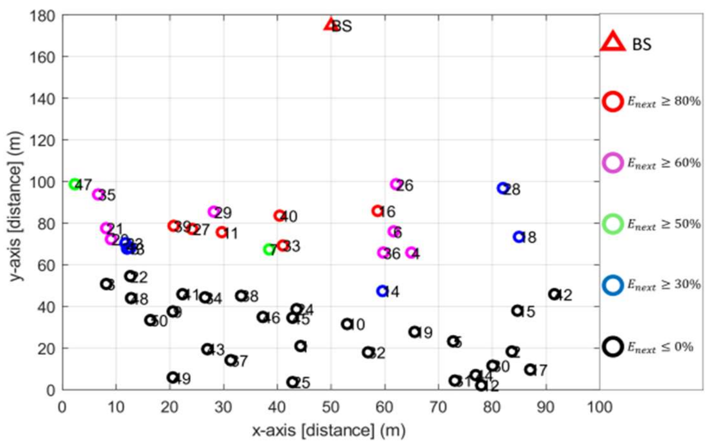

Fig.4. Energy network map after HND.

The performance of LEACH-DEEH with energy harvesting is shown in Figs 4 . After 10000 transmission rounds, the novel protocol nearly reaches energy neutral state (ENS), as average network energy is balanced as high as 0.18J, as shown in Fig 5.

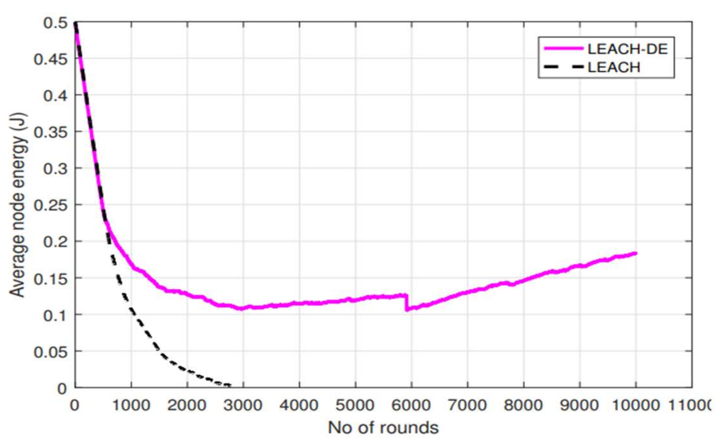

Fig.4. Average node energy per message round in an energy harvesting network.

In terms of network lifetime, round 5960 saw the highest mortality of 17 nodes, while the average number of alive nodes remains at 45.

V. Conclusion & Future Work

In comparison to ABC, PSO, and SA, DE was the greatest contender for dealing with the complex energy-efficient routing challenge WSNs face to extend network lifetime. These MOAs, including DE, did not perform well when it came to clustering. LEACH-CS, a LEACH variation, outperformed other LEACH variants in clustering. LEACH-DE, a new cluster-based routing method, is developed as a result of these considerations. In comparison to previous MOAs, the proposed hybrid LEACH-DE protocol can retain higher node energy and provide superior load balancing in the network. LEACH-DE achieves ENS when it is further integrated into an energy harvesting network. In the future, Hybrid protocols combining other clustering approaches that will perform better than LEACH will investigate in detail.

References

[1] I.E. Agbehadji, R.C. Millham, A. Abayomi, J.J. Jung, Simon, J. Fong, S.O. Frimpong, Cluster ing algorithm based on nature-inspired approach for energy optimization in heterogeneous wireless sensor network, Appl. Soft Comput. 104 (2021) 107171.

[2] V. Narayan and A. K. Daniel, “Multi-Tier Cluster Based Smart Farming Using Wireless Sensor Network,” in 2020 5th International Conference on Computing, Communication and Security (ICCCS), 2020, pp. 1–5.

[3] V. Narayan and A. K. Daniel, “RBCHS: Region-Based Cluster Head Selection Protocol in Wireless Sensor Network,” in 2021 Proceedings of Integrated Intelligence Enable Networks and Computing, Springer, 2021, pp. 863–869.

[4] A.Ari, B.O. Yenke, N. Labraoui,I. Damakoa, A. Gueroui, A power efficient cluster-based routing algorithm for wireless sensor networks: Honeybees swarm intelligence based approach, J. Netw. Comput. Appl. 69 (2016) 77–97

[5] S. Famila, A. Jawahar, Improved artificial bee colony optimization-based clustering technique for WSNs, Wirel. Pers. Commun. 110 (4) (2020) 2195–212.

[6] V. Narayan and A. K. Daniel, “A Novel Approach for Cluster Head Selection using Trust Function in WSN,” Scalable Comput. Pract. Exp., vol. 22, no. 1, pp. 1–13, 2021.

[7] V. Narayan, A. K. Daniel, and A. K. Rai, “Energy efficient two tier cluster based protocol for wireless sensor network,” in 2020 International Conference on Electrical and Electronics Engineering (ICE3), 2020, pp. 574–579.

[8] X. Li, L. Xu, H. Wang, J. Song, S.X. Yang, A differential evolution-based routing algorithm for environmental monitoring wireless sensor networks, Sensors 10 (6) (2010) 5425–5442. doi: 10.3390/s100605425.

[9] Sharma, V. Vashisht, U. Singh, Eefcmde: energy-efficient clustering based on fuzzy c means and differential evolution algorithm in wsns, IET Comm. 13 (2019) 996–1007.

[10] Faiz, Mohammad, and A. K. Daniel. "Wireless Sensor Network Based Distribution and Prediction of Water Consumption in Residential Houses Using ANN." International Conference on Internet of Things and Connected Technologies. Springer, Cham, 2021.

[11] V.Narayan and A.K. Daniel, "A novel approach for cluster head selection using trust function in WSN," in 2021 Scalable Computing: Practice and Experience, 22(1), pp.1-13.

[12] Wang, C. Low, Energy neutral clustering for energy harvesting wireless sensors networks, Ad Hoc Netw. 28 (2015) 1–16.

[13] Faiz, Mohammad, and A. K. Daniel. "Multi-criteria Based Cloud Service Selection Model Using Fuzzy Logic for QoS." International Conference on Advanced Network Technologies and Intelligent Computing. Springer, Cham, 2021.

[14] Kumar Dwivedi, Anshu, et al. "SCSZB: Sensor Congregate Stable Zonal-Based Routing Protocol Designed for Optimal WSN." Advances in Smart Communication and Imaging Systems. Springer, Singapore, 2021. 139-149.

[15] F. Fanian, M.K. Rafsanjani, Cluster-based routing protocols in wireless sensor networks: A survey based on methodology, J. Netw. Comput.Appl. 142 (2019) 111–142.

[16] R. Storn, K. Price, Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces, J. Glob. Optim. 11 (4)(1997) 341–359.

[17] G. Li, Q. Lin, L. Cui, Z. Du, Z. Liang, J. Chen, N. Lu, Z. Ming, A novel hybrid differential evolution algorithm with modified code and jade,Appl. Soft Comput. 47 (2016) 577–599.

[18] I. Boussa¨ıd, J. Lepagnot, P. Siarry, A survey on optimization metaheuristics, Information sciences 237 (2013) 82–117