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Improved Power Effective Node Combined Heterogeneous Path Protocol for Enhance Network Lifetime Based on Cloud Resource Management in WSN

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Abstract: Nowadays, sensor nodes are connected wirelessly to the Wireless Sensor Network (WSN). A WSN contains frequent sensor nodes spread throughout surroundings. These nodes are responsible for identifying, approximating, and receiving information. There is a unique technology called a "sensor cloud" that combines the sensor capabilities of WSNs with the architecture of Cloud Computing (CC). The small sensor nodes can sense, process, and transmit data. However, it is difficult and expensive to extend the lifespan of WSNs. Using energy-efficient routing protocols ensures reliable data transmission and prolongs the network's lifespan. However, control limitations can have a substantial control on the overall lifetime of the network. Since batteries power nodes in WSNs, they will eventually lose all power after a certain period. Therefore, we introduced the Improved Power Effective Node Combined Heterogeneous Path (IPENCHP) protocol to solve the above problem. Initially, we use the Enhanced Butterfly Optimal Cluster Algorithm (EBOCA) to select an ideal Cluster Head (CH) from a group of nodes. Furthermore, the ONND method can enhance the network's energy efficiency of the node. The path between CHs and BSs is found using the Ant Colony Optimum Based Path Distance (ACOPD) algorithm. Finally, the IPENCHP protocol can prolong the network lifetime of cloud resource management by assessing the energy communication level within a cluster. According to the simulation results, IPENCHP outperforms regarding energy efficiency, packet loss rate, energy consumption, performance latency, and Throughput.

Keywords: *Energy-Efficient, WSN, cluster head, EBOCA, ACOPD, ONND, IPENCHP, Network lifetime, and Throughput.*

Introduction

In modern times, a WSN consists of multiple sensors positioned in different locations to detect the surrounding environment. These sensors communicate with each other wirelessly, allowing for flexible networking options. They can be easily relocated and connected to wired or wireless internet. WSNs are known for their ability to self-organize, provide comprehensive coverage, and their low cost. They are used in various fields, including military, computer, communication, and aerospace.

The CC model can fulfil the resource needs of different requests by expanding the physical media of devices. Other sensor nodes connect with receivers in a typical WSN. These receivers gather and process the data before transferring the information to a server. Before sending the data, the receivers typically perform setup, processing, and description operations [1-2].

By utilizing CC technology, individuals can rent and use a cloud service provider's platform, infrastructure, and software support. Sensor cloud incorporates a blend of WSN and CC, enabling users to access sensors through it, utilize CC applications, and enhance the performance of sensor networks [3].

When there are more nodes in WSNs, transmitting such data to remote nodes without losing any of it is necessary. However, sending such a massive amount of data can overwhelm the network's capacity and cause congestion, delays, and packet loss. Congestion in WSNs can lead to information loss and consume much power [4]. However, integrating different cloud-based technologies for battlefield surveillance can be a significant challenge. Many wireless devices in WSNs are small, low-power, and often placed in challenging locations [5].

This part aims to lower energy usage and increase network service life. To address these issues, we first use EBOCA to choose the most suitable CH among the available nodes. We can

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use these to determine a node's distance from its neighbours and remaining energy. The network's energy efficiency is enhanced using the ONND algorithm. Next, the path between the CH and the base station can be found by implementing the ACOPD algorithm. Finally, the IPENCHP protocol is proposed to reduce energy consumption and extend network lifetime for cloud resource management. Moreover, the IPENCHP protocol provides a reliable and comprehensive space to maintain constant energy and distance weights. The simulation results show that IPENCHP has high energy efficiency regarding the network life cycle, data packet transmission rate, and transmission delay.

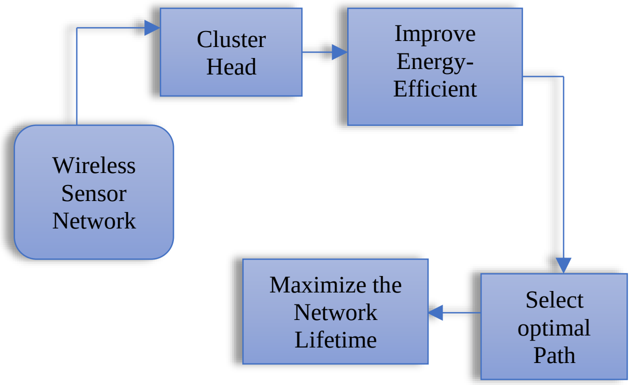

Fig. 1. Architecture Diagram for Wireless Sensor Network

Figure 1 shows the fundamental structure of a WSN. Multiple procedures are employed to recognize opportunities for resource management. The cluster head can assess tactics for enhancing energy efficiency, identifying path distance, and optimizing the network's lifespan.

2. Literature Survey

A novel energy-sharing algorithm can be proposed using the Energy-Efficient Regional Resource Routing (ER-SR) protocol. Also, based on the network, these can dynamically select the higher residual energy nodes as source routing nodes [6]. The Enhanced Clustering Hierarchy (ECH) technique is designed to advance energy efficiency in WSNs. These techniques also include sleep/wake mechanisms for duplicate and adjacent nodes [7]. The novel proposed that using a routing protocol called Enhanced Balanced Energy-Efficient Network Integrated Super-Heterogeneous (E-BEENISH) to measure and optimize energy consumption in WSNs can provide a viable solution for analyzing and optimizing energy consumption in clusters and heterogeneous WSNs [8]. An energy-efficient architecture for WSNs can be described based on environmental conditions using Machine Learning (ML) and metaheuristic techniques. Energy-saving methods based on topology in WSN require the sensor nodes to be attentive [9]. To further progress them, a new process of Sensor Node Training for Intellectual Data Transmission using Clustering and Reinforcement Learning (SARSA) is defined using Clustering SARSA (C-SARSA) and the optimum key of the objective function [10].

The novel reports that different techniques can be used to implement algorithms of ML-based WSNs with strengths, weaknesses, and network lifetime parameters. Furthermore, synchronization, congestion control, scheduling for mobile receivers, and energy harvesting can be efficiently managed [11]. A practical example of using a Received Signal Strength (RSS) method in a residential location is proposed. This method is cost-effective regarding operation time, calibration, and energy consumption [12]. The novel discussed the use of tiny sensing devices in various systems, including household appliances, communique devices, medical electronics, and transportation organizations. These small and low-power devices use Energy-Harvesting Spectrum Harvesting (EH-SH) technology [13]. A WSN energy by Wireless Power Transfer (WPT) is assisted by Multi-Access Edge Computing (MEC) that multiple users can access via mobile devices. The BS has various antennas that serve the entire sensor network, and the sensor nodes solely rely on WPT for power [14]. The novel describes using mobile sinks (MS) to collect various data. It proves to be NP-hard because it requires more attention to contain data from WSN to the cloud within a certain period [15].

A new control method, CC-Knowledge Compression-Sensitive Routing Intelligent Migration (CSR-IM), has been proposed. This method uses pressure-sensitive theory to calculate the movement speed and position of the target node [16]. The novel recommends using the RLSSA-CDG algorithm for compressive data gathering, which utilizes reinforcement learning. The algorithm models active node selection as a finite Markov decision process [17]. The novel explored different energy-saving strategies researched by other groups in WSN and applied them to decrease the energy usage of nodes and prolong the lifespan of the entire network. [18]. In the novel, a new approach called Energy-Aware Graph Clustering and Intelligent Routing (EGCIR) aimed to balance energy consumption and load balancing by utilizing WSN supervisory systems [19]. Reinforcement Learning (RL) algorithms empower network nodes to perceive their surroundings and independently choose the most effective actions to maintain a stable network operation [20].

The novel suggested that the Dynamic Energy Efficient Routing (DEER) protocol can guarantee communication transfer, maximum network lifetime, and message tide [21]. The technology uses a hybrid approach to manage resources through virtualization. It employs K-means clustering for task mapping and dynamic clustering techniques, which are improved with micro genetic algorithms [22]. The novel used a Wireless Power Transmission-based Energy Re-Distribution (WPTERD) process. Further, these steps are divided into two sub problems, WPTERD-Egy and WPTERD-Time. WPTERD-Egy aims to optimize energy loss, while WPTERD-Time focuses on optimizing time [23]. Two important aspects are discussed and emphasized to understand and analyse WSN deployment problems. Elements utilize optimization models and Artificial Intelligence (AI) to offer potential solutions [24]. It focuses on fundamental concepts related to WSNs and describes research on metaheuristics and heuristic algorithms used to solve these problems [25].

The novel classifies sophisticated WSNs based on various aspects such as sensor type, deployment strategy, sensing model, coverage, and energy efficiency [26]. WSNs extensively utilize clustering and routing algorithms to upturn the network's lifetime. The Butterfly Optimization Algorithm (BOA) has been established to select the best cluster head from a group of nodes [27]. The novel proposed utilizing Support Vector Regression (SVR) and Genetic Algorithms (GA) for estimating resource allocation and creating a structure to execute it [28]. The resource allocation strategy is designed to dynamically allocate resources based on CC's Adaptive Multi-Objective Teaching Learning Optimization (AMO-TLBO) algorithm [29]. The novel approach uses virtualization technology to map the hardware resources of WSNs to CC resources. Similarly, the proposed method can be manipulated for network architecture by implementing resource allocation strategies [30]. Securing WSNs can be challenging because of the self-organization and randomness of sensor nodes. However, WSNs are becoming more popular due to their low power consumption, cost savings, and self-organization benefits [31]. According to the novel, a new method suggests genetic mechanisms can support decreased energy consumption. However, the issue of energy consumption is becoming increasingly critical for WSNs [32]. The novel reported that the back-propagation method can design a 16-bit Ripple Carry Adder (RCA) and a 16-bit carry-select adder [33]. The novel suggested that implementing the Adaptive Neuro-Fuzzy Inference System (AFIS) method can realize a flawed node credentials system based on the classifier. Moreover, ANFIS assists in extracting the confidence parameters of the classifier from certified trusted and malicious nodes [34]. The novel proposed that the Internet of Things (IoT) and Mobile Ad Hoc Network (MANET) will create a new MANET-IoT system. The main objective is to lower network implementation costs while also improving users' mobility [5].

2.1 Problem of Statement

- Considering routing in WSN can lead to substantial energy expenses throughout the network caused by frequent changes in topology based on events.
- However, it reduces network performance regarding network lifetime and reliable routing.
- It is challenging and expensive to prolong the lifespan of WSNs because sensor nodes rely on low-power series.
- The energy consumption of sensor nodes poses a significant challenge that can cause a gradual reduction in the lifetime of the entire network.
- WSN's massive computational requirements and limited energy storage are one of the most critical challenges.

3. Proposed Methodology

The IPHENHP protocol is discussed in this section as a method to conserve energy and prolong network lifespan. EBOCA enables us to choose the best cluster head for managing cloud resources from a collection of nodes. The leftover energy and proximity from the node's neighbours can be ascertained by selecting a cluster head. The ONND mechanism is used to increase the network's energy effectiveness. The ACOPD method should determine the path between the CH and the BS. Finally, the IPENCHP protocol offers a trustworthy, comprehensive space for maintaining consistent energy and distance weights. By doing this, cloud resource management will use fewer resources overall and prolong the network life cycle.

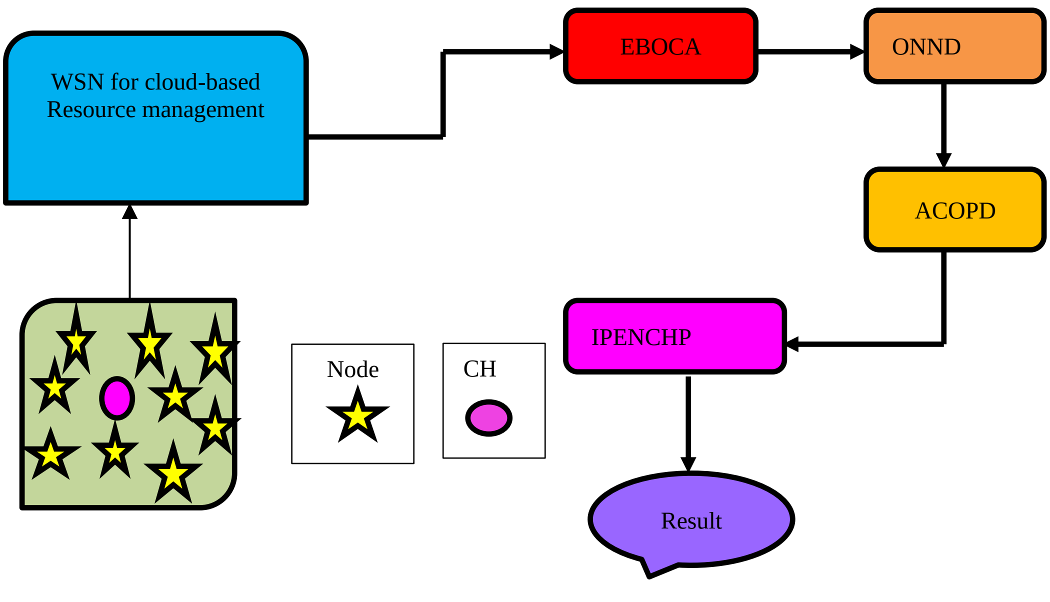

Fig. 2. Architecture Diagram for Proposed IPENCHP Method

Figure 2. Illustrated architecture diagram for IPENCHP protocol to reduce overall energy consumption and increase the cloud resource management network lifetime. These provide a reliable and comprehensive space to maintain consistent energy and distance weights for cloud resource management.

3.1 Enhanced Butterfly Optimal Cluster Algorithm (EBOCA)

In this segment, the CH selection phase of EBOCA, the butterfly network sensors control which sensor groups to select as CHs. The size of each butterfly parallels the quantity of CHs in the network. EBOCA is an algorithm inspired by nature and falls under metaheuristic algorithms. The Butterfly algorithm is a potent metaheuristic that mimics the feeding behaviours of butterflies. These insects have numerous olfactory receptors on their bodies, which consist of neurons known as chemoreceptors. These receptors are also utilized to identify and locate a compatible mate. Additionally, it utilizes search algorithms to categorize butterfly behaviour. The ability of EBOCA to select the most suitable CH from all of the network's sensors depends on the node degree. Various factors can help improve the management of cloud resources, such as node degree, node centrality, distance to the nearest node and BS, and the amount of energy still available. It is recommended to identify the most suitable sensor using EBOCA to evaluate the fitness feature in cloud resource management. The ideal CH is determined based on the distance between nodes and from the candidate CH to the BS to minimize energy consumption.

Equation 1 calculates the total number of nodes for every stage of the butterfly in the network. Let's assume B-Butterfly initialized node, q-amount of CH network, I-butterfly position, and T-total amount of node.

$$b_I = \left(b_{I,1}(T), b_{I,2}(T), \dots, b_{I,q}(T)\right) \quad (1)$$

In the global search phase or solution-based approach, Equation 2 calculates the ideal butterfly movement. a-vector solution, F-butterfly fragrance, R-random number generate current iteration, G-global search phase.

$$a_I^{T+1} = a_I^T + \left(R^2 \times G^* - a_I^T\right) \times F_I \quad (2)$$

As a local random walk, a butterfly can be approximated by equation 3. Where J and Z-Represent butterfly random numbers, a_J^T and a_Z^T-local random walk.

$$a_I^{T+1} = a_I^T + \left(R^2 \times a_J^T - a_Z^T\right) \times F_I \quad (3)$$

Equation (4) generates the scents of the butterflies at every location. Let's assume d-sensory modality, i-simulation intensity, A-power exponent.

$$F = di^A$$
(4)

As shown in Equation 5, calculate the CH node with the highest residual energy. Where, e_{CHI} –residual energy cluster head.

$$F_1 = \sum_{I=1}^{q} \frac{1}{e_{CHI}} \quad (5)$$

To determine the exposure distance CH for a fixed sensor, refer to Equation 6. Where, dis-distance, w-sensor node.

$$F_2 = \sum_{J=1}^{M} \left(\sum_{I=1}^{i_J} \mathrm{dis}(w_I, CH_J)/i_J\right) \quad (6)$$

Equation 7 illustrates the objective function used for measuring the distance between the CH and BS. Let's assume BS-Base station.

$$F_3 = \sum_{I=1}^{q} \mathrm{dis}\left(CH_J, BS\right) \quad (7)$$

Compute the node size, refer to Equation 8, and choose the CH with the lowest number of sensors.

$$F_4 = \sum_{I=1}^{q} i_I \quad (8)$$

Calculate the node centrality from the adjacent nodes as shown in Equation 9. Where, L-node.

$$F_5 = \sum_{I=1}^{q} \frac{\sqrt{\left(\sum_{J\in I} \mathrm{dis}T^2(I,J)/L(I)\right)}}{\text{Network Dimension}} \quad (9)$$

Compute the weighted values for the single objective function in equation 10. Let's assume δ-delta, δ_1 to δ_6- weighted value.

$$F = \delta_1 F_1 + \delta_2 F_2 + \delta_3 F_3 + \delta_4 F_4 + \delta_5 F_5 + \delta_6 F_6 \text{ where, } \sum_{I=1}^{5} \delta_I = 1, \delta_I \in (0,1) \quad (10)$$

In this category, during the CH selection process, the improved status of butterflies was considered to enhance their condition.

3.2 Optimal Neural Network Distance (ONND)

This section offers the ONND method to improve network energy efficiency in cloud resource management. To efficiently allocate resources to consumers through fast-changing channels, it's essential to incorporate performance metrics. ONND energy efficiency optimization process involves two stages. The first stage, spiral, involves updating and rotating the prey. The second stage consists of searching for the target randomly. Based on the ONND algorithm, the critical factor for optimal performance is the quality of the display. The ONND algorithm may produce inconsistent results for whale populations if cloud resource management has a functionally optimal solution. To achieve final recognition, the error rate value goes through a threshold function utilizing the standard error of the mean method.

As shown in Equation 11, the optimal wireless design problem can be calculated using a vector ergodic mean to relax the inequality. Where, u-Channel realization, Q (u)-resource allocation, ⅇ-Ergodic average vector, a-Performance Matrix.

$$a \leq ⅇ[F(Q(u), u)] \quad (11)$$

Equation 12 demonstrates that performance measurement can quantify the resource allocation to enhance a specific function. Where, Q-bounded function.

$$Q^* := \max_{Q(H), X^{Go(X)}} a \leq ⅇ[F(Q(u), u)] \; G(a) \geq 0. a \in \chi, Q \in Q \quad (12)$$

Calculate the performance improvement for the search agent behavior represented in Equation 13. Let's assume y-current location, b and d-coefficient vector, v-iteration,

$$\vec{y}(v+1) = \vec{y}^*(v) - \vec{b}.\vec{d}$$
$$\vec{e} = |\vec{d}.\vec{y}^2(v) - \vec{y}(v)| \quad (13)$$

The calculation formula for determining the absolute value of the coefficient vector is (14). Where b- lowered value from 2 to 0 iteration, B-minimize the value from 2 to 0.

$$\vec{b} = 2.\vec{B}.\vec{w} + \vec{B}$$
$$\vec{d} = 2.\vec{w} \quad (14)$$

Calculate the distance between the whale locations as shown in Equation 15.

$$\vec{e} = |\vec{y}^2(v) - \vec{y}(v)| \quad (15)$$

Evaluate the identified logarithmic curve and the stochastic curve shown in Equation 16. Rand- random number.

$$\vec{y}(v+1) = \vec{y}_{rand} - \vec{b}, \vec{e} \quad (16)$$

The minimization of the local optimization problem can be evaluated through random selection, as demonstrated in Equation 17. Let's assume $\vec{y}_{rand}$ r-randomly select whale from the specified population.

$$\vec{y}(v+1) = \vec{y}_{rand} - \vec{b}, \vec{e}$$
$$e = |\vec{d}.\vec{y}_{rand} - \vec{y}| \quad (17)$$

Equation 18 calculates the average standard error and applies it to the threshold function. SEM-Standard Error Mean, σ −sigma, μ −Mu.

$$SEM(X_I) = \frac{\sigma}{L}, \sigma = \sqrt{\sigma^2, \sigma^2} = e[(y_1 - \mu)^2] \quad (18)$$

In this category, the error rate values were determined using the standard error of the mean procedure as a threshold function.

3.3 Ant Colony Optimum-based Path Distance (ACOPD)

This section uses the ACOPD algorithm to discover the routing between cluster heads and BSs. It considers distance, residual energy, and node extents to select optimum paths. The ACOPD algorithm is a metaheuristic that takes inspiration from the behaviour of ant optimization. Usually, ants determine food sources by taking the rapidest route through their colony. The sensor nodes must send the collected data and have a path to reach it. Typically, cloud resource management requests are sent throughout the network, and a response is received from the BS. ACOPD challenges a specific task: a graph that contains nodes and numerous connections. Every node retains a particular capacity of ants; every relationship is linked to weight. The ACOPD can be enhanced by considering elements such as remaining energy, distance to BSs, and node order in the cloud resource allocation period edge of improbability convergence. This section comprehensively explains how the path generation process uses ACOPD.

Based on Equation 19, the ant determines its next move using the node transfer rule. Let's assume I and J-node, z-represents group of node, τ_{IJ} and η_{IJ}-heuristic value and pheromone intensity, α abd β-Parameter.

$$Q_{IJ}^{z}(T) = \begin{cases} \frac{[\tau_{IJ}(T)]^{\alpha}[\eta_{IJ}]^{\beta}}{\sum_{o \in n_z}[\tau_{IJ}(T)]^{\alpha}[\eta_{IJ}]^{\beta}} \end{cases} \quad (19)$$

Equation (20) states that the distance between CHs is evaluated as the heuristic information.

$$\eta_{IJ} = \frac{1}{c_{CH}} \quad (20)$$

Equation (21) provides the formula for calculating the pheromone update rule. Where, q-initialized amount, $\Delta_{\tau_{IJ}}^{z}$-quantity of pheromone present the link.

$$\tau_{IJ} = (1-\rho)\tau_{IJ}^{old} + \sum_{z=1}^{q} \Delta_{\tau_{IJ}}^{z} \quad (21)$$

Calculate the concentration of pheromone in the patch as shown in equation 22. Where, P-Constant value, d_z-detected cost path.

$$\Delta_{\tau_{IJ}}^{z} = \begin{cases} \frac{P}{d_z} \\ 0 \end{cases} \quad (22)$$

To determine the path cost, adjust the scale of pheromone values in Equation 23. Let's assume φ_1 to φ_3-weighted value.

$$d_z = \varphi_1 e_R + \varphi_2 c_{CH,BS} + \varphi_3 L_c \quad (23)$$

In this category, when choosing the shortest Path with the most minor energy consumption between CH and BS, it's essential to consider the node's size. Therefore, choosing a next-hop CH node with fewer cluster members is recommended.

3.4 Improved Power Effective Node Combined Heterogeneous Path (IPENCHP)

This section uses the IPENCHP protocol to minimize energy consumption and extend network lifetime for cloud resource management. This protocol assumes that the WSNs within a CH are selected based on the node's power level. The heterogeneous WSN differs from the traditional homogeneous WSN because it comprises various types of nodes. The diversity of it makes it better suited for practical usage. WSNs use cloud-based resource management to generate different power levels that select channels to increase the lifetime of network energy. In addition, we can enhance performance and maximize energy efficiency over the network's lifetime by estimating the power levels and transmitting different probabilities at each power level.

Calculate the initial power of the advanced node at average power using Equation 24. Let's assume e_{org}-Initial energy, e_{Ac}-advanced node, and ϑ –energy factor.

$$e_{Ac} = e_{org}.(1+\vartheta) \quad (24)$$

Compute the total energy of the new manifold as shown in Equation 25.

$$e = l.(1-q)e_{org} + lqe_{org}(1+\vartheta) = l.e_{org}(1+\vartheta q) \quad (25)$$

To calculate the random number node threshold as shown in equation 26. Let's assume t-threshold, R-number of nodes, w-normal node set, $1/Q_I$ – round of normal node, [1, 0]-random interval.

$$t_L = \begin{cases} \frac{Q_I}{1-Q_I\left(R.\mathrm{mod}\frac{1}{Q_I}\right)} & w_I \in w \\ 0 \end{cases} \quad (26)$$

To compute the average power of three nodes, refer to equations 27 to 29. Let's assume the R-current number of nodes, e_{normal}^{ave}, $e_{advance}^{ave}$, and e_{super}^{ave}-average energy.

$$e_{normal}^{ave} = \frac{1}{n_{normal}} \sum_{I=1}^{L_{normal}} e_{(LI)}(R) \quad (27)$$

$$e_{advance}^{ave} = \frac{1}{n_{advance}} \sum_{I=1}^{L_{advance}} e_{(advI)}(R) \quad (28)$$

$$e_{super}^{ave} = \frac{1}{n_{super}} \sum_{I=1}^{L_{super}} e_{(supI)}(R) \quad (29)$$

Compute the probability of four-state nodes as shown in equation 30.

$$Q_I = \begin{cases} \frac{Q_I e_I}{\left(1+q\left(\vartheta+q_0\left(-\vartheta+B+q_1((-B+d))\right)\right)\right)e_{ave}} & w_I \text{ is normal node} \\ \frac{Q_I.(1+\vartheta)e_I}{\left(1+q\left(\vartheta+q_0\left(-\alpha+B+q_1((-B+d))\right)\right)\right)e_{ave}} & w_I \text{ is advanced node} \\ \frac{Q_I.(1+b)e_I}{\left(1+q\left(\vartheta+q_0\left(-\vartheta+B+q_1((-B+d))\right)\right)\right)e_{ave}} & w_I \text{ is super node} \\ \frac{Q_I.(1+c)e_I}{\left(1+q\left(\vartheta+q_0\left(-\vartheta+B+q_1((-B+d))\right)\right)\right)e_{ave}} & w_I \text{ is ultra-node node} \end{cases} \quad (30)$$

Evaluate the threshold for the four-layer heterogeneous WSN as shown in Equation 31. Let's assume w_I-decision by the node, $t_{(w_I)}$-random number of less than threshold, 1-random number

$$t_{(w_I)} = \begin{cases} \frac{Q_I}{1-Q_I.\left(R.\mathrm{mod}\frac{1}{Q_I}\right)} & \text{if } w_I\{w,w',w'',w'''\} \\ & \text{else} \end{cases} \quad (31)$$

Equation 32 calculates a reasonable weight for both by assigning the weight value. Where γ and θ-analystic hierarchy process, s-weight value.

$$s = \gamma.\frac{\bar{c}}{c_{toSINK}} + \theta.\frac{e_{Rsidual}}{e_0} \quad (32)$$

In Equation 33, the weight vector of the assessment unit is calculated. Let's assume the $\bar{Q}$ –judgement matrix,

$$\bar{Q} = \begin{Bmatrix} \frac{s_1}{s_1} & \frac{s_1}{s_2} & \cdots & \frac{s_1}{s_N} \\ \frac{s_2}{s_1} & \frac{s_2}{s_2} & \cdots & \frac{s_2}{s_N} \\ \frac{s_N}{s_1} & \frac{s_N}{s_2} & \cdots & \frac{s_n}{s_n} \end{Bmatrix} \quad (33)$$

Compute the eigenvalues and eigenvectors as shown in equation 34. Let's assume s-corresponding normalized feature vector,

$$t = \lambda_{max^{s'}} = X_{IJ}(M \times M) \quad (34)$$

Calculate the largest eigenvalue of the judgment matrix and its associated eigenvector, as shown in Equation 35.

$$X_{IJ}^{normalize} = \frac{X_{IJ}}{\sum_{I=1}^{M} X_{IJ}} \quad (35)$$

Equations 36 and 37 show that computes a matrix normalized by columns collapsed by rows and vectors.

$$\bar{s} = (\bar{s}_1, \bar{s}_2, \bar{s}_3 \ldots \bar{s}_n) \quad (36)$$

$$s_I = \frac{\bar{s}_I}{\sum_{I=1}^{M} \bar{S}_I} \quad (37)$$

Compute the largest eigenvalue as shown in equation 38.

$$\lambda_{max} = \sum_{I=1}^{M} \frac{(Q_s)_I}{Ms_I} \quad (38)$$

The Consistency Index (CI) can be calculated according to equation 39.

$$CI = \frac{\lambda_{max} - M}{M-1} \quad (39)$$

Equation 40 computes the random positive and negative matrices. RI- Random Index, the λ_{max} –average value of the most significant root.

$$RI = \frac{\bar{\lambda}_{max} - M}{M-1} \quad (40)$$

Calculate the agreement ratio in Equation 41 to determine the range of inconsistency.

$$CR = \frac{CI}{RI} \quad (41)$$

Evaluate the weighting coefficients as shown in Equation 42.

$$s_I = \frac{\sum_{J=1}^{M} x_{IJ}}{\sum_{IJ=1}^{M} x_{IJ}} \quad (42)$$

Equations 43 and 44 compute the average distance between various sink nodes. Where, $\bar{c}$-average distance, c_{toBs}-sink node.$w_N(I)$ –Normal node, $w_N(I+1)$- position of sink node.

$$\bar{c} = \frac{1}{N}\sum_{I=1}^{N} c_{toBs} \quad (43)$$

$$c_{toBs} = \sqrt{(w_N(I).X_{cT} - w_N(I+1)X_{cT})^2, (w_N(I).Y_{cT} - w_N(I+1)Y_{cT})^2} \quad (44)$$

Calculate the energy consumed by CH expressed as ECH as shown in equation 45. Let's assume e_{elec} –transmitter electronic Energy e_{DA}-Data aggregation energy. φ-Phi.

$$e_{CH} = 0.e_{elec}\left(\frac{N}{Z}+1\right) + 0.e_{DA}\frac{N}{Z} + 0.e_{elec} + 0.\varphi_{Fw}c_{toCH}^2 \quad (45)$$

This model computes elevated energy levels and establishes distinct energies for each group to enhance effectiveness and prolong the network's energy-saving capacity.

4. Result and Discussion

In this segment, the uses of the IENCHR protocol that has been proposed will be discussed. The resource allocation platform's WSN, which is cloud-based, improves the network's durability. We present numerical results to compare the proposed algorithm with existing schemes in IPENCHP. Also, after analysing the energy consumption of cluster communication, we offer to use the IPENCHP protocol to reduce energy consumption and restore network lifetime. Various parameters, including performance, energy efficiency, packet delivery speed, and packet loss efficiency, and network lifetime, can determine the accuracy of cloud-based resource management.

Table 1. Simulation Parameter

Parameter	**Value**
Language	NS2
Energy	0.5J
Initial Energy	1J
No of Nodes	400
No of Packet	4000bit
Threshold Distance	75m
Transmission Radius of nodes	20m
Network coverage area	200X200
Transmitter electronic Energy	40 nJ/bit
Data aggregation energy	5nJ/bit/signal

According to Table 1, the simulation parameter models being discussed can be achieved in NS2 experimental findings. The presents a comparative WSN-based cloud resource allocation analysis using energy efficiency and data optimization. Through this analysis, the suggested method was able to optimize both energy efficiency and data optimization.

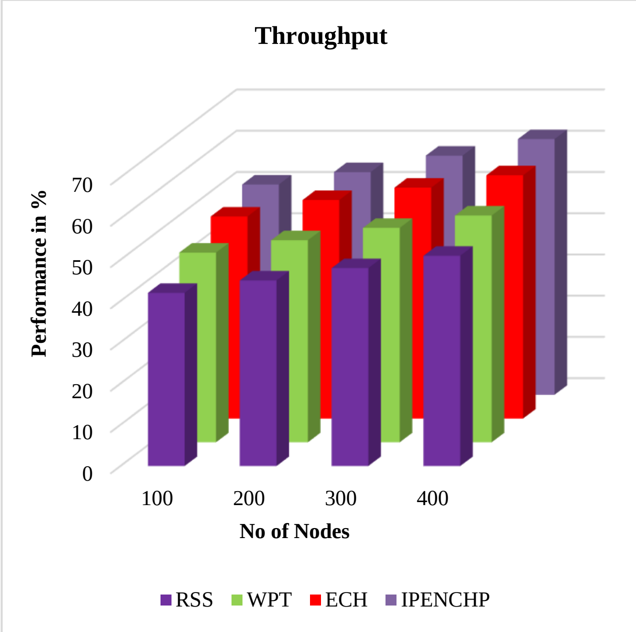

Fig. 3. Analysis in Throughput

In Figure 3, it is demonstrated that WSN utilizes cloud-based resource allocation to decrease energy usage and prolong the network's lifespan. Throughput analysis is implemented to enhance accuracy. IPENCHP protocol's precision is 69% greater than the RSS, ECH, and WPT approaches discussed in the literature analysis. The IPENCHP algorithm for cloud resource management considers the distance between nodes. It can provide various weighting factors by integrating the continuity energy of nodes for BS and CH conversion and evaluating the importance of distance and power on structural performance.

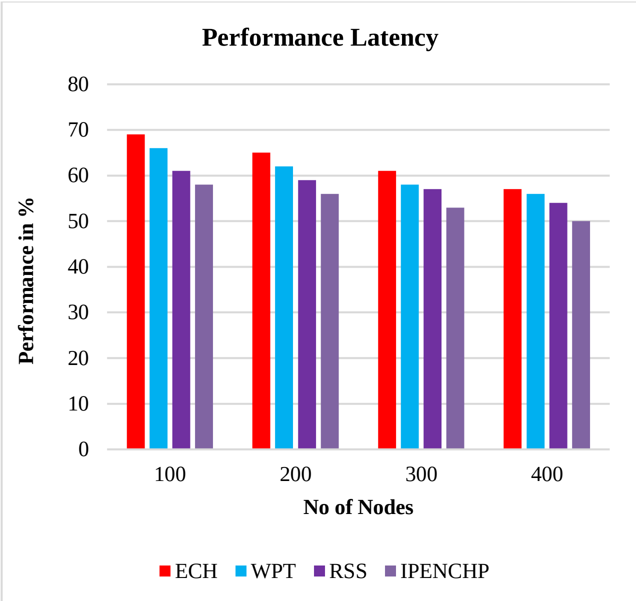

Fig. 4. Analysis of Performance Latency

Figure 4 displays the techniques utilized to measure resource management performance through performance latency. In comparing the IPENCHP protocol with three other methods, it was found that its accuracy in determining performance delay improved by 50%. Additionally, after analyzing various forms such as ECH, RSS, and WPT, it was discovered that their accuracy also improved. The allocation of cloud-based resources management in WSN is beneficial as it reduces energy consumption and extends the network's lifetime.

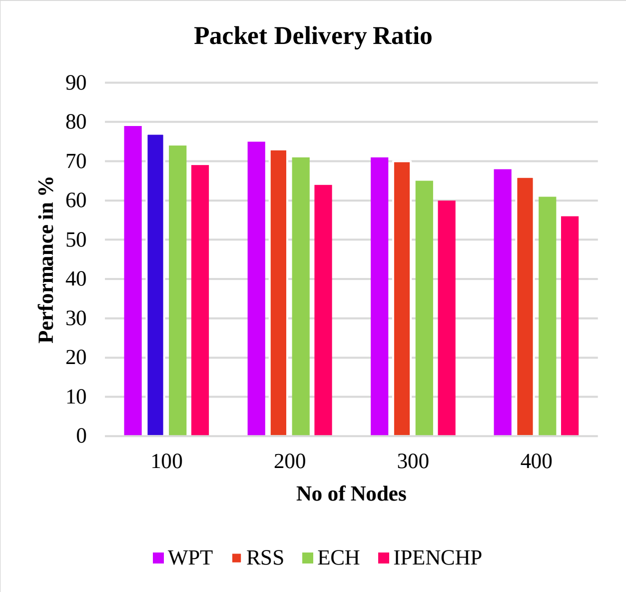

Fig. 5. Analysis of Packet Delivery Ratio

Figure 5 shows that WSN employs cloud-based resource allocation to reduce energy usage and enhance the network's lifespan. The packet delivery rate serves as a metric for evaluating resource management efficiency. After analyzing the accuracy of packet delivery rates in the literature using RSS, ECH, and WPT methods, it is evident that their accuracy has improved. However, their accuracy is still 56% lower than the suggested IPENCHP protocol.

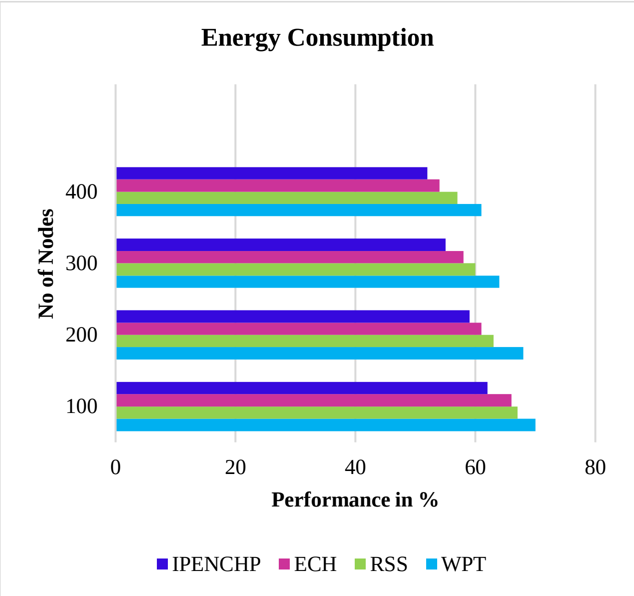

Fig. 6. Analysis of Energy Consumption

Using cloud-based resource allocation in WSN, as depicted in Figure 6, helps minimize energy usage and prolong the network's lifespan. Various methods are employed to measure resource management efficiency through energy consumption. After analyzing different methods like WPT, RSS, and ECH, it's been found that using energy consumption leads to increased accuracy.

Also, the exactness of energy consumption is reduced to 52% when comparing the proposed IPENCHP protocol with the other three methods.

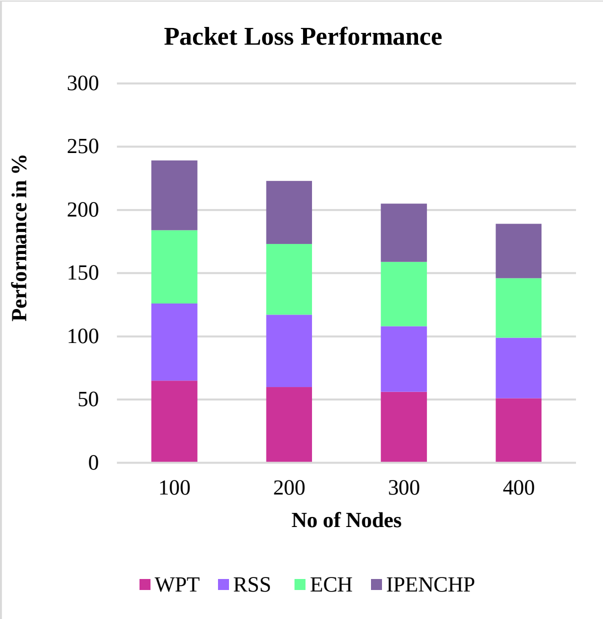

Fig. 7. Analysis of Packet Loss Performance

Figure 7 displays the different techniques utilized to gauge the value of resource management in terms of packet loss performance. Cloud-based resource allocation in WSN minimizes energy consumption and increases network longevity. Upon evaluating various methods such as RSS, ECH, and WPT, it was determined that their precision improved. Additionally, it was discovered that the IPENCHP protocol exhibited a lower packet loss rate of only 43% compared to the other three techniques.

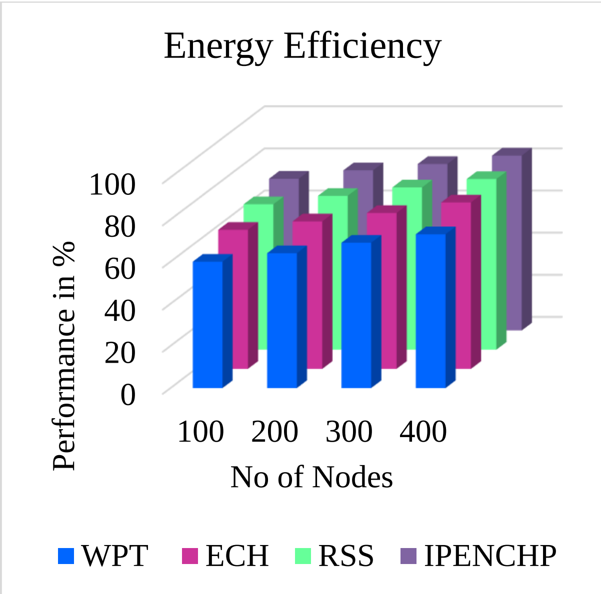

Fig. 8. Analysis of Energy Efficiency

Figure 8 illustrates several techniques for measuring cloud resource management performance regarding energy efficiency. Further, these cloud-based resource allocation in WSN helps reduce energy consumption and extend network lifespan. Thus, the accuracy of energy efficiency when testing the proposed IPENCHP protocol increased their estimate to 83%.

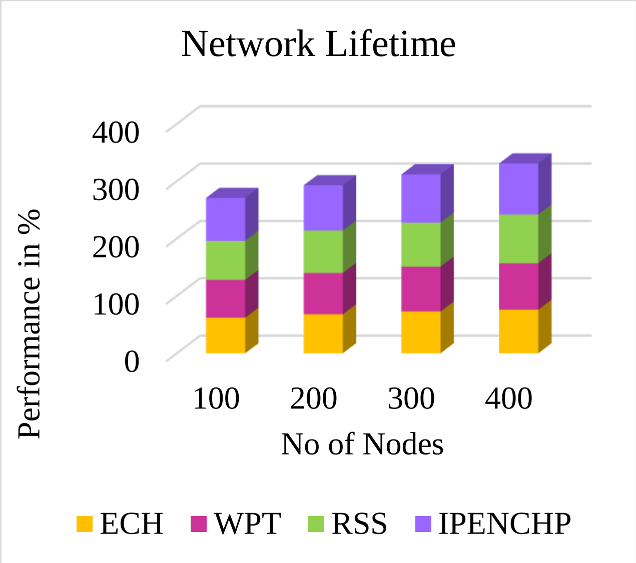

Fig. 9. Analysis in Network Lifetime

Several techniques are used to measure cloud resource management performance based on network lifetime analysis, as illustrated in Figure 9. Through these, cloud-based resource allocation in WSN helps reduce energy consumption and increase network lifetime. Compared to methods found in literature, such as RSS, ECH, and WPT, the accuracy of network lifetime analysis is 63% decreased. However, when testing the proposed IPENCHP protocol for network lifetime analysis accuracy, their accuracy increased to 89%. Instead of considering only the distance of sink nodes or the continuous power of nodes for BS and CH selection, the proposed IPENCHP protocol helps to evaluate the importance of space and control for classification performance, and multiple weighting features can be generated.

5. Conclusion

This paper presents the IPENCHP protocol to enhance the network's performance by optimizing its lifetime and number of stable regions through a novel threshold algorithm. The strength of the network can be firm by computing the percentage of the enduring energy to the total ordinary power. To determine the proximity of a node to the BS, it's essential to equalize the distance between the CH and the BS. EBOCA assists in choosing the best CH for the network among the nodes in cloud resource management. It also computes the remaining energy of each node and measures the distance to neighbouring nodes. The energy usage of the network is then enhanced using the ONND algorithm. The cluster head and the BS are connected by a path generated by the ACOPD algorithm. It can improve the network's lifetime through cloud resource management using the provided IPENCHP protocol. In addition, the IPENCHP protocol provides a reliable and complete solution for managing constant power levels and weights in cloud resource management. Energy efficiency can be determined based on network lifetime, packet transmission rate, energy efficiency, energy consumption, and transmission delay to determine this accuracy. The accuracy of the proposed IPENCHP protocol is increased to 89% based on network lifetime analysis. Furthermore, a theoretical analysis using several techniques can increase the energy lifetime of the network. This analysis takes into account all network loads caused by routing protocols.

Declarations

Availability of data and materials

The data that support the findings of this study are available on request from the corresponding author,

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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