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Energy Efficient Networks Using Ant Colony Optimization with Game Theory Clustering

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Abstract: Real-time applications based on Wireless Sensor Network (WSN) technologies quickly lead to the growth of an intelligent environment. Sensor nodes play an essential role in distributing information from networking and its transfer to the sinks. The ability of dynamical technologies and related techniques to be aided by data collection and analysis across the Internet of Things (IoT) network is widely recognized. Sensor nodes are low-power devices with low power devices, storage, and quantitative processing capabilities. The existing system uses the Artificial Immune System-Particle Swarm Optimization method to minimize the energy and improve the network's lifespan. In the proposed system, a hybrid Energy Efficient and Reliable Ant Colony Optimization (ACO) based on the Routing protocol (E-RARP) and game theory-based energy-efficient clustering algorithm (GEC) were used. E-RARP is a new Energy Efficient, and Reliable ACO-based Routing Protocol for Wireless Sensor Networks. The suggested protocol provides communications dependability and high-quality channels of communication to improve energy. For wireless sensor networks, a game theory-based energy-efficient clustering technique (GEC) is used, in which each sensor node is treated as a player on the team. The sensor node can choose beneficial methods for itself, determined by the length of idle playback time in the active phase, and then decide whether or not to rest. The proposed E-RARP-GEC improves the network's lifetime and data transmission; it also takes a minimum amount of energy compared with the existing algorithms.

Keywords: Ant colony optimization; game theory; wireless sensor network; network lifetime; routing protocol; data transmission; energy efficiency

1 Introduction

The Wireless Sensor Network (WSN) comprises several connected sensors used to detect external environmental factors, including pressures, heat, noise, etc., and jointly transmit their acquired data over the network towards the centralized spot. WSN comprises several nodes, each of which would communicate with some other devices. WSNs are used in a diverse range of products. The Internet of Things (IoT) is described as a system of natural objects, such as various sensors with programming, networking capabilities, and hardware that allow components to collect and share files with others. In the environment, transportation, monitoring systems, robotics, communities, houses, object tracking, and routes, IoT has multiple uses.

Sensor nodes in WSNs detect, communicate, and collaboratively gather data. Some certain quantities of energy will be consumed during this procedure. On the other hand, many nodes are stored in a battery and have energy. When the batteries die, and the energy source is not changed or supplied promptly, the transfer of collected information is hampered, and the entire sensor node may become paralyzed [1]. As a result, extending the lifespan of full sensor nodes by being as powerful as feasible in the presence of significant power became a considerable challenge in real-world remote sensing applications.

Depending on how the regional information is transmitted and integrated at the Fusion Center, various methods emerge (FC). Directly routes (also known as a point-to-point technique) or multihop forwarding to an FC that is the Internet of Things (IoT) equipped with the main two methods for collecting data from SNs. WSNs are restricted in electricity, storage, computational power, and bandwidth since batteries power them. Such systems are maximum throughput and have significant latencies due to shared wireless network architecture. Because WSNs are battery-powered, energy efficiency has increased concern [2].

Compared to many previous meta-heuristic methods [3], the ACO method [DORIGO, 1992] can identify the shortest way in very little time and at a lower price. The ACO is a class of optimizing meta-heuristics influenced by bio-inspired algorithms (particularly ants' movement or similar creatures that create a remarkably). It was motivated by ants searching for a route among the nest and a food supply. An initial idea has been decided to expand to a far broader range of issues, and multiple methods were proposed depending on various elements of ant behavior. On the other hand, such approaches focus solely on renewable energy and overlook any component of dependability before after losses. This could prove to be problematic and cause power consumption difficulties. As a result, overcoming energy availability and effectiveness concerns is a time-consuming process [4]. In waiting for time, WSNs systems in which any method of giving the warning to firefighting in a timely basis could have a considerable expense (e.g., it poses significant harm to human lives, the functioning of ecosystems, and infrastructures) rely on the effects are critical [5].

Numerous researchers and academics have undertaken numerous studies to optimize overall network energy consumption [6–10]. Following thorough reviews of relevant literature, it was discovered that research had been undertaken on the power usage of IoT devices during the inactive monitoring period. In reality, whenever a sensor network is operational, there is a significant amount of fixed playback time, and this period will cost considerable power [11,12]. If a substantial quantity of energy is wasted at this point, the power required by the sensing nodes to gather and send data will be considerably minimized, reducing the sensing node's lifespan to some extent.

The major contribution of the proposed E-RARP-GEC is given as follows:

Ø We explore cluster-based networks in which the SNs are organized into groups and managed by a Cluster Head to optimize power usage and maintain energy balance in the networks (CH).

Ø These CHs are chosen based on the energy state, which does not necessitate much control cost. We shall demonstrate considerably improve the program's operating lifespan and dependability.

Ø A game design is produced by considering the effects of numerous factors that influence the actual power loss. A threshold of sensor devices reaching deep sleep is computed based on energy usage during inactive monitoring of the sensor network and the transfer of the sensor network from deep sleep to the exciting phase.

Ø The experimental findings indicate that utilizing gaming to govern the sensor nodes' movement among sleep and active states can lower its power usage, essentially extending the network's lifespan.

The remaining part of the paper is followed: Section 2 explains the review of literature, Section 3 describes the proposed Energy Efficient and Reliable Ant Colony Optimization based on the Routing protocol (E-RARP) and game theory-based energy-efficient clustering algorithm (GEC), Section 4 describes the experimental results and evaluation, Section 5 discuss the conclusion and future work.

2 Related Work

The gaming concept is just a relatively recent mathematical study. It frequently regarded players' approaches and advantages and their methodologies. Gaming theory is increasingly employed in WSNs, with applications primarily in power generation, authentication protocols, transmission power, data collecting, and other areas [13–17]. The applicability of behavioral economics to WSN energy efficiency has produced very impressive outcomes in recent years. The relevance of behavioral economics to WSN power generation has produced awe-inspiring results in current history. A voltage regulation game model, for instance, was developed in [18] to maximize the proportion of power usage and data packet effectiveness of the control. The article first used a multivariate optimization model to characterize the tradeoffs and combine the outcomes of its actions and node density.

The author [19] suggested a power clustering method game-theoretic, which uses dual technology to examine sensor network power usage. The widely used open-source high-efficiency cluster (DEEC) methodology for heterogeneous Wireless sensor networks was enhanced in [20]. Like an optimization procedure, the gaming concept was utilized, and the likelihood of nodes becoming a clusters leader was changed highest residual power, extending the lifespan of groups. A game theory-based energy-efficient hierarchical clustering is described in [21]. Every node fights as a prospective member node during the cluster-based stage by participating in localized clustered games. A possible cluster is chosen to become a genuine root node using a probability method that has been appropriately developed.

The author [22] suggested a hybrid game theory-based cluster-based routing method for WSNs. The restrict communications and increase the longevity of the WSN, the strategy uses behavioral economics to govern the actions of a sensor network and its neighbors. Every node is depicted as just a player who will choose whether or to be not the cluster's leader on its terms. Moreover, while adopting various techniques, the reward of each group was established, taking into account both the number of sensor nodes and the distances to the access point. A method for power generation penetration in wireless communication based on cooperative operations research was proposed [23].

A collaborative trading game has been used to estimate the association among sensor networks. In these games, every sensor network must satisfy the program knowledge requirements yet consume minimal energy. A game-theoretic method is suggested in [24] for regulating energy usage in clustering wireless communication. A punishment system was implemented to encourage nodes having a greater intensity to proactively acquire cluster-head, taking into account the inconsistently applied of the sensor network. The power balancing efficiency of the clustering method based on game theory suggested in the literature was demonstrated.

[25] proposed the best navigation optimization technique for subsurface sensor networks on Q-learning behavioral economics. Its Q-learning modeling approach captures the underwater acoustic sensor organization's decentralized characteristics. The technology is efficient in terms of power and can construct the network's lifespan. Regarding improving energy efficiency in a diverse mobile sensing environment, a heterogeneity games conceptual grouping technique termed portable clustered theory 1 was suggested in [26]. This system was optimized for energy conservation by using power clusters leader elections and multipath forwarding. In [27], a concept and upgraded ant colony-based mobility sink path choosing and data collection method was given. Integrating game theory is a genuinely efficient

approach skill with the optimum meeting locations choice. Data transfer and administration, power usage, and transmitting data latency were all decreased thanks to GTAC-DG.

A CDMA WSN-based noncompliant game-theoretic power management technique was suggested in [28]. Just on the foundation of noncompliant behavioral economics, the Nash equilibrium of the energy control scheme was investigated in the present study. It has the potential to conserve the sensor energy of nodes, increase overall system performance, and extend the lifespan of the WSN. A game theory-based power-optimized framework of nodes collaboration was suggested in [29]. The primary power usage component of nodes, communications power consumption, was used as an explanatory variable in this approach, and a compensation mechanism for the node's remaining energy was constructed. Furthermore, the greatest game theory of node cooperation's energy usage was found to be more accurate.

Meta-heuristics can provide optimum or relatively close route choices both in small-and large-scale systems in a reasonable period. In numerous domains of study, meta-heuristics, including Particle Swarm Optimization (PSO) algorithms, genetic algorithms, and Ant Colony Optimization (ACO) methodologies, have been commonly used to detect the quickest route. Compared to specific other current heuristic methods [30], the ACO method [DORIGO, 1992] can identify the fastest way in less time and at a reasonable cost. The ACO is a microbial method that consists of a series of optimizations and meta-heuristics. This is influenced by the behavior of ants or even other organisms that create an organism.

It was motivated by insects searching for a route among its colonies, and it provides nutrients. The initial idea has been expanded or applied to a far broader range of issues, and multiple methods have already been proposed based on various elements of ant behavior. Innovative plans are established using the ACO methods [31–33]. While existing approaches in their current incarnation may give satisfactory results in certain situations, they may perform poorly in others. On the other hand, such systems focus solely on renewable energy and overlook any component of dependability before after breakdowns. The above-mentioned determined period of time of present methods could be flexibly changed to meet application requirements.

3 Proposed Energy Efficient Methodology

The proposed E-RARP-GEC method optimizes the cluster head (CH) selection. It consists of a network model, energy model, game model, and mathematical model also it uses a routing protocol to optimize the efficiency of the energy. Fig. 1 shows the architecture of the proposed method.

3.1 Network Model

A wireless sensor network (WSN) is a system made up of a randomized number of nodes that form various groups, each with a cluster head node and many cluster members (CMs). Each CM decides if it connects to clusters and its appropriate place. Additionally, every CM has a detection range. Every node may gather information from observed objects and transmit it to the corresponding CH, who subsequently communicates it to the mobile sink. The operational phases of a sensor network in the active mode are when required to send and receive information. The inactive waiting stages are if the nodes have little information to process and transmit. To save power, all functionalities on the sensor node were switched down when in idle mode. The sensor node's power consumption can be regarded as zero in this condition.

This work considers sensor networks appropriate and that power in severe settings is constrained and dispersed. The sensor network will be as energy-efficient as feasible for its advantage. The sensor network will be as energy-efficient as possible for its benefit to meet the goal of maximizing lifespan. As a result, to ensure system performance, the sensor network must reach an inactive condition often as feasible while being in the idling listen-to phase to save energy and maximize system lifetime.

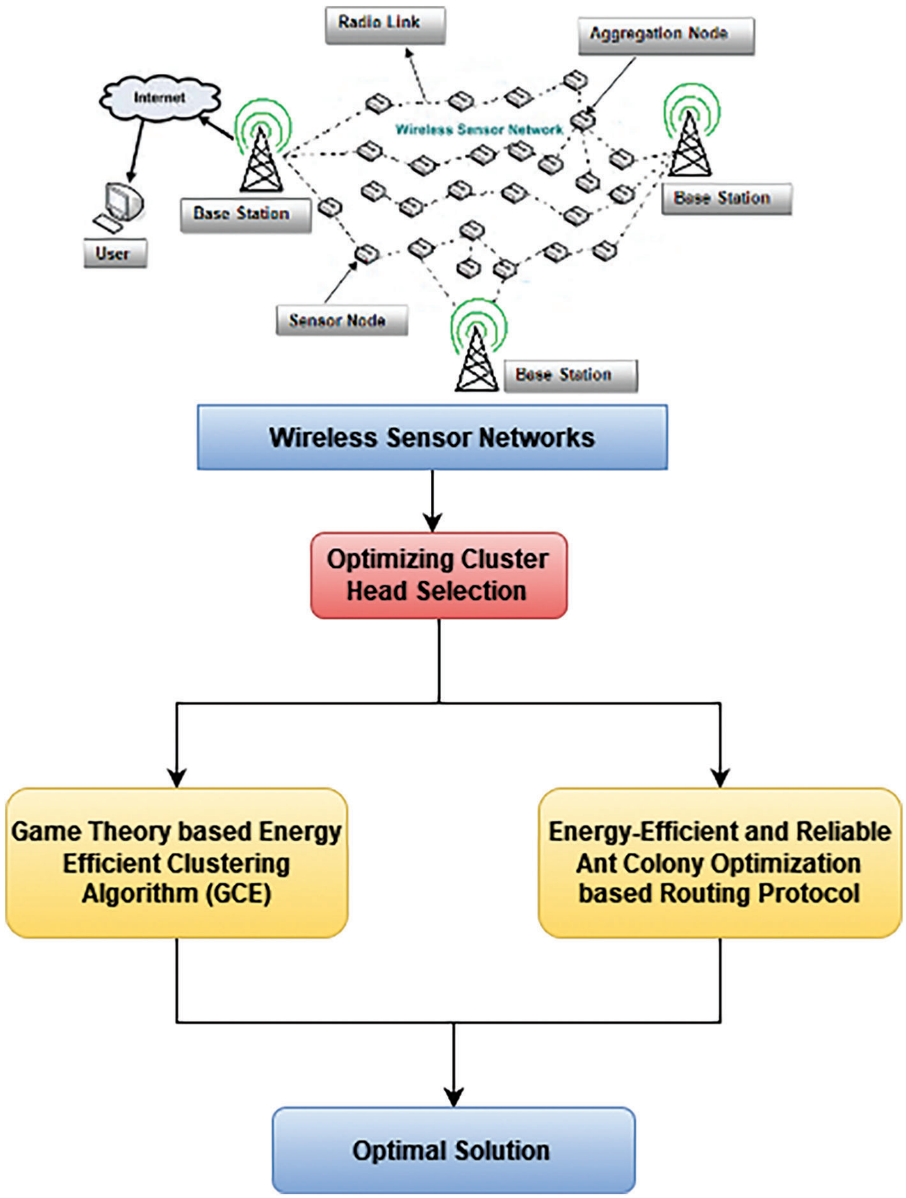

Figure 1: Architectural overview of the proposed system

3.2 Energy Model

It is required to investigate different sensor network energy usage aspects throughout information processing to determine the sensing node's excess power. A variety of elements influences a sensor node's energy usage. The primary factors that seriously influence sensor network power usage are listed here.

3.2.1 Sensing the Cost of Energy

Whenever the sensors are in operation, it initially detects the natural area before acquiring sensed information from that too. Furthermore, the amount of energy required by sensor nodes is proportional to the size of the sensors. Varying sensors utilize varying amounts of detecting power. In principle, the sensors component S_i·s detecting energy usage is specified by

$$En_s(S_i) = Lc(S_i) * Ic(S_i) * Td(S_i) * Vo_s \tag{1}$$

Here I (S_i) is the required power, Vo_s seems to be the supply voltage, and $Td(S_i)$ is the time it takes to identify and gather $Lc(S_i)$ pieces of information.

3.2.2 Processing the Cost for Energy

Each sensors network requires power while reading and storing information, hence the energy usage may be stated as:

$$En_p(S_i) = \frac{Lc(S_i) * Vo_s}{8}(Ic_{Write} * Tc_{Write} + Ic_{Read} * Tc_{Read}) \tag{2}$$

Tc_{Write} and Tc_{Read} represent the time it takes by sensor network to learn to read L(Si) pieces of information, respectively, while Ic_{Write} and Ic_{Read} represent the required power by the sensor network to read and study per part of the information, in both.

3.2.3 Communicating Energy Consumption

Sensors' communications power consumption mostly comprises the power used to deliver and receive data. As a result, the sensing node's energy usage while transmitting messages can be represented as

$$En_t(S_i) = \begin{cases} Lc(S_i) * En_{elec} + Lc(S_i) * En_{fs} * d^2 & when \quad d < d_0 \\ Lc(S_i) * En_{elec} + Lc(S_i) * En_{mp} * d^4 & when \quad d > d_0 \end{cases} \tag{3}$$

These values En_{fs} and En_{mp} are dependent just on transmitters amplifiers architecture, indicating the empty spaces and multi-path models, correspondingly, and En_{elec} is the power required to receives or broadcast each bits signal. A difference between adjacent sensor networks is denoted by d. A thresholds range, denoted by D_0, could be represented as

$$D_0 = \sqrt{En_{fs}/En_{mp}} \tag{4}$$

After gathering data, the power needed by the sensor network can be stated as

$$En_r(S_i) = Lc(S_i) * En_{elec} \tag{5}$$

3.2.4 Transitioning from Sleeping to Ready State for Energy Usage

This shift from the resting state to the activated state, and conversely, consume a higher amount of energy whenever the sensing network is functioning. The power used to transition out of an activity to a resting state, on either hand, is very little and therefore insignificant. As a result, the amount of energy used by the sensor network to change its operational status is given at

$$En_w(S_i) = \frac{Vc_s}{2} * (Ic_a - Ic_s) * Tc_{as} \tag{6}$$

Here Ic_a is just the present inside the sensing node's excited phase, Ic_s then the present in the sensing node's deep sleep, and Tc_{as} seems to be the time it takes for the sensor network to change between sleeping to activity.

3.2.5 Sensor Node Total Energy Consumption

The overall power usage of the sensor network could be calculated by Using the Eqs. (1)–(6) as described in the following:

$$Co_i = En_s(S_i) + En_p(S_i) + En_t(S_i) + En_r(S_i) + En_w(S_i) \tag{7}$$

3.3 Game Theory Based Energy Efficient Clustering Algorithm

3.3.1 Developing a Game Model

Sensor networks can move among engaged and sleeping states reasonably to extend the lifespan of a WSN; consequently, sensors nodes dynamically switching could be considered a gaming issue. The following is an example of the framework:

$$GT = \{Np, Kp, \{u_j\}\} \tag{8}$$

Here Np is the name of the WSN players. Because all sensing network nodes are active in collecting and delivering sensing data, all sensing network nodes are included in the game players. To put it another way, the game players are sensing nodes Si, with I = {1, 2, and n}. Throughout this study, an operational area of teams is denoted by the letter K. Throughout this study. The sensor network can establish the help the game players by evaluating the power usage, *i.e.*, the sensors join the sleep state out from the activated state, as well, as the sensor network doesn't enter the stable state from the activated state due to the sensible choice of the sensor network. UI represents the functional form of players.

$$u_i(s_i, s_{-i}) = U_i(s_i, s_{-1}) - C_i(s_i, s_{-1}) \tag{9}$$

Here sn_i denotes the sensing node's approach. Besides from sensor network, sn_i is the approach used by nodes. A revenues value of networking device S_i is S_i, U_i (sn_i, sn_i), whereas the expense value of sensor network S_i is C_i (sn_i, sn_i).

Data packets passing are communicated in a multi-hop way by the wireless sensor network. A revenues component of a sensor network is described as the reward received by a sensor network for effectively transferring an incoming packets to next sensed data, based on the reasoned consideration of sensor network. As a result, the revenues functional are formulated as having:

$$U(s_i, s_{-i}) = Gr * Pr \tag{10}$$

Here Gr is a sensing node's compensation for correctly sending incoming packets to other sensing nodes, and Pr is the likelihood that number of packets will be properly sent.

$$X_j(S_i) = \begin{cases} 1 & Active \quad mode \\ 0 & Sleeping \quad mode \end{cases} \tag{11}$$

Whenever the sensor network Si is sleeping and needs to be passed data packets, it will get one of two schemes: selfishness and non-forwarding or collaborative and advancing. As a result, the 2 tactics used whenever the sensor network is inactive are just as follows:

$$Y_j(S_i) = \begin{cases} 1 & Forwarding\ the\ data\ packets \\ 0 & Do\ not\ forwarding\ the\ data\ packets \end{cases} \tag{12}$$

3.3.2 Determining the Threshold for Sleep State

Whenever a sensor node in a wireless sensor network is operational, the method for determining the changeover between sleeping and functional states varies depending on the sensor node's power usage. At the exact moment, it provides several advantages to the participants. In those other terms, the sensors' power usage could be minimized by transitioning to a resting state at such a suitable inactive monitoring period, extending the sensor system lifetime.

A wins sensor networks are in charge of gathering and delivering data. Inside this article, the sensor networks are set to be capable of switching among idle monitoring and sleep stages in a reasonable time, minimizing sensor network power usage throughout inactive music playback and minimizing the resource load imposed by frequently changing among passive hearing and sleeping modes.

3.4 Routing Protocol Based on Ant Colony Optimization

A possibility of selecting every next step routing protocol to achieve the level in the classic ACO algorithm is provided here. This is only reliant on a single effect component, the pheromones.

$$Pr_{n,d} = \left\{ \frac{(T_{n,d})^{\beta}}{\sum_{j\varepsilon N} (T_{j,d})^{\beta}} \right. \tag{13}$$

$Pr_{n,d}$ is the possibility of choosing neighbour n for a next jump to target d, $T_{n,d}$ is the pheromone valuation at neighbour n to attain destinations d, N is the collection of neighbours, β and is a continuous pheromones factor.

The classic ACO method uses only one effect element, which would be the pheromones. SNs on the optimization algorithm, on either hand, lose their energy supplies faster than some other networks. As a result, there is an issue with energy usage unbalance throughout the system. As a result, we devised a new probabilistic model that includes, in addition to pheromones, a slew of various additional indicators, including remaining energy, number of hops, neighbor nodes tally, and weak-link counters. This enables you to choose from multiple power and dedicated routes for transmitting data from a source address to a destination address. Below are the factors that have an effect:

3.4.1 Residual Energy

When an ideal determine the WSN's energy consumption [34,35]. Given that such power resources of SNs are retained, it is clear that transmitting information across fewer hops is desired. Every SN knows the identities of the adjacent nodes, and the number of routes is heavily used. Some other courses become dormant. When compared to SNs of different ways, the SNs of the hop-based optimum solution possibly resulted in their power. It results in inequitable power use and system gaps. Incorporating remaining energy into route decisions enables non-hop dependent optimum routes to be selected over a singular optimum solution when transmitting data packets. This uniformly spreads power usage throughout the WSN's units. The system would then be informed of its power use, which increases its lifespan. Eq. (14) is used to compute the residual energy (Enr).

$$En_r = En_i - En_s \tag{14}$$

Here En_i denotes the starting power and En_s is the power expended, as determined by Eq. (15).

$$En_s = En_{rx} + En_{tx} + En_{sleep} \tag{15}$$

Here En_{sleep} is the type of power spends on sleep, and En_{rx} and En_{tx} are the amounts of effort consumed getting (including idle waiting) and sending incoming packets, correspondingly.

3.4.2 Hop Count (HC)

This is a crucial metric for links necessary to attain there, in backwards training. When an SN discovers the best way, that is, the route with the fewest hops, it initiates a route database to include the new optimised route.

3.4.3 Neighbor Nodes Count

This is a crucial factor for determining which node to use as next neighbouring node. More and more neighbours there really are, so more possibilities there would be. As just a result, we remove the risk of local optimum solutions and improve the chances of selecting optimal routes. The NNC is calculated using Eq. (16).

$$NNC = \sum_{k=1}^{Nn} Neighbor_k \tag{16}$$

Here Nn represents the number of nodes inside the neighbourhood.

3.4.4 Link Quality Indicator (LQI)

Such connections in WSNs are typically unstable, highly dynamic surroundings, wherein connection might fluctuate for factors such as storms, rainfall, etc. Since low-power transmitters are vulnerable to certain features such as interfering, sound, and multipath distortions, they can contribute to route instability. As a result, the LQI is used to improve the transport protocol's dependability, involved in real applications such as fire detection. LQI is an exciting thought derived from the higher layers of the IEEE 802.15.4 specification.

The following expression (17) is used to determine the LQI.

$$LQI = (Corr - a) \times b \tag{17}$$

Here Corr is the correlation value (the actual LQI calculated value from the statement's final byte), and a and b are experimentally determined.

The extent of the ants' searching and the number of the grouping have a massive effect on the ACO system's resolution rate of productivity. Since the data link in WSNs consumes power, the extent of ants' searching does have a proportional impact on energy. As a result, we limit the scope of ants' searching to save power, improve convergence speed, and remove unnecessary. We restrict our searches to those vertices that meet the lesser criteria to accomplish this. The searching is limited to nodes (N) with energy transferred is much less than the length between both the origin and the FC. A revised suggested equation, which considers the revised significant criteria, is below.

$$Pr_{n,d} = \left\{ \frac{(T_{n,d})^{\alpha}\ (h_{n,d})^{-\beta} (E_n)^{\gamma} (CoW_{n,d})^{-\delta} (NC_n)^{\omega}}{\sum_{j\varepsilon N} (T_{j,d})^{\alpha}\ (h_{j,d})^{-\beta}\ (E_{j,d})^{\gamma}\ (CoW_{j,d})^{-\delta}\ (NC_{j,d})^{\omega}} \right. \tag{18}$$

Here n is just the ant's second choice for getting to a target. h is the amount of connections required by such an ant to reaches the target nodes d. d, n,d is indeed a analyse valuation from neighbour n to attain target d. A node's neighbours are defined by the number N. An amount of energy in the node is denoted by E, the amount of nearest neighbours is denoted by NC, $\alpha, \beta, \gamma, \delta$ and ω and the quality of the route is denoted by CoW.

Every loop updates the ant pheromones trails information to enhance speed even more. This enables the evaluation of the method's reliability and the demonstration of ant activity. Because it helps develop the following answers, the updating plan is an integral part of ACO's identity technique. These pheromones trails upgrading method includes both locally and globally changes. As just an outcome, the localized updating is ensured by the following expression:

$$T_{i,j}(t+1) = (1-p)T_{ij}(t) + \Delta T_{i,j} \tag{19}$$

$$\Delta T_{i,j} = \sum_{k=1}^{Mn} \Delta T_{i,j}^{k} \tag{20}$$

An overall amount of ants is represented by Mn.

Every ant k departing at i^{th} terminal and entering at the j^{th} node leaves the following pheromones quantity:

$$\Delta T_{i,j}^{k} = \sum_{k=1}^{Mn} \Delta T_{i,j}^{k} \tag{21}$$

$$\Delta T_{i,j}^{k} = \frac{Qc}{Ld_{i,j}} \tag{22}$$

Here Qc is a constant, and Ldij is the ratio of the distance by the ant k from nodes I to column j. The method is repeated till the required threshold is reached, or a satisfactory solution is obtained. Many routes are discovered during the route discovery process just after the ACO-based sequencing method's operation. In reality, many channels enable the system to equalize power usage across all nodes rather than imposing a straight route that will deplete all the nodes in the network's power more quickly if used heavily. Multiple pathways are helpful not just in terms of energy consumption but also in terms of maintenance. If a transmitting data link fails, an alternative back route is found in the forwarding table, reducing the failure's restoration delay and avoiding any more significant control cost transferred for the rescue.

3.5 A Mathematical Formulation for the Challenge of Energy Balanced Routing

Designers present a statistical method for an energy balancing transportation problem in this part, which it describes as a mathematical optimization modeling challenge. This research considered the following assumptions for such a reason:

We assume a WSN with n SNs distributed across the ROI at randomness. Those routers also relay the information taken to the FC. A collection of SNs and the FC node are represented by SN and S, accordingly. SNi is also defined as the collection of surrounding modules of actual nodes I where I SN.

Both power and information traffic supplied by sensor system I throughout any period [0,T] are denoted by ENi and DTi. Accordingly, the input power to send information and the number of the transmission between I to j is represented by N Eij and N Tij.

This initial information includes the collection of data collected by SN I as well as the information that has been aggregated by this nodes in [0,T], whereas the outbound data contains of the information sent out by I to surrounding networks and the FC. As a result, the network data formula is as follows:

$$\sum_{j:i \in SN_j} NT_{ji} + DT_i(T) = \sum_{j \in SN_i + \{S\}} NT_{ij} \quad \text{for all } i \in SN \tag{23}$$

The suggested cluster-based routing protocol (E-RARP) saves energy within the two essential stages, grouping and networking. Because of the low to the ground clustering technique and the avoidance of repeated bunch, the program's energy demand is relatively low when collection. The routing protocol also favors high-quality routes to reduce energy consumption and dependability. These intriguing aspects have a good impact on WSN's power usage management. As just an outcome, the amount of wasted energy is minimized, and the network's performance is extended.

4 Result Analysis

4.1 Simulation Environment

We compare E-RARP-GEC to numerous routing algorithms, including LEACH-HPR [30] and AIS-PSO [31]. We assess the potential route optimization methods' efficiency in terms of actual data isn't any more capable of reaching the FC and networking reaction speed or the time required for data transmission from across the system to its target (FC). Duration before information, a lifetime of the network, and so on are examples of measurements. The Omnet ++ based Castalia simulation environment is used. We placed 49 SNs in the ROI at the chance to achieve this analysis. Every SN's starting power is estimated to be 29160 joules, with a communication capacity of 46.2 mW. (–5 dBm). For all simulations, the Tunable MAC protocol was employed.

The LEACH-HPR [30] and AIS-PSO [31] techniques are used in this section. Research with 500 to 3500 nodes is conducted. Tab. 1 displays the number of clusters established, the maximum in Tab. 2 end-to-end latency, the maximum packet drop, and the proportion of nodes alive.

Table 1: Total amount of cluster formations

Total amount of nodes	AIS-PSO	LEACH-HPR	E-RARP-GEC
500	20	15	28
1000	21	17	37
1500	33	27	53
2000	49	41	67
2500	65	54	65
3000	63	53	81
3500	78	65	85

Fig. 2 shows the proposed E-RARP-GEC has a higher cluster formation compared with the existing methods. The proposed method achieves 9.6% for 3500 nodes.

Table 2: End to end latency

Total amount of nodes	AIS-PSO	LEACH-HPR	E-RARP-GEC
500	0.0041	0.0045	0.0012
1000	0.0047	0.0049	0.0041
1500	0.0048	0.0052	0.0036
2000	0.0463	0.0501	0.0351
2500	0.0797	0.0842	0.0894
3000	0.1694	0.1787	0.1754
3500	0.172	0.1816	0.1213

Fig. 3 shows that the proposed E-RARP-GEC has minimum end to end latency compared with the existing methods AIS-PSO and LEACH-HPR. The proposed method achieves 1.98% for 3500 nodes.

Fig. 4 shows that the proposed E-RARP-GEC has a minimum packet loss rate compared with existing methods in Tab. 3. The proposed method achieves 3.2% for 3500 nodes.

Fig. 5 shows the proposed E-RARP-GEC achieve higher alive nodes compared with the existing methods.

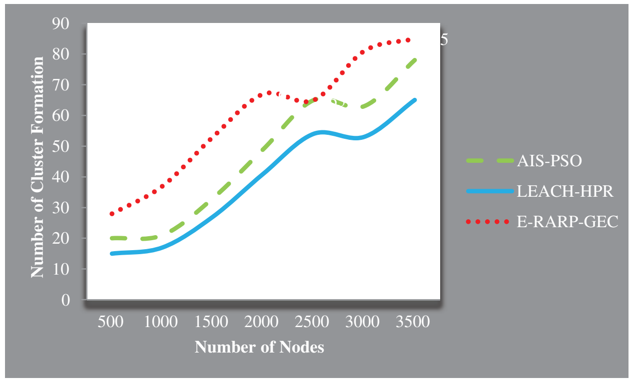

Figure 2: Proposed E-RARP-GEC cluster formations

Table 3: Total packet loss rate

Total amount of nodes	AIS-PSO	LEACH-HPR	E-RARP-GEC
500	7.52	7.89	6.95
1000	7.22	7.53	7.12
1500	11.19	12.41	11.03
2000	10.84	12.11	10.10
2500	15.27	16.27	13.65
3000	21.87	23.27	20.35
3500	24.57	25.56	23.14

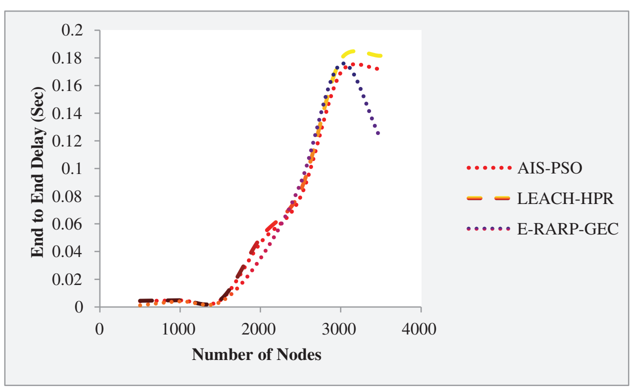

Figure 3: Proposed E-RARP-GEC end to end latency

Because the sensing node and their associated energy have different amounts of energy, power usage is among the most important things to consider when analyzing the load-balancing systems. As a response, energy usage has become an important statistic. The current models were tested to the proposed models E-RARP-GEC by changing the number of sensor nodes to 500, 1000, 2000, and 2500. Fig. 6 shows the energy consumption of the proposed method.

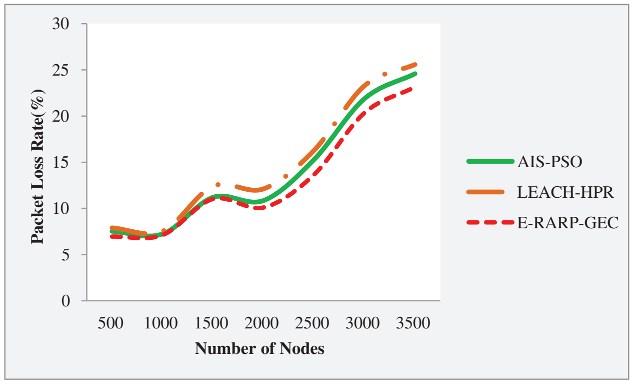

Figure 4: Proposed E-RARP-GEC loss rate of packets

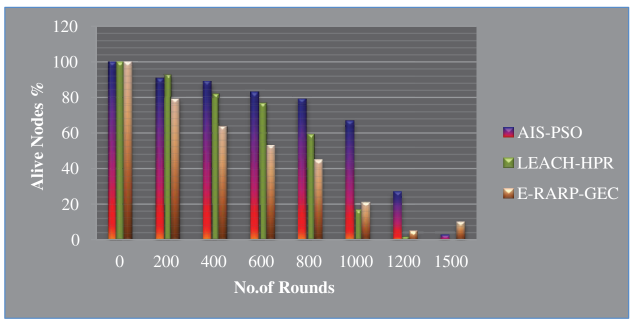

Figure 5: Alive nodes % for roposed E-RARP-GEC

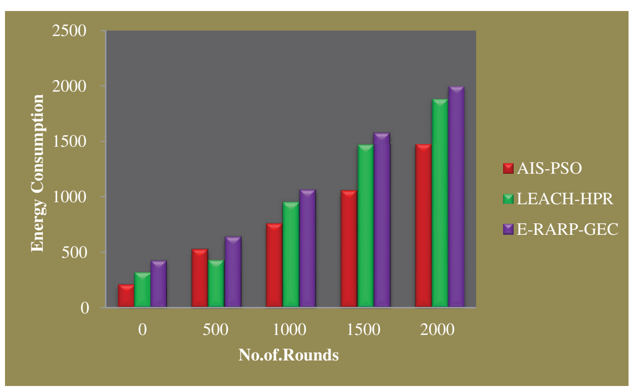

Figure 6: Energy consumption

5 Conclusion

We suggest a power and effective routing scheme for WSNs in this study. An optimized resource classification method is used to split the networks. We designed an ACO-based route method for data transfer that attempts to achieve simultaneously power consumption and dependability. The suggested innovative E-RARP-GEC method has a distinguishing feature that none of the traditional algorithms have. To extend the expected lifespan of the sensor network in a WSN in the face of a restricted power, a framework based on straight games was developed. The approach taken by sensor nodes was selected by analyzing the duration of an inactive observing phase. Whenever the fixed monitoring time exceeds the sleeping criterion, the sensor network goes into sleep mode to conserve power. Whenever the fixed reading period is smaller than the sleeping phase limit, the sensor network continues inside an inactive monitoring mode, reducing energy usage generated by the sensor node's change from sleep to active phase. The experimental findings indicate that the proposed E-RARP-GEC approach successfully reduces the sensor energy consumption of the network, enhances sensor node data transmission, minimizes the end-to-end latency, lowers the packet loss, and maximizes the cluster formation.

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