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RESEARCH ARTICLE

# ENERGY EFFICIENT ADAPTIVE ROUTING VIA ENHANCED TEMPORAL CONVOLUTIONAL NEURAL NETWORK

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**Abstract – A Wireless Sensor Network (WSN) comprises numerous resource-constrained sensor nodes (SNs) that are tasked with sensing, processing, and transmitting data. Among the primary challenges in WSNs are optimizing energy consumption (EC) and extending network lifetime (NL). In this paper, a novel Energy-based Routing Algorithm for Adaptive Wireless Sensor Networks (ERA-WSN) is proposed to address these challenges. The ERA-WSN framework employs an Enhanced Temporal Convolutional Network (ETCN) for optimal cluster head (CH) selection, ensuring energy-efficient clustering. Subsequently, routing is performed using the Grey Wolf Optimization (GWO) algorithm to improve data transmission efficiency. The proposed method is evaluated using the NS2 simulator. Experimental findings show that ERA-WSN outperforms existing models such as FTOPOSIS-HJBO, EEACHS, and M-PSO methods in terms of latency, EC, packet delivery ratio (PDR), and NL. ERA-WSN decreases latency by 19.6% compared to FTOPOSIS-HJBO, 13.5% compared to EEACHS, and 16.1% compared to M-PSO methods respectively.**

***Keywords –*** *Wireless Sensor Networks, Enhanced Temporal Convolutional Network, Grey Wolf Optimization, data transmission.*

## 1. INTRODUCTION

A wireless sensor network (WSN) is a network made up of many tiny devices that measure the surroundings in respect to specific parameters [1]. The functional advantages are provided by the sensors' compact size, affordability, low power consumption, and simple neighbor communications [2]. Numerous industries, including industrial automation, military systems, and intelligent infrastructure, use WSN real-time applications [3]. In certain situations, the WSN needs a large number of SNs in order to manage real-time applications [4]. Node mobility, environmental changes, and node additions or deletions can all cause WSN to dynamically alter the network structure in order to maximize network performance [5].

Utilizing resource-constrained SNs to increase the total NL is a difficult task in WSN since the SNs are equipped with restricted processing power, poor memory capacity, and minimal battery power [6]. Thus, one of the core problems in WSN is balancing the energy of nodes [7–10]. To extend NL and improve network efficiency, nodes' EC must be optimized and balanced [11–13]. Hierarchical clustering techniques, which offer advantages in terms of scalability and efficiency, have proposed substitutes for network energy harvesting in order to address energy-related problems. Using data aggregation, clustering algorithms effectively balance node energy in WSNs [14].

Each cluster comprises CH, which uses single-hop communication to collect, aggregate, compress, and send data from cluster members (CM) to the base station (BS) or sink node [15]. However, these protocols have limitations that hinder them from extending network lifetime, such as choosing a random CH without taking energy metrics into account, failing to achieve optimal cluster formation and CH, having higher communication overhead, routing through a single hop, and having more energy expedite. In this paper, we suggested an ERA-WSN, which seeks to increase network lifetime by finding an energy-efficient path to the BS. The main contributions of ERA-WSN are:

- Initially, the CHs are selected using the Enhanced Temporal Convolutional Network (ETCN), ensuring accurate and energy-efficient CH selection.
- After CH selection, routing is optimized using the GWO algorithm to improve data transmission efficiency and reduce delays.
- The efficacy of the suggested ERA-WSN framework has been assessed based on key metrics, including EC, latency, PDR, and NL, demonstrating superior results compared to existing techniques.

The remaining portion is organized as follows. Literature review is covered in Part 2, and the ERA-WSN approach is defined in Section 3. The result and conclusion are defined in Parts 4 and 5, respectively.

## 2. LITERATURE REVIEW

In 2023, Chaurasia et al [16] presented a Meta-heuristic Optimized CH selection-based Routing algorithm for WSNs (MOCRAW). It reduces node EC and promotes faster data transmission. Results from simulations show that the proposed approach is more energy-efficient (EE) than its existing methods.

In 2023, Rami Reddy et al [17] provided an Artificial Bee Colony (ABC) algorithm to effectively elect CHs and multipath routing in WSNs to facilitate efficient data transfer. The local optima problem is avoided during the solution space search process with this suggested method. Experiments on a large WSN network with node mobility difficulties have been carried out.

In 2023, Ambareesh et al. [18] provided the Fuzzy TOPSIS-based Hybrid Jarratt Butterfly Optimization (FTOPSIS-HJBO) technique for finding the best route between CH and BS. The suggested technique achieved a high throughput rate and high PDR of almost 99% and 55 kbps for 100 s, respectively, according to the comparative analysis conducted for the suggested technique and several other models.

In 2023, Vijayalakshmi et al. [19] developed the EE Adaptive CH Selection Algorithm (EEACHS). The integrated cluster's role is dynamically adjusted based on its remaining energy, balancing the EC of the entire underground network. According to the simulation results, a network's lifespan can be greatly increased by achieving high energy efficiency.

In 2024, Prakash et al. [20] examined the Genetic algorithm (GA) and the modified particle swarm optimization (M-PSO) approach for choosing CHs and non-CHs. Furthermore, when compared to current new methods like GAPSO-H, EC-PSO, and NEST, the suggested approach operates better. Nonetheless, DMPRP outperforms NEST, EC-PSO, and GAPSO-H by 12% on average [21].

## 3. PROPOSED METHOD

In this section, a novel Energy based Routing for Adaptive WSN (ERA-WSN) technique has been proposed. Initially, the cluster heads (CH) are selected using the Enhanced Temporal Convolutional Network (ETCN), ensuring accurate and energy-efficient CH selection. After CH selection, routing is optimized using the Grey Wolf Optimization (GWO) algorithm to enhance data transmission efficiency and reduce delays. Figure 1 represents the overall block diagram of the suggested ERA-WSN technique.

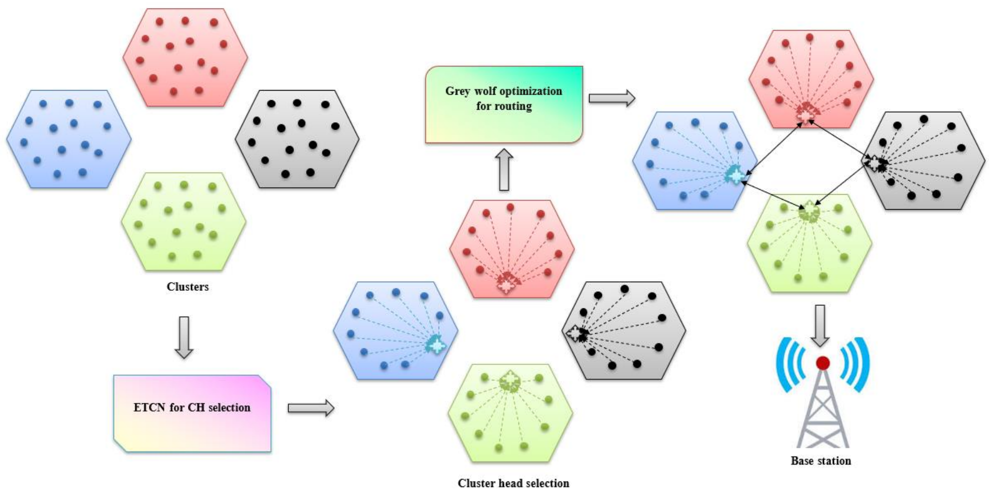


**Figure 1.** ERA-WSN framework

### *3.1. Cluster head selection*

For selecting the cluster heads, Enhanced Temporal Convolutional Network (ETCN) has been used. Multiple convolutional layers can be accumulated in the TCN structure by employing the block structure in deep learning (DL). Each TCN layer is used as a block of input is output. As a result, the flow in the network is more transparent, improving the model's readability. Overfitting and predict effects may worsen, and the model's performance is negligible as the number of convolutional layers increases. The recurrent processing of the convolutional layer is the root cause of the issue. We use a dual-residue model to solve this issue and aggregate more significant data. We introduce the TCN model's application of a doubly residual TCN stack.

The overall structure separates each layer's output into two information streams: anticipated branches and backtracking. The output flow of each convolutional block layer connects to the input flow of the subsequent layer. Let C stand for the backtracking branch. The following formula 1 describes how it works. Enter $C_l$ for the current layer to go back. The input at each layer for the preceding layer of output $\hat{C}_{l-1}$ is the output less the input from the previous layer. Forecasts for any stratum can be obtained using the complete system. The model can more accurately approximate the usable backwards push signal by processing data based on the anticipated result of the preceding layer of input minus the output. For any stratification, forecasts can be obtained using the full system. To improve the model's approximation of the useful rearward push signal, data processing based on the prediction result of the preceding layer of the output can be used. Each fundamental module's processed data is combined using many layers. R should be used to represent the prediction branch. At the same time, the final output $\hat{R}$ value is a data fusion for the expected output of all layers for the predicted output $\hat{R}_l$ of the present layer. Each layer block's output in the dual-residue TCN structure allows for 1 × 1 convolution, which facilitates inter-layer interaction and integration. It is possible to handle more significant information flows with this structural design. The output is categorized into two types, such as CH node and member node.

$$C_1 = C_l - \hat{C}_{i-1} \tag{1}$$

$$\hat{P} = \sum_l \hat{P}_l V_l \tag{2}$$

### 3.2. Routing

After CH selection, routing has been performed using GWO algorithm. GWO is based on the structured leadership hierarchy of grey wolf packs, which is divided into four levels: alpha (the leader), beta (second in command), delta (subordinates), and omega (followers). The algorithm emulates the collaborative hunting process of grey wolves, which involves tracking, encircling, and attacking prey. During the optimization process, candidate solutions are represented as grey wolves, and their positions are updated iteratively based on the influence of the $\alpha, \beta, and\ \delta$ wolves, which represent the best solutions found so far. The GWO algorithm's steps include initializing a population of solutions, evaluating their fitness, and updating their positions to converge towards the optimal solution. A termination condition, like a maximum number of iterations or a suitable fitness level, is reached at the end of this iterative process. Complex optimization problems can be effectively solved by GWO because of its capacity to strike a balance between solution space exploration and exploitation, yielding reliable and effective results. The steps are explained as follows.

***Initialization***

The first step in using Grey Wolf Optimization (GWO) for routing in WSN involves initializing a population of candidate prioritization schemes. Each scheme is denoted by a grey wolf, with its position in the solution space defined by a set of variables that dictate the priority levels assigned to different types of data frames. These initial positions are generated randomly within the defined boundaries of the solution space to ensure a diverse set of starting points for the optimization process.

***Fitness Function (FF)***

The FF is crucial for evaluating the effectiveness of each candidate prioritization scheme. In the context of WSN, the fitness function measures how well a prioritization scheme meets the network's performance criteria, such as minimizing latency, reducing packet loss, and maximizing throughput. The FF value for each candidate solution is calculated based on these criteria, with higher fitness values indicating more effective prioritization schemes that ensure timely and reliable data transmission.

***Update Positions***

Once the fitness values are determined, the positions of the grey wolves are updated to reflect the influence of the top three solutions: $\alpha$ (best), $\beta$ (second best), and $\delta$ (third best). The other wolves adjust their positions based on the locations of these three leaders. This process involves simulating the encircling and hunting behavior of grey wolves, where the wolves move towards the prey (optimal solution) by updating their positions according to mathematical models that mimic the wolves' natural movements.

***Exploration and Exploitation***

GWO balances exploration and exploitation through its iterative position updates. During the early iterations, the model emphasizes exploration to cover a wide area of the solution space. As the iterations progress, the focus shifts towards exploitation, honing in on the most promising regions identified by the $\alpha, \beta, and\ \delta$ wolves. This equilibrium guarantees that the algorithm can identify the optimal frame prioritization solution without becoming trapped in local optima.

***Termination***

Until a termination criterion such as attaining a predetermined fitness threshold or a maximum number of iterations is satisfied, the iterative process of updating locations and assessing fitness keeps going. The final result is the prioritization scheme represented by the alpha wolf, which has been optimized to ensure the most efficient and effective transmission of data in the WSN network.

## 4. RESULTS AND DISCUSSIONS

Simulations of the suggested technique have been conducted in NS2 simulator. Additionally, experiments were carried out on a wide range of nodes, starting with 100 and testing up to 500. Each of these nodes is positioned on a surface that measures (200×200) m 2. The proposed ERA-WSN framework is compared with existing methods such as FTOPOSIS-HJBO, EEACHS, and M-PSO in terms of specific parameters such as EC, average latency, PDR, and NL.

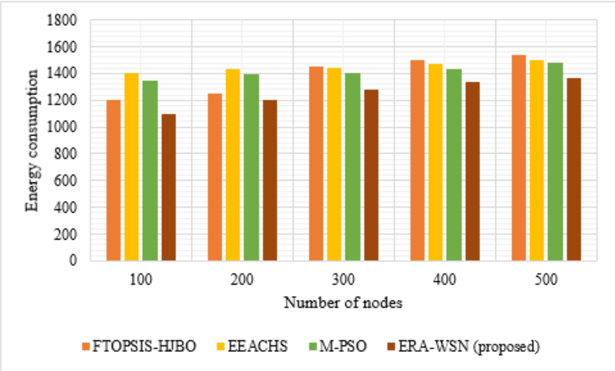


**Figure 2.** Energy consumption

Figure 2 compares the EC of the ERA-WSN framework with other approaches such as FTOPOSIS-HJBO, EEACHS, and M-PSO. It highlights how the proposed method optimally selects cluster heads and routes data, reducing unnecessary energy usage. Figure 2 demonstrates ERA-WSN's superior efficiency in conserving node energy, enhancing overall network performance.

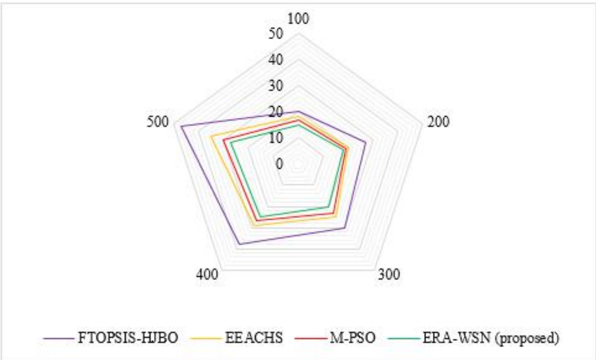


**Figure 3.** Latency comparison

Figure 3 shows the latency in data transmission for the ERA-WSN framework against competing methods. It emphasizes the efficiency of ERA-WSN's routing protocol, which minimizes delays by leveraging optimal paths. The results show a significant reduction in delay, improving real-time data processing capabilities for WSN applications. ERA-WSN decreases end-to-end delay by 19.6% compared to FTOPOSIS-HJBO, 13.5% compared to EEACHS, and 16.1% compared to M-PSO methods.

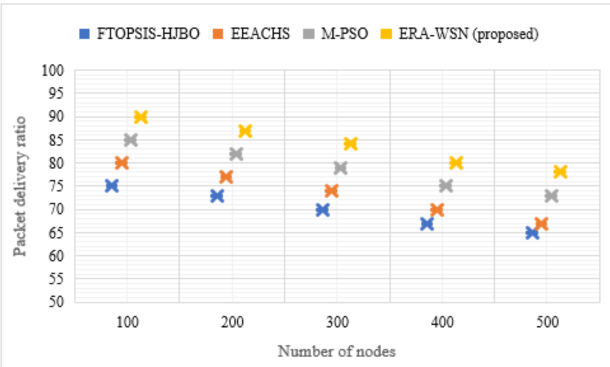


**Figure 4.** Packet delivery ratio comparison

Figure 4 shows the PDR achieved by the ERA-WSN framework compared to other methods. It highlights the robustness of ERA-WSN's routing mechanism, which ensures reliable data transmission. The higher PDR observed for ERA-WSN underlines its ability to maintain network performance even under challenging conditions.

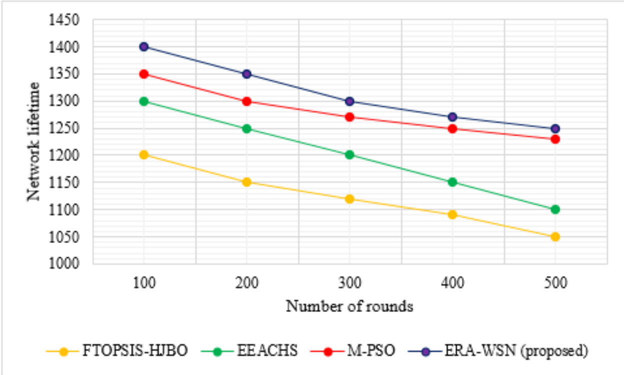


**Figure 5.** Network lifetime comparison

Figure 5 compares the NL achieved by ERA-WSN with other existing approaches. By efficiently balancing energy consumption across nodes, the proposed method extends the operational NL. The results demonstrate ERA-WSN's capability to significantly extend network longevity compared to FTOPOSIS-HJBO, EEACHS, and M-PSO.

## 5. CONCLUSION

In this paper, a novel ERA-WSN has been proposed, aimed at reducing EC and latecy while improving NL and PDR. Initially, cluster heads (CH) are selected using the Enhanced Temporal Convolutional Network (ETCN) for accurate and energy-efficient CH selection. Following this, the routing is optimized using the Grey Wolf Optimization (GWO) algorithm to ensure efficient data transmission. The suggested method has been implemented in the NS2 simulator, and experimental results indicate that ERA-WSN outperforms existing approaches like FTOPOSIS-HJBO, EEACHS, and M-PSO methods. ERA-WSN decreases end-to-end delay by 19.6% compared to FTOPOSIS-HJBO, 13.5% compared to EEACHS, and 16.1% compared to M-PSO methods. The ERA-WSN framework achieves a better network lifetime, energy efficiency, and performance metrics. In the future, this approach can be extended to incorporate advanced machine learning models and security mechanisms to develop robust and secure WSN protocols.

## CONFLICTS OF INTEREST

This paper has no conflict of interest for publishing.

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