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Collaborative Energy-Efficient Routing Protocol for Sustainable Communication in 5G/6G Wireless Sensor Networks

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ABSTRACT One of the main problems with WSNs is that most sensor nodes in wireless sensor networks (WSNs) are motorized by energy-constrained, which significantly affects the system's effectiveness, dependability, and lifespan. Numerous clustering strategies have been created to enhance the energy efficiency of WSNs in 5G and 6G transmission. To overcome these issues, we suggest a collaborative energy-efficient routing protocol (CEEPR) for sustainable communication in 5G/6G wireless sensor networks (WSNs). Initially, this study gathered and collected the data at the sink node. The network's nodes are clustered using the reinforcement learning technique (R.L.). Cluster head selection is employed for better data transmission using residual energy (RE) based cluster head selection algorithm. A collaborative energy-efficient routing protocol (CEERP) is proposed. We use a multi-objective improved seagull algorithm (MOISA) as an optimization technique to enhance the system's performance. Finally, the presentation of the system is analyzed. Compare with the existing methods, the primary metrics are throughput, energy consumption, network lifetime, packet transmission, routing overhead, and transmission speed. The proposed approach uses 50% less energy while improving network lifespan and energy efficiency compared to the current protocols.

INDEX TERMS Wireless sensor networks (WSNs), 5G/6G transmission, reinforcement algorithm (R.L.), residual energy (RE) based cluster head selection, collaborative energy-efficient routing protocol (CEERP), multi-objective improved seagull algorithm (MOISA).

I. INTRODUCTION

THE APPEARANCE of revolutionary technology like IoT, artificial intelligence, as well as 5G, to highlight a few, modernization has wholly changed our existing reality. As a result of integrating such technologies into the environment, more robust intellectual designs with distinct capabilities have been created [1]. As a result, it has uses in smart industries, smart cities, and smart grids, among others. This technology improves throughput, reduces latency, and has a good transmission range while requiring more significant data speeds and vast bandwidth. Enormous machine-type communication is an essential component of 5G wireless communication [2]. Figure 1 depicts the 6G communication in WSN.

Wireless communications techniques must be integrated into advanced processing applications, big data platforms,

FIGURE 1. 6G communication in WSN.

and smart communications systems. In 6G technology, this combination will be fully involved and is already available in 5G technologies substantially. 6G networks are designed to include high-speed telephony, mapping, and interactive media systems [3]. Wireless sensor networks are essential for 5G telecommunications because they provide an active component for communication. Future 6G networks will provide high-speed, dependable, and all-encompassing connections for various electronics and uses. They provide improved wireless communication capabilities with features like higher data speeds, reduced latency, broad device connection, and network slicing. WSNs may enhance their communication capabilities by using the connection infrastructure offered by 5G/6G networks, especially in situations when long-distance communication or network integration is necessary. Due to their specific features and needs, 5G/6G WSNs present some obstacles to achieving long-term and reliable connectivity. Communication in WSNs must be efficient in terms of energy use if it is to last over time. Higher energy consumption might result from the higher data rates and greater complexity of 5G/6G networks. Energy-efficient communication protocol design and algorithm optimization are vital to lowering energy usage without compromising on performance. WSNs are notorious for making do with little power supplies, processor speed, memory, and network throughput. Higher data speeds and more traffic on 5G/6G networks might strain these systems. Sustainable communication in the face of resource restrictions requires the development of resource allocation and management techniques that consider the specific needs of WSNs.

A WSN comprises network nodes that detect objects and send information to a source. Every round's sink is where the communication system ends [4]. The major suggestion with IoT-based WSNs is increasing the network's lifespan and reducing energy consumption. Wireless routers or edge devices must be installed to distribute the data collected at the front-end servers. These nodes compute the input and remotely transmit it to the neighbors in their locality. This transmission employs a variety of multihop communication systems. This kind of data transfer is risky and scattered (wireless channel). Routing protocol for networks with low power and loss (RPL) manages to neighbor discovery and communication scheduling tasks while supporting fundamental security techniques. Standard security concepts must be revised to implement safe routing in IoT [5]. In wireless technology, a router is an automatic machine that delivers data and packets across the shortest possible range and in the smallest possible amount of time. This task is completed dynamically and statistically. Static routing aids in transmitting packets from one node to another, but one drawback is that it cannot be updated automatically; instead, data must be actively maintained and added. Dynamic routing transmits information over a varied path, is managed dynamically, and automatically distributes information. The routing tables are modified, and the routers may interact with one another due to a set of rules called a protocol [6].

This research is required to optimize energy use, advertise sustainability in the environment, assure flexibility and dependability, enhance the standard of service, lengthen the lifespan of networks, and capitalize on technological advancements. By focusing on these areas, the protocol hopes to improve the sensor network's functionality and effectiveness, leading to things like longer battery life, less of an environmental impact, more reliable networks, higher quality of service for individual applications, and compatibility with emerging 5G/6G requirements and technological advances.

The primary contributions of this research are simple to apply to a LAN-sized small network. It offers greater security since neither advertisement nor dynamic routing transmits information. Since the path to the goal is consistently the same, it is relatively predictable. No sophisticated algorithms are necessary. Due to the scalability of WSN, any more nodes or sensors may be added whenever required. Physical categories are conceivable since it is adaptive. All the WSN nodes will be accessible via a single monitoring system. Since it uses wireless technology, it doesn't require cables or connections. Hence, we developed a collaborative energy-efficient routing protocol (CEERP) for sustainable communication in 5G/6G WSN.

The following is a list of CEEPR's main contributions to 5G/6G WSNs' sustained communication:

- Improved energy efficiency using clustering based on R.L.
- Enhanced data transmission by the choice of the cluster head based on RE.
- Cooperative and energy-efficient routing facilitation.
- MOISA is used to improve system effectiveness.
- The analysis of important performance indicators includes efficiency, power usage, packet delivery, routing overhead, and transmission speed.
- While MOISA simultaneously improves numerous performance indicators, CEEPR achieves a 50% energy savings, increases network durability, and beats existing

techniques in productivity, packet transfer, routing overhead, and transmission speed.

The remainder of this paper is covered as follows. The problem statement and its related works are described in Section II. The suggested technique is presented in Section III. Experimental evaluation is included in Section IV. The conclusion is found in Section V.

II. RELATED WORK

A Deep Belief Network (DBN)-based routing system is created, which uses less energy and improves data transfer along the chosen route [7]. A more effective wireless sensor network (WSN) deployed optimally and energy-efficient is needed for IoT data transmission between heterogeneous devices. Nevertheless, several protocols have lately been created for efficient routing, although none has yet to achieve a faster and more efficient routing [8]. Adopting such strategies (5G/6G) to have larger data rates with low latency is crucial. The typical 5G/6G technologies data rate is gigabits per second (Gbps). Comparing 5G/6G networks to older technologies like 3G, 4G, LTE, and other networks, they provide improved base station bandwidth and higher Quality of Service (quality of service) [9]. To achieve the greatest quality of service, increase capacity, and resolve the most recent cellular network problem, 5G/6G networks are the most appropriate choice given the development of technology and the increase in the consumption and demand of multimedia data. Since 5G and 6G networks link many base stations and systems [10]. Mobile Ad Hoc Network (MANET) routing set of rules provide a steady packet transmission ratio, minimal overhead connection, and lower end-of-the-market delay in common standard situations and attack conditions. They demonstrated to be greater efficient than other state-of-the-art routing protocols of MANETs, like Ad-hoc On-demand Distance Vector (AODV), its routing organization implemented via Optimized Fuzzy based Ant Colony Optimization (ACO) Algorithm [11]. The study suggested a quick authentication approach involving time constraints and user requests to integrate e-health systems in wireless sensor networks based on 5G. Since it enables e-health users to store and exchange data conveniently, the healthcare system has attracted much study interest. However, as the variety of sensors and wireless devices grows, privacy and safety concerns grow significantly [12]. Researchers discussed an energy-conscious zone-based routing protocol (ZBRP) that uses game hypothesis to improve node collaboration and power effectiveness. The network lifespan rises because the networks use the communication channel with the most significant average energy and offer one another assistance [13]. The authors examined unwanted eavesdroppers of secured routing to send data to the network nodes. A hybrid energy-efficient routing method improves the smart device's stability. A cluster of antennas is used with wideband technology to focus on known individuals for security reasons [14]. A multidisciplinary method combining wireless sensor networks with automated manufacturing facilities is proposed to further the development of this sixth sense innovation [15]. The Ad-hoc On-Demand Distance Vector Routing (NAODV) protocol reduces energy usage and increases WSN longevity. The implementation outcomes show that 11 nodes have extended the network's lifetime without compromising packet delivery speed. Some areas are still without 5G service [16]. An effective networking strategy is explained to enhance IoT node efficiency for 5G data transmission. The next-generation cellular network protocol, 5G, will emerge fast. The Internet of Things (IoT) is evolving and overgrowing. They looked at several studies related to routing techniques. In the node-to-node simulation scenario, many multicast routing protocols are used [17]. A deep deterministic policy gradient (DDPG)-based on interface resource timing is presented. A technique of centralized training and dispersed performance is implemented, and a response assessor is created to increase the computation stability and training effectiveness [18]. Low-latency and energy-efficient routing based on network connectivity (LENC) are introduced to study network connection and use Internet links as the major routing indicators. However, the growth of vehicular ad hoc networks (VANETs) might be considerably accelerated by 5G technology and infrastructure [19]. Optimal Cluster-Based Routing (Optimal-CBR) protocol is proposed for greater energy efficiency. At the same time, the network's lifespan is higher when utilizing an intellectual routing method for deployments on the 5G environment and the IoT and beyond [20]. Study [26] presented a concept for a wireless sensor mote that is both energy-efficient and self-sufficient for the kind of NG-CPS that has been envisioned. Utilizing Mobile Edge Computing (MEC) is intended to divide the NG-CPS operational architecture. The newly suggested method is tested using electronics prototypes, and the findings reveal 720 Joule energy savings with utilization of just 700 mW while considering 80% energy conservation. A study [27] demonstrated that IoT has an opportunity to improve the effectiveness and efficiency of smart cities when combined with environmentally friendly 6G technology. Cities that are already smart could become much smarter with the usage of 6G by IoT devices. The study's results underlined the importance of developments, including symbiosis wireless blockchain technology, VLC, 6G BCI, and quantum technology. The study [28] introduced a revolutionary Low-Latency Fog-based Framework, dubbed Fog Fed, to protect IoT applications combining FL and fog computing. The FL provides a collaborative learning amongst IoT while protecting their privacy, while the fog delivers security measures close to IoT devices to reduce communication latency. The study [29] developed a revolutionary Explainable artificial intelligence XAI-powered structure that enable analyzing critical decisions made by ML/DL-based Intelligent detection systems in addition to detecting intrusions and attacks in IoT networks. The study [30] focused on Internet of Everything (IoE) services enabled by artificial intelligence (AI) in next-generation wireless networks. With millions of people and billions of equipment connected, these networks are experiencing significant changes. These networks are promoted as being a crucial component of the IoE services, which are unprecedented.

By considering energy limits and using energy-aware routing techniques, CEER protocols are particularly created to optimize energy use. Contrarily, traditional approaches may not emphasize energy efficiency, resultant in inefficient power use and a decreased network lifetime. The operational lifespan of the network may be increased using CEER protocols by efficiently managing energy resources and balancing energy usage. Conventional approaches may need the necessary mechanisms to deal with energy limits, which would cause energy to be used up more quickly and reduce the network's lifespan. When network circumstances change, such as node failures or fluctuations in energy levels, CEER protocols provide methods to alter routing techniques dynamically. Most conventional approaches depend on static routing algorithms, which are less adaptable and sensitive to changing network settings. Energy efficiency and quality of service (quality of service) standards are only two of the many goals CEER protocols might consider. Contrary to more traditional approaches that may not consider these requirements, CEER protocols can provide greater quality of service guarantees by optimizing routing choices depending on particular application demands.

In conclusion, CEER protocols include benefits including increased energy efficiency, extended network lifespan, adaptation to dynamic situations, cooperative decision-making, scalability, fault tolerance, and application-specific optimization. Compared to traditional approaches, which often lack these qualities, CEER protocols are more suited for energy-restricted wireless sensor networks.

A. PROBLEM STATEMENT

Routing is a critical responsibility in WSN-assisted IoT that must be managed appropriately. The purpose of routing must create a data transmission connection between the base station (B.S.) and the sensor nodes (S.N.s). WSN routing procedure comprises three main primary issues. First, creating a worldwide addressing mechanism for developing additional S.N.s is not conceivable. Furthermore, all sensor network applications need a flow of observed data from several sources to get to a particular sink node. Finally, numerous sensors around the phenomenon data are used to generate comparable data. Therefore, we suggested a collaborative energy-efficient routing protocol (CEERP) for sustainable communication in 5G/6G wireless sensor networks.

III. PROPOSED WORK

WSN in 5G transmission requires a routing protocol. Energy use and network lifespan are the main characteristics of this protocol. The Medium Access Control (MAC) and Physical layers of Wireless Sensor Networks (WSNs) are developed with WSN-specific needs and features in consideration. The MAC layer of a WSN regulates communications between sensor nodes and limits who may use the network's common wireless channel. For a WSN to function, data transmission and reception across the wireless medium must occur at the Physical layer. The characteristics of the suggested approach are briefly detailed in this section. Figure 2 depicts the designed work's flow.They are creating a sink node to receive information from sensor nodes. They optimize energy use by clustering sensor nodes using reinforcement learning (R.L.), utilizing residual energy (RE) based cluster head selection technique to enhance data transmission and prolong the network lifetime. A collaborative energy-efficient routing protocol (CEERP) will be introduced to strengthen routing. System optimization using the multi-objective improved seagull algorithm (MOISA) and examining and contrasting performance indicators such as transmission speed, energy usage, network longevity, packet transmission, and throughput and compared to conventional protocols, demonstrating a 50% reduction in energy usage, increased network lifespan, and energy efficiency.

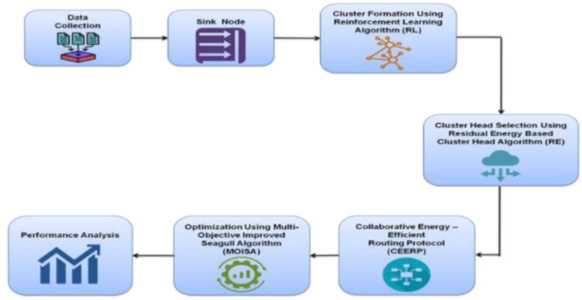

FIGURE 2. The workflow of the proposed approach.

A. DATA COLLECTION

The simulation makes use of the healthcare dataset (available at https://www.kaggle.com/datasets/iqrayousaf/healthcare-dataset-for-defects-prediction). The research on software defects in medical applications and the faults in different medical apps were taken into consideration while creating the dataset for healthcare systems. In this healthcare dataset, boolean classifications labeled as damaged and non-defective are present. On Kaggle, the dataset is easily accessible. The collection of information is split into two separate training and testing information sets, with 70% of the information being used to educate the recommended strategy and 30% being used to test the suggested model [21]. After the data is collected, these are transmitted to the sink node (S.N.) for clustering. The proposed system model includes a source node, a destination node, and many intermediate nodes. To express the information often to the end node, the basis node communicates with many intermediary nodes of the network. S(N, Q) describes the topology of the system, where N is the set of nodes (1, 2, . . . , nl). Connecting two nodes is represented by Q, while the size of the network's nodes is denoted by l.

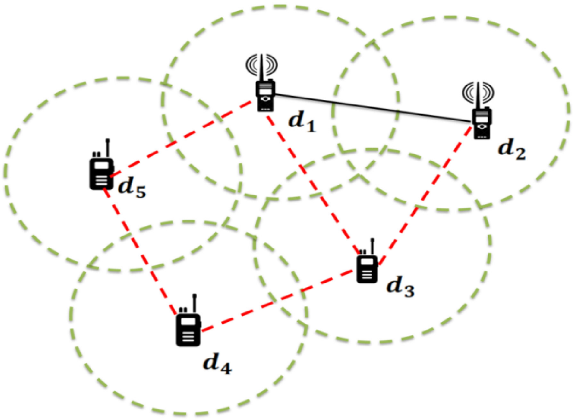

FIGURE 3. The reinforcement learning in WSN.

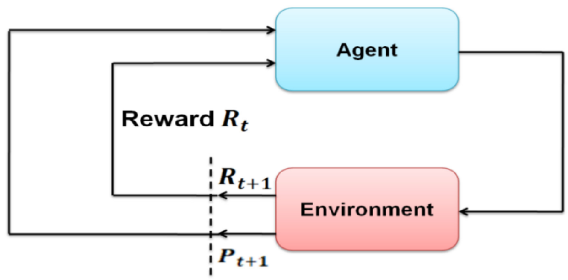

FIGURE 4. Function of R.L.

B. CLUSTER FORMATION USING REINFORCEMENT LEARNING (R.L.) ALGORITHM

RL is a procedure that carries out the learning experience and gives positive behaviors a reward value. Advisor, response, position, benefit, principle, target value, and environmental approach are crucial parts of the R.L. mechanism. The R.L. accomplishes its procedure, which incorporates -greedy selections and cyclical variance methods as a decision and computational analysis system based on the Markov decision process (MDP). To optimize a cumulative reward signal, an agent learns to make successive choices in its interactions with its environment using a machine learning approach called Reinforcement Learning (R.L.). There are several features of wireless sensor networks (WSNs) that R.L. can improve. Figure 3 shows the reinforcement learning in WSN.

An R.L. technique is used to cluster the S.N.s in this case. The educational agent for RL-based clustering is the WSN nodes. The education operators examine each neighboring neighbor's activation energy for grouping based on specific regulations. Each node's MDP is assessed when the clusters are created. Within the MDP, status, activity, rule, and benefit are interwoven. The learning operators use the dynamical variance method to establish the action policy for the communication network. Figure 4 demonstrates the function of R.L.

Figure 4 represents the function of R.L. Based on a revised Q-value, each S.N. incorporates the R.L. idea for clustering, first analyses the route expense, and then communicates that data to the cluster head. The reward parameter is an example of the price of the connection between the present node and the subsequent node. A collection of phases, a transformation system, a sequence of actions and a learning algorithm make up the fundamental rule of the MDP. The learning agent chooses all of the phases P that displays activity A, and using this activity; it estimates the amount of energy used by each group. The next phase is to evaluate the reward R-value acquired from the anticipated energy usage and come to the best option. The present phases along with activity be then increased by 1, as shown by the symbols P to Pi+1 (phases) and A to Ai+1 (activity). The education agent creates the greatest strategy Q based on the education experience, it raises the value of the award. The best number of clusters is chosen using this optimum strategy.

The current activity and phase are tied to the reward R and phase transition T. The creation of policies is the learning agents' main objective. Following the analysis of the initial phase Pi to derive the continuous value function C(Pi), which is described in equation (1), the discovering agent calculates the activity Ai based on the present situation Pi (i.e., (Pi) = Ai).

$$\begin{aligned} \boldsymbol{C}(\mathbf{Pi}) &= \boldsymbol{q_i} + \boldsymbol{a}\boldsymbol{q_{i+1}} + \boldsymbol{a^2}\boldsymbol{q_{i+2}} + \cdots + = \boldsymbol{q_i} + \boldsymbol{a} + \boldsymbol{C^{\pi}}.(\boldsymbol{P_{i+1}}) \\ &= \sum_{i=1}^{\infty} \boldsymbol{a}\boldsymbol{q_{i+1}} \end{aligned} \tag{1}$$

By raising the C(Pi) value, the learning agent seeks to enhance the effective approach. This procedure is known as strategy, and equation (2) depicts it:

$$\boldsymbol{C^{\#}} = \boldsymbol{maxC^{\pi}}(\boldsymbol{P_i})\boldsymbol{C_P} \tag{2}$$

Lastly, equation (3) is used to update the Q-value

$$\begin{aligned} \boldsymbol{Q_{t+1}}(\boldsymbol{P_t}, \boldsymbol{\beta_t}) &= (\mathbf{1} - \boldsymbol{\beta})\boldsymbol{Q_t}(\boldsymbol{P_t}, \boldsymbol{\beta_t}) \\ &\quad + \boldsymbol{\beta}\left[\boldsymbol{r^{t+1}} + \boldsymbol{amaxQ_t}(\boldsymbol{P_{t+1}}, \boldsymbol{\beta'}) - \boldsymbol{Q_t}(\boldsymbol{P}, \boldsymbol{\beta_t})\right] \end{aligned} \tag{3}$$

The symbols max Qt Pt+1, 0, and rt stand for the greatest Q-value and return value, respectively. The activity of each development operator is indicated at 0 (Zero). A sample of an algorithm for creating Reinforcement Learning based clusters is represented in Algorithm 1.

C. RESIDUAL ENERGY (RE) BASED CLUSTER HEAD SELECTION

Each node's energy estimate is updated after transmitting or receiving k bytes of data. Each node is declared to be dead after repeating this method. When a node's residual energy reaches 0 or a negative value, it is lifeless. The initial goal for determining the ideal cluster is the remaining energy of the node in the current round. Since the cluster head is in charge of sending, acquiring, and processing the data, it uses more energy than other sensor nodes. The cluster head depletes its energy more quickly than the other nodes. As a result, it is necessary to re-establish cluster heads every round using a

Algorithm 1 Reinforcement Learning-Based Cluster Formation Algorithm

The parameters

Phase & activity pair (P, β)

Start

Set 0 as the value for table entry $\boldsymbol{Q}(\boldsymbol{P}, \beta)$

Iterate

Perform the chosen activity.

Reward the action that was completed right away with R.

Check out the new phase P'

Update the table entry $\boldsymbol{Q}$ (P,β) by applying equation (3).

It is characterized as follows,

$$Q_{t+1}(P_t, \beta_t) = (1-\beta)Q_t(P_t, \beta_t) + \beta\left[r^{t+1} + amaxQ_t(P_{t+1}, \beta') - Q_t(P, \beta_t)\right]$$
$$P = P'$$

Select action

$$\pi(P_i) = argmaxQ(P, \beta)$$

Exploration

$$\frac{P(\beta i|P) = kQ(P, \beta)}{\sum kQ(P, \beta)}$$

End loop

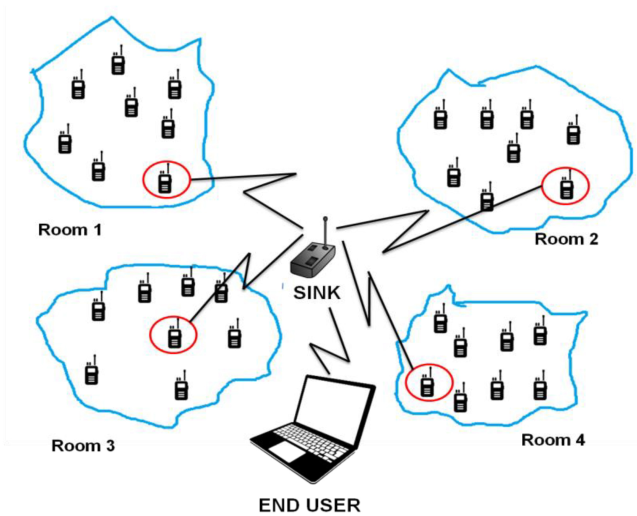

FIGURE 5. Residual energy-based C.H. selection in WSN.

node's remaining energy. The mathematical formula for the node's remaining energy is depicted in Equation (4).

$$E_L{}^{t_r+1}(j) = E_L{}^{t_r}(j) - E_S{}^{t_r}(j)(j = 1, 2, \ldots, m) \tag{4}$$

where $E_S{}^{t_r}$ is the energy spent in the trth round, and $E_L{}^{t_r}$ is the energy left over at the end of tr rounds at node j. The quantity of $E_L{}^{t_r}$ will vary depending on the kind of nodes for each diverse node type. $E_L{}^{t_r}$ would be EADV, EINT, and ENRM for enhanced, moderate, and ordinary nodes, correspondingly, for the first round (tr is equal to 1). The nodes with the greater energy value are chosen as the cluster head. Figure 5 illustrates the residual energy-based cluster head selection in WSN.

D. COLLABORATIVE ENERGY-EFFICIENT ROUTING PROTOCOL (CEERP)

A collaborative energy-efficient routing protocol (CEERP) improves nodes' coordination and energy efficiency. The network lifespan is extended because the nodes use the route with the highest percentage of energy for communication and offering team support. This requests its zone leader (ZL) to determine the optimal route for the sink. Due to the dynamic data sharing across Z.L.s, the Z.L. is aware of the position of the sink's Z.L. When sending two path discovery commands (PDC) for simultaneous transmission from the source and sink, Z.L. computes timing methods to estimate the duration and sequence. It guarantees that PDC is received simultaneously at the source and the destination. The CEERP is shown in Figure 6.

PDC includes the zone-to-live, transmission I.D., origin, and sink addresses that must be targeted throughout the transmission. Origin and sink both broadcast route requests (RREQ) to locate each other whenever they get PDC. An RREQ collision occurs when two RREQs belonging to the same transmission I.D. arrive at an access point, with one RREQ's origin I.D. serving as the other's target I.D. and vice versa. Until both RREQs collide at an access point, retransmission goes on. Repeated retransmission is stopped by interaction, and the access point creates packets to the sender:

$$Energy = n * size + a \tag{5}$$

With packet size, the value is additive at n, while the constant cost of energy of route access is at a. Equation (5) is used to calculate the consumption of energy in routing by CEERP. The routing mechanism consumes 9214.8 μW s of energy in total. More energy is utilized for the routing protocol than other routing aspects. As a result, CEERP outperforms other energy-efficient routing protocols in terms of speed. On the premise that nodes are interactive, CEERP performs well in terms of scalability, flexibility, and minimum transmission time. Collaborative decision-making, dynamic cluster formation, energy-aware cluster head selection, energy-efficient routing, and protocol adaptability are all novel features introduced by the proposed CEEPR that improve upon previous clustering approaches. CEEPR is an important contribution to the literature on WSNs because of the ways in which it improves energy efficiency, network longevity, and overall performance. Scalability is a common issue with 5G and 6G WSNs due to the high density of sensor nodes in these networks. CEEPR employs decision-making and dynamic cluster formation to overcome this difficulty. CEEPR guarantees improved load balancing and scalability by dividing the cluster formation process among numerous nodes, enabling the network to efficiently support a greater number of nodes.

The network density, or the quantity of nodes in a certain region, determines whether CEEPR is feasible. The computational complexity and communication costs associated with group decision-making and dynamic cluster formation

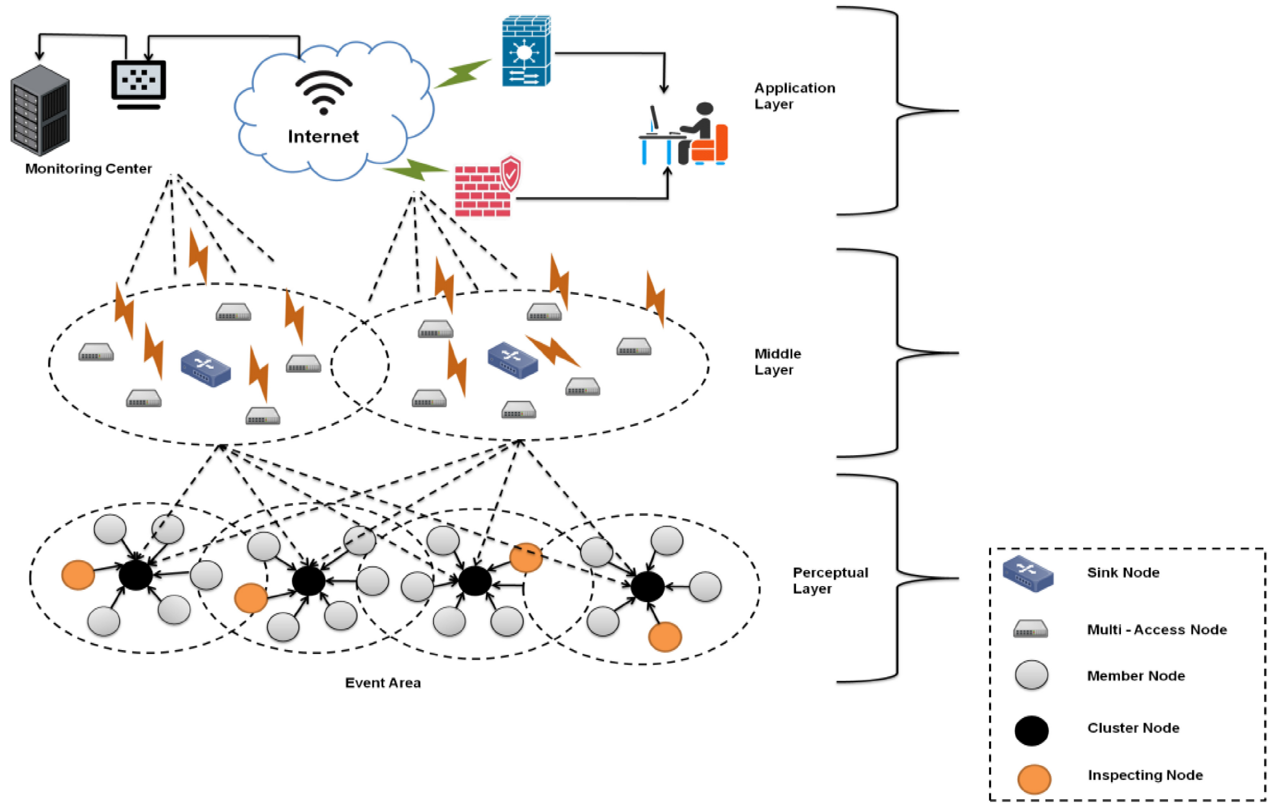

FIGURE 6. CEERP.

may climb as network density rises. Determining the viability of these activities in terms of memory, computing power, and communication overhead is crucial. Algorithm 2 for the proposed CEERP is described below:

E. OPTIMIZATION USING MULTI-OBJECTIVE IMPROVED SEAGULL ALGORITHM (MOISA)

In this case, the MOISA is set up to select the cluster/routing procedure leader. We may get a thorough description of MOISA in this section. Laridae, the family of which seagulls are a member, is a diverse ecosystem. There are many kinds of sea birds, but seagulls have appealing qualities, including aggression and a high hunting drive. Seagulls are considered intelligent birds since they have distinct migratory and hunting patterns. Because of their unique characteristics and quick judgment, seagulls are preferred over other aquatic and marine birds. Two crucial processes, migration and attack, are part of the multi-objective improved seagull algorithm and are described below.

1) MIGRATION

Additional restrictions are implemented to estimate the best exploring agent position throughout the migration process to prevent interference between neighbors. The detection of the exploring agents in the region of the best neighbor movements occurs as soon as the neighbor collision is removed. The optimum search agent is linked to the position of the revised search agent.

2) ATTACK

This approach is used because the exploring process requires less computation than other methods. Seagulls change their migratory condition during the attacking phase when they concentrate on maintaining their height depending on body weight and air currents. They may make twisting movements in midair while attacking the victim. Hence, we are utilizing this approach for the optimization of CEERP in WSN.

Integrating MOISA to the CEEPR allows the protocol to make use of MOISA's multi-objective optimization features. This allows CEEPR to adapt to changing network circumstances and promotes collaborative decision-making across sensor nodes, all while maximizing energy efficiency, network lifespan, and other goals.

Depending on the problem's complexity and the available solutions, MOISA's convergence qualities may change. The number of targets, the size of the problem, and the fitness function all have a role in the algorithm's computational complexity. Balance between exploration and exploitation, as well as trade-offs between distinct goals on the Pareto-optimal front, are at the core of MOISA's performance trade-offs. When these details are known, MOISA may be better evaluated for application to a certain class of problems, and its performance can be improved in the field. Algorithm 3 for Multi-Objective Improved Seagull Algorithm is described below:

Algorithm 2 CEERP

Initialization
- Initialize the energy levels, node placements, and network structure.
- Define energy and routing thresholds.
- Create channels for communication between nearby nodes.

Energy Monitoring
- Regularly check each node's energy levels.
- Update the data on energy use in a network-wide energy database.

Collaborative Neighbor Selection
- Each node notifies its neighbors of its energy condition.
- Nodes get energy data from their surrounding neighbors.
- Each node chooses a selection of cooperative neighbors based on energy levels and proximity.

Route Discovery
- A route discovery procedure is initiated by a node when it needs to transfer data.
- To its cooperative neighbors, the source node transmits a route request packet.
- Neighboring nodes continue to relay the route request packet until it reaches the destination or a node that has a predetermined route there.
- Energy details and routing metrics are included in the route request packet.

Route Selection
- Routing metrics (such as energy efficiency and path length) are calculated by nodes that receive the route request packet.
- Nodes choose the optimum route by comparing the received routing data with their own local metrics.
- The chosen path is saved for the next data transfer.

Data Forwarding
- Data packets are sent by nodes along the chosen path after a route has been created.
- Intermediate nodes maintain an energy database and track their own energy levels.
- To reduce energy use, nodes may use strategies like data aggregation or hop-by-hop energy balancing.

Energy Management
- Nodes also keep tabs on their neighbors' energy use by occasionally updating their own energy levels in the energy database.
- A node has the ability to begin energy-aware routing modifications, such as looking for other routes, if it notices that a neighbor's energy level is below a threshold.

Route Maintenance
- Nodes frequently exchange control packets to check on the status of the developed routes, and they send route request packets to begin the route repair procedure when they discover a broken or ineffective route.

Termination
- The protocol keeps running until termination requirements are satisfied or until the network is no longer necessary to transmit data.

Algorithm 3 MOISA

Initialization:
    Set the population size (N) and maximum iterations (MaxIter).
    Define each variable's search space.
Population Initialization:
    Create a random population of seagulls representing possible solutions.
    Assign seagulls random search space positions.
Fitness Evaluation:
    Use the optimization problem's multiple objectives to assess each seagull's fitness.
    Calculate fitness values for each seagull based on goals.
Main Loop (Iterative Process):
  Repeat until maximum iterations are reached:
    Communication:
    Seagulls share positions and fitness values with one another.
    Movement:
    Foraging-inspired movement equations update seagull positions.
    In the movement equations, integrate the exploration and exploitation components.
    Fitness Evaluation:
    Determine if the seagulls' new locations are fit.
    Pareto Front Determination:
    To find the Pareto fronts based on the seagulls' fitness levels, use non-dominated sorting.
    Crowding Distance Assignment:
    To sustain variety, determine the crowding distances for each Pareto front's solutions.
    Selection and Reproduction:
    Use tournament or roulette wheel selection to choose parents for reproduction.
    Create offspring through crossover and mutation.
    Assess offspring fitness.
    Add the offspring to the population.
    Migration:
    Choose seagulls from each front depending on crowding distances.
    Exchange individuals between fronts or subpopulations to promote variety and prevent convergence.
    Attack:
    Select a fitness-based subset of seagulls from each front.
    Use an attack method to randomize and explore their placements or fitness values.
    Population Update:
    Select the finest solutions from the population and offspring to create a new population.
    Preserve potential ideas to maintain population size.
    Iteration Update:
    The iteration counter is incremented.
Termination:
    Return the Pareto front of the final population, which represents the algorithm's non-dominated solutions.

IV. PERFORMANCE ANALYSIS

The NS-2 network simulator was used in the study's proposal of the collaborative energy-efficient (EE) routing procedure (CEEPR) for 5G and 6G WSNs. To reproduce CEEPR's conduct, NS-2 was set up with the protocol's principles and parameters; this required a laptop running a Linux-based operating system like Ubuntu, having an effective CPU, and having at least 8 G.B. of RAM. The efficiency of CEEPR was evaluated using performance assessment measures such as throughput, energy consumption, network longevity, packet transmission, routing overhead, and transmission speed. The suggested method was benchmarked against existing approaches including EERBM, DRS, AGEN-AODV, and CEELBRP. The efficiency of the protocols was assessed using experiments using NS-2, taking into account various network scenarios, node deployments, and traffic patterns. The results of the experiments were analyzed and compared to show the benefits of CEEPR over the existing protocols. A computer with an Intel Core i7-2640M CPU running at

TABLE 1. Outcomes of existing and proposed methods.

Methods	Throughput (%)	Energy Consumption (%)	Network Lifetime (%)	Packet Permission (%)	Routing Overhead (%)	Transmission Speed(%)
EERBM [22]	70	84	65	65	60	60
DRS [23]	65	80	72	70	70	80
AGEN-AODV [24]	84	75	75	76	75	70
CEELBRP [25]	87	70	80	80	85	85
CEEPR [Proposed]	90	90	95	85	95	92

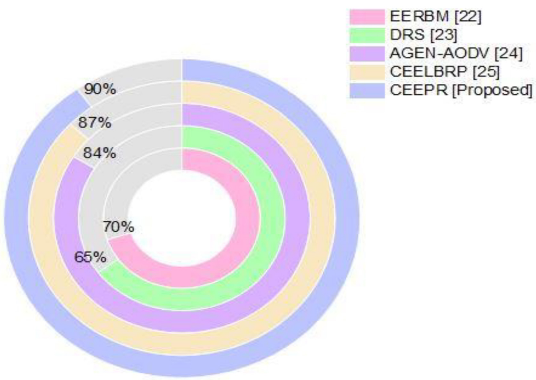

FIGURE 7. Throughput.

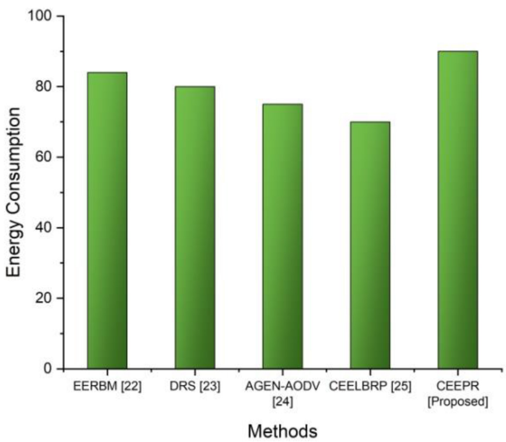

FIGURE 8. Energy consumption.

2.80 GHz, 4 G.B. of RAM, and a 64-bit operating system is used for the experiment. PYTHON is a tool for doing experiments.

Table 1 depicts the outcomes of existing and proposed methods.

A. THROUGHPUT

Throughput is used to quantify the proportion of the total data packets to the runtime. Packets are used to transfer data. The most effective cluster head is the one that transfers a huge volume of data. Based on the transferred packets, the throughput is calculated. Network topology, traffic patterns, protocol design, and network circumstances are only a few of the elements that might have an impact on performance of a CEER. Nonetheless, the goal of most CEER protocols is to maximize both energy efficiency and throughput. CEER protocols have the ability to give the same or better throughput compared to traditional routing approaches. When the suggested algorithm's throughput is contrasted to that of current methods, the comparative results are represented in Figure 7 and Table 1. The suggested technique is found to have greater throughput compared to the other current techniques.

B. ENERGY CONSUMPTION

Energy consumption is the term used to describe the energy required to carry out an activity, generate something, or just inhabit a space. It is possible to determine the overall energy usage by looking at how much power each routing process consumes. CEERP actively includes energy-aware tactics and coordination among nodes to decrease energy usage, as opposed to standard routing methods, which may not emphasize energy conservation. The energy efficiency of WSNs may be greatly improved using CEER protocols by improving data transmission, clustering, routing choices, and power management. Figure 8 and Table 1 represent the energy consumption. The amount of energy utilized by (EERBM), (DRS), (AGEN-AODV), and (CEELBRP) were discovered to be 84%, 80%, 75% and 70%. Here, the suggested work consumed 90% of the energy.

C. NETWORK LIFETIME

The network lifespan statistic measures how many rounds or how long it took the network to complete the activity. Additionally, it details the moment the node passes away while completing the data transmission process. An effective routing algorithm, network design, and traffic patterns all play a role in determining the precise advantages of CEERP. However, in comparison to traditional routing methods in WSNs, these protocols have the ability to considerably lengthen the network's lifespan by explicitly addressing energy conservation and employing collaborative strategies.

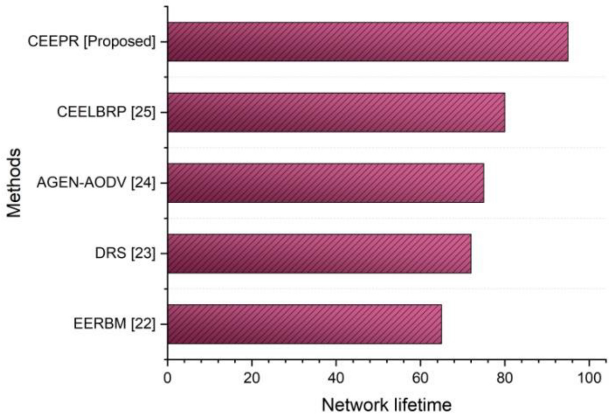

FIGURE 9. Network lifetime.

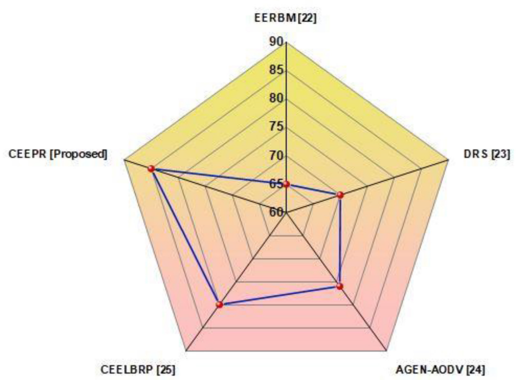

FIGURE 10. Packet transmission.

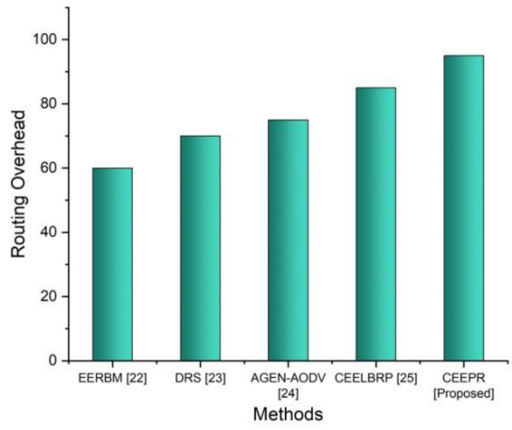

FIGURE 11. Routing overhead.

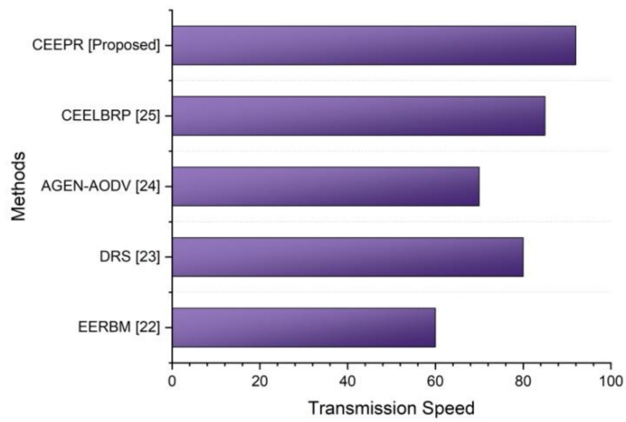

FIGURE 12. Transmission speed.

In Figure 9 and Table 1, the network lifetime is shown. While the proposed CEERP achieved 95% of the network lifetime, the EERBM achieved 65%, DRS accomplished 72%, AGEN-AODV accomplished 75%, and CEELBRP accomplished 80%.

D. PACKET TRANSMISSION

When compared to traditional techniques, packet transmission benefits from CEERP. They provide fault-tolerant packet transmission, cooperative communication, and reduced energy usage, load balancing, and increased network longevity. Because of these benefits, packet transmission in WSN is both more efficient and reliable, leading to higher network performance and lower energy consumption. Figure 10 and Table 1 display the typical enhancement the suggested technique makes when sending the data packets to the sink. DRS outperforms other known methods with an overall improvement of 70.252% when sending data to the sink. However, there is only a little decline in network efficiency, which is reversed by the suggested CEERP routing procedure. The data packet transmission performance of other current algorithms like EERBM at 65%, DRS at 70%, AGEN-AODV at 76%, and CEELBRP at 80% has mostly stayed the same.

E. ROUTING OVERHEAD

It might be interpreted as the amount of transferring packets transmitted for path discovery and maintenance. The number of packets used for routing is counted once for each hop. The routing overhead is illustrated in Figure 11 and Table 1. Routing overhead is introduced by CEERP as a result of an increase in control messages, data sharing, aggregation, and node cooperation. However, the advantages they provide in terms of energy efficiency and network performance often surpass this expense and enable the WSN to remain effective and durable overall. In contrast to the proposed CEERP, this only achieved 95% of routing overhead, the EERBM, DRS, AGEN-AODV, and CEELBRP achieved 60%, 70%, 75%, and 85%, respectively.

F. TRANSMISSION SPEED

Data packets are sent between servers on a network connection at a pace known as transmission speed. A fraction or percentage of the maximum speed is thought to be the optimal rate for data transmission through lines or cables. The speed of the transmission is shown in Figure 12 and Table 1. It's crucial to take into account the trade-off between energy efficiency and speed, even while collaborative energy-efficient routing techniques may result in a little increase in transmission speed compared to traditional approaches. These protocols seek to maximize energy efficiency while preserving network performance and connection. The advantages they provide in terms of longer network lifespan, increased energy efficiency, and flexibility often outweigh the possibility of a transmission delay increase. The EERBM, DRS, AGEN-AODV, and CEELBRP obtained 60%, 80%, 70%, and 85% in transmission speed, while the proposed CEERP outperformed high speed by about 92%.

V. CONCLUSION

In this study, a CEERP for 5G/6G communication in WSN is created, which contains the R.L. algorithm for cluster grouping. The suggested architecture's learning algorithm has increased the architecture's overall network lifespan. The cluster head from each cluster must then be chosen to carry out efficient data transfer. In this design, an effective RE-based method is used choosing on the cluster head (CH), which is recognized as the primary factor in WSN. Four main goals are considered to choose the most effective cluster head for sending the information to the descend node. The cluster head selection considers the following criteria: range, latency, reducing congestion, and resources. Without generating any network congestion, the data is delivered to the sink node, R.L. does the cluster formation, and then the cluster heads are selected through RE. Generally, the routing protocols created for the existing designs must provide satisfactory outcomes. CEERP architecture for shortest route discovery is developed to circumvent these problems. Effective data transfer can be accomplished using the indicated channel. The suggested CEERP is found to be more effective than the existing methods used. For data transmission, choosing the shortest route has improved network lifetime and energy efficiency. The future scope is accomplished by using a different optimization approach with more sophisticated data transmission.

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