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An IRGA-MACS Based Cluster-Head Selection Protocol for Wireless Sensor Networks

Muhammad Inam[1], *Li Zhuo*[2], *Masood Ahmad*[3], *Zulfiar Ali Zardari*[4]

[1]*Faculty of Information, Beijing University of Technology, Beijing 100124, China*
[2]*Beijing Key Laboratory of Computational Intelligence and Intelligent System, Beijing University of Technology, Beijing 100124, China*
[3]*Department of Computer Science, Abdul Wali Khan University, Mardan, Pakistan*
[4]*Department of Computer Science, Abasyn University Peshawar, Pakistan*
E-mails: Inam@emails.bjut.edu.cn zhuoli@bjut.edu.cn Masood@awkum.edu.pk zulfiqar@emails.bjut.edu.cn

Abstract: *In a volatile environment, a substantial number of sensor nodes are extensively dispatched to track and detect changes in physical environment. Although sensor nodes have limited energy resources, so energy-efficient routing is a major concern in Wireless Sensor Networks* (*WSN*) *to extend the network's lifespan. Recent research shows that less throughput, increased delay, and high execution time have been provided with high energy usage. A new mechanism called the IRGA-MACS is proposed to overcome these inherent problems. Firstly, the Improved Resampling Genetic Algorithm* (*IRGA*) *is used for the best Cluster Head* (*CH*) *selection. Secondly, to assess the shortest path among CHs and nodes, the Modified Ant Colony Optimization based Simulated Annealing* (*MACS*) *has been speculated to minimize the time consumption during the transmission. The results show that the proposed approaches attain the supreme goal of increasing the network lifetime compared to existing methods.*

Keywords: *WSN, IRGA-MACS, resampling, CH selection, energy efficiency.*

1. Introduction

Wireless Sensor Networks (WSNs) networks have gained recently unprecedented attention owing to their massive volume of applications in multiple domains like military surveillance, environmental monitoring, health care, forest fire detection, etc. The wireless sensor network comprises sensor nodes capable of detecting humidity, temperature, and pressure levels. The sensor nodes may also collect physiological area details and afterwards process it to the Base Station (BS) [1]. In the Internet of Things (IoT) paradigms, the WSNs are presumed to serve a leading role. WSN's durability, flexibility, and energy-efficient attributes make them a crucial applicant to dominate an IoT framework's knowledge gathering task [2].

Nevertheless, several criteria are required in some of these networks, such as low latency data transfer, long-life framework, and easy to manage seamless implementation. Thus, a sensor node in the network's main objective is to achieve fast data computation, identify events, and exchange data. WSN generally consists of several sensor nodes distributed geographically, which can track physiological or environmental factors. Many such sensor nodes function correctly using a non-rechargeable battery [3] that lasts for many years or months [4, 5]. Therefore, energy efficiency is the wireless sensor network's main goal and seems to be jointly and severally liable for improving the network's expected lifespan. Indeed, this can be achieved by selecting adequate Cluster Heads (CH) through which the information sharing link between the sensor nodes and the sink is established. Through distributed communication, network nodes can be divided into small communities designated as more of a cluster through which knowledge transmission can be achieved [3-6].

Generally, almost every cluster has a cluster head related to particular cluster information, categorization, and aggregation mechanism. Frequently, the information packets are transmitted by the nodes of the corresponding cluster to the cluster head. In WSN, clustering offers an energy-efficient routing with many sensor nodes and saves energy during communication. Clustering further enhances WSN's interoperability as the clustering phase reduces a need for a central organization and facilitates local decisions [7, 8].

The latest hierarchical clustering includes several drawbacks such as short network life expectancy, high energy usage, lack of tolerance with a large and diverse network [9], weak stability [10], node death [11], latency in the delivery of information [12], difficulty in the processing of WSN [13] on a large scale, inadequate acknowledgement of residual energy nodes [14], excessive overhead and resources coverage [15] and imbalanced handling [16]. Researchers have used numerous optimization techniques such as Particle Swarm Optimization (PSO) [17], Ant Colony Optimization (ACO) [18], Genetic Algorithm (GA) [19], etc., to evaluate the cluster head.

Many protocols do not guarantee the even distribution of CHs across the regions of the whole network. Therefore, specific sensor nodes opt-out of the CHs (meaning the sensor node sometimes doesn't fall except under particular CH coverage area), considered an isolated node. Multiple CHs in the same transmission region have access, resulting in more connection failure, more packet collision, higher packet prioritization, more redundant control and data packets, exposed node problem, and isolated node problem. In article [20], the ACO is used to find the optimal solution whereas ACO leads to more execution time. All this leads to an increase in energy usage and reduction in network stability and throughput.

To overcome the problems as mentioned earlier, we propose our new algorithm called Improved Resampling Genetic Algorithm (IRGA)-Modified Ant Colony Optimization based Simulated Annealing (MACS), (IRGA-MACS) protocol. The contribution of our paper is as follow:

- The traditional GA and PSO does not provide an optimal solution due to random population initialization, so we have introduced the Improved GA to overcome this issue.

- The re-sampling method is used to initialize the population. The partially modified crossover method is used for the crossover section, and the tournament method is used for the selection process.
- In ACO, more time is needed for execution. Here we are hybridizing the SA with the ACO. The best score for the ACO is determined with the help of SA.

The remainder of the paper is structured as follows. The System and energy model are discussed in Section 3. Section 4 explores the models of the proposed IRGA algorithms. Section 5 explores the models of the proposed ACO-SA algorithms. Section 6 shows the findings of the simulation. Finally, Section 7 reveals the conclusion of this paper.

2. Related work

The science community has comprehensively undertaken sensor nodes into clusters to accomplish the goal of network scalability. There would also be a figurehead in all clusters, known as the Cluster Head (CH). Although numerous clustering algorithms have been presented in ad-hoc literature, the objective [21-23] was primarily to build stable clusters with mobile nodes in the environment. Almost all of these strategies are solely concerned with node interconnection and route flexibility, without much susceptibility to vital WSN design objectives, except for network durability and coverage**.** A series of clustering algorithms [24] have subsequently been developed for WSNs specifically. The authors suggested the Low Energy Adaptive Cluster Hierarchical (LEACH) routing protocol, which is focused on a cluster [25]. The existing CH is checked in LEACH after each round and, if the CH energy is greater than the threshold value, new CH will be chosen based on deterministic theory [26].

The authors proposed an improved LEACH protocol in [27]. In [28], a cluster-based energy-efficient routing protocol is suggested. They used Z-MAC to transmit data, and CH rotates across active nodes, probably depending on the battery recovery regime. In [29]**,** a PSO Hybrid Algorithm and Harmony Search Algorithm (HSA) find the optimum CH. The CH Selection process was established based on technology-Efficient energy, relying on the PSO (PSO-ECHS) process [30]. In choosing the optimal CH solution for the WSN environment, a Firefly algorithm for Cyclical Randomization (FCR) has been suggested [31]. The Firefly methodology has also been expanded to improve the network's energy efficiency and sensor node lifetime.

A clustering algorithm, called the Stable Election Protocol (SEP) introduced heterogeneity, i.e., "Normal Nodes" and "Advanced Nodes" in SEP. The HACH Algorithm for controlling and maximizing the energy of dispersed sensor nodes as CHs has been proposed in [32]. The selected algorithm has been used as a hierarchical clustering protocol. The advanced Meta-heuristic Artificial Bee Algorithm (ABC) has been developed to achieve the maximum use of the network search method [8]. The technique used was an efficient energy strategy, maximizing CHs based on a well-defined fitness function and increasing the search equation. Swarm intelligence based SIF (Swarm Intelligent Fuzzy protocol) has been developed to analyze residual

energy, the distance between the nodes to select CHs, and the distance between nodes and sinks.

The random number selection relying on the sliding window technique is presented in [33]. The upper bounds of the random number and the anticipated number of CHs are modified based on the current residing nodes and the estimated node capacity. Besides, the remaining energy and degree of the node are considered in the selection of CH. Energy-Aware Unequal Clustering and Ant Colony Optimization (EAUC-ACO) is described in [34], where CHs are preferred based on residual energy, number of neighboring nodes, and quality of links.

3. System model and energy consumption model

3.1. System model

We are enforcing our network topology and attempting to make some fundamental assumptions about the model in [35]. Consider that the entire system has 100 sensor nodes that can be positioned in the $N_{\text{side}} \times N_{\text{side}} = 100\text{ m} \times 100\text{ m}$ region. This paper is based on the following assumptions:

a) All the nodes are randomly distributed throughout the region.
b) The sensor node's battery can't be replaced or charged.
c) The Base Station (BS) is placed at the center or corner of the sensing domain.

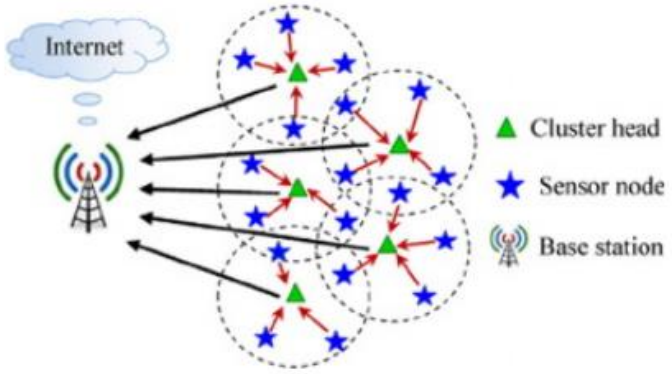

Fig. 1. Cluster-based WSN [20]

3.2. Energy model

We employ similar energy prototypes as in [36]. To mitigate nodes' excessive energy consumption, we emulate a free space Model and use a multi-path fading strategy. The appropriate Signal-to-Noise Ratio (SNR) can be obtained when transmitting a ζ-bit message over a distance dist_{val}, the energy consumed is indicated by

(1) $$\text{Energy}_{\text{TX}}(\zeta, d) = E_{\text{elec}}(\zeta) + E_{\text{amplif}}(\zeta, d),$$

(2) $$\text{Energy}_{\text{TX}}(l, \text{dist}_{\text{val}}) = \begin{cases} \zeta . E_{\text{elec}} + \zeta . \varphi S_{\text{f}} . d^2 & \text{if } d < d_0, \\ \zeta . E_{\text{elec}} + \zeta . \varphi P_{\text{m}} . d^4 & \text{if } d \geq d_0. \end{cases}$$

The energy needed for a unit of data to be received is

(3) $$\text{Energy}_{\text{RX}}(\zeta) = \ E_{\text{elec}}(\zeta) = \zeta . E_{\text{elec}},$$

where $E_{\text{elec}}(\zeta)$ is the energy used per bit by the transmitter or receiver circuit. The free-space (S_{f}) model is used if the distance is less than the threshold; otherwise the multipath (P_{m}) model is used [26]. $E_{\text{amplif}}(\zeta, d)$ is the amplification energy. In Equation (1), the amplification factors (S_{f}) and (P_{m}) for the free-space model (S_{f}) and the multipath (P_{m}) model are described, respectively.

4. Proposed methodology

The conventional cluster-based wireless sensor infrastructure is shown in Fig. 1, and Fig. 2 reflects the flow-chart of proposed work, the system model and the energy model is developed initially. Cluster head selection and routing are performed by IRGA and MACS, respectively. GA is believed to be an efficient optimization technique for discovering efficient solutions to various challenges; therefore, the CH is selected through IRGA Algorithm.

4.1. Cluster head selection: improved GA

The steps involved in cluster head selection are five as follows.

4.1.1. Population initialization

The goal of initialization is to establish an initial population randomly for subsequent genetic manipulation. There are, however, potential issues with the current GA. In all instances, the best solution to the issue may not be found. It is also challenging to select parameters such as generations, population size, etc. To address the above significant problems and to improve the performance of GA, the GA Re-sampling process (RGA) is encouraged by the particle filter in [37, 38], the steps are two.

Step 1. Assign a weight value to each individual a, a = 1, 2, …, P_{size}, as the equations

(4) $$\text{wei}_a \rightarrow \frac{1}{\sqrt{2\upsilon\pi}} \exp\left(-\frac{f(x_a)-c_{\text{best}}}{2\upsilon}\right),$$

(5) $$\text{uni}_{\text{wei}} \rightarrow \frac{\text{wei}_a}{\sum_{a=1}^{N} \text{wei}_a},$$

where wei_a represents the weight value given to individuals, $f(x)$ represents the fitness function, c_{best} is the current global optimal value, υ is the sample variance of $f(x_a) - c_{\text{best}}$, uni_{wei} stands for the unitary weight value given to the individual.

Step 2. For each individual, if $\text{uni}_{\text{wei}} > \text{wei}_a$, then $x_a(t) = \bar{x}_a(t)$, where, $\bar{x}_a(t)$ is the new optimal value introduced randomly.

4.1.2. Enhanced selection

This kind of selection mechanism is used to select perfect chromosomes from the current population. When the nutrition of individual candidates tends to increase, the statistical likelihood of being chosen increases, and the tournament selection process is used for the selection process. Here chromosomes represent the node.

Initially, we prioritize the individuals with the maximum fitness value to guarantee that they can meet the next level and then choose the remaining individuals using the tournament method. This means that the best individual values are not eliminated. The following steps are the specific operations.

Step 1. Estimate each individual's fitness within the population $f(a = 1, 2, \ldots, P_{\text{size}})$.

Step 2. Individuals with the highest adjustment value directly begin the next stage.

Step 3. Compare the probability for the remaining individual to be passed on to the upcoming generator

$$p(x_a) = \frac{f(x_a)}{\sum_{b=1}^{N} f(x_b)}. \tag{6}$$

Step 4. Estimate the Cumulative-probability (Cp)of each individual *a* (*a* = 1, 2, …, P_{size}),

$$\text{Cp}_a = \sum_{b=1}^{a} p(x_{ab}). \tag{7}$$

Step 5. Create a pseudo-random number r_{num} that is uniformly distributed in the interval $[0, 1]$.

Step 6. If $r_{\text{num}} < \text{Cp}_a$ (1), then pick the individual 1, else chose the individual m when $\text{Cp}_a\,[\,m-1] < r_{\text{num}} \leq r_{\text{num}}\,[m]$.

Step 7. Repeat Step 4 to Step 6 unto $P_{\text{size}} - 1$ times.

4.1.3. Enhanced crossover

Crossover promotes the Modified-Partially Matched Crossover (M-PMC), the process of exchanging randomly selected chromosomes (nodes) from two neighboring chromosomes. However, the two surrounding chromosomes determined by the roulette selection are sometimes the same, so that two chromosomes change significantly after the crossover operation. Therefore, this crossover operation does not affect. So we take the crossover time window as given in the next equation. For example, when we have *n* chromosomes, we cross the first one with (*n*/2+ 1), the second one with (*n*/2+ 2), and so on:

$$\text{ind}_{\text{intersection}} = a^{\text{th}} \text{ cross with } \left(\frac{\text{ch}}{2} + a\right)^{\text{th}}, \tag{8}$$

where *a* = 1, 2, …, ch/2, $\text{ind}_{\text{intersection}}$ is the individual created after the intersection, and th is …, ch is … Using that same type of transaction will avoid becoming locally optimal, thus increasing the next generation's inclusiveness and speeding up the convergence system.

4.1.4. Mutation

The obstacle of the mutation is to change the chromosome a smidge completely. It could use the random search capabilities of the mutation operator. Whenever the functional outcome is similar to the ideal solution, the optimal solution can be quickly converged.

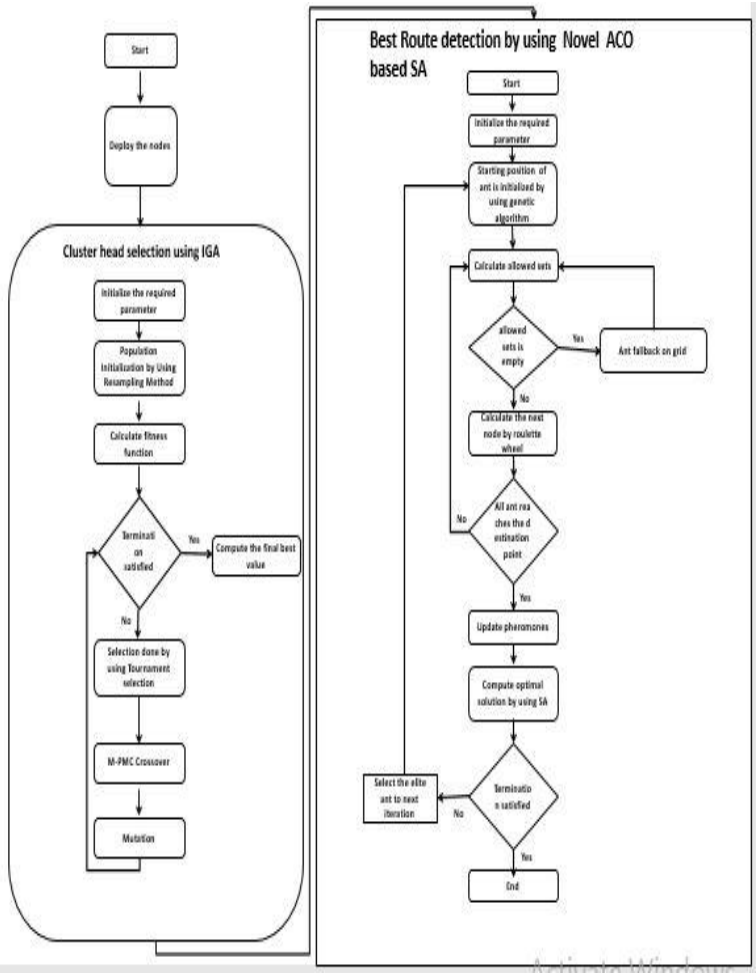

Fig. 2. Proposed flow-chart

4.1.5. Fitness function

The fitness function goal is to optimize network existence and have the following three criteria.

1) The **R**ound in which nodes **f**irst die $\mathrm{fd_R}$.

2) The **R**ound in which nodes **l**ast die $\mathrm{ld_R}$

3) Cluster **dis**tance $\mathrm{clu_{ds}}$.

The cluster's distance is the sum of the distances between the member nodes and the CH and the difference between the CH and the BS. The cluster size for a cluster with m member nodes is denoted as follows:

$$\mathrm{clu_{ds}} \to \sum_{i=1}^{m} \mathrm{dnode}_{i\mathrm{th}} + \mathrm{dclus}_{h\mathrm{bs}}, \tag{9}$$

where $\mathrm{dnode}_{i\mathrm{th}}$ is the distance from node i to the cluster head, and $\mathrm{dclus}_{h\mathrm{bs}}$ is the distance from the cluster head h to the base node.

The function of fitness, f, is a function of the parameters mentioned above and used in the genetic algorithm which can be expressed as follows:

(10) $$f = \sum_i (e_i \times w_i)\ \forall e_i \in (\mathrm{fd_R}, \mathrm{ld_R}, -\mathrm{clu_{ds}}).$$

The w value is a fitness parameter application-dependent weight showing the parameter is more efficient for the function. By adjusting its weight, we can render a health parameter more essential than the other or give them equal value by making the weight equivalent.

4.2. Optimal routing protocol: Ant colony optimization based SA

In general, the Ant Colony Optimization (ACO) Algorithm takes time to construct the route initially. So, we are hybridizing ACO with Simulated Annealing (SA) to reduce the calculation time. By using SA, the initial time was calculated firstly. Rest of the steps are according to conventional ACO. It is fast calculating the route and reduces the time consumption.

ACO is encouraged by the scavenging behavior of ant species. These ants are dumping pheromones on the surface to recognize a beneficial path that attracts other colony laborers. Optimization of the Ant Colony offers a similar method to solve optimization problems [39]. Here we are crossbreeding the SA with the ACO. While random activation in ACO can contribute to time-consumption, we use SA to evaluate the original best score for ACO to rising time usage.

The key steps for ACO are as follows:

Step 1. To make a list that contains the unvisited nodes and the pheromone on the path.

Step 2. Selecting the next node.

Step 3. Upgrading the pheromone concentration. If an ant reaches base station, it will calculate the distance it travelled, and then update the pheromone concentration.

Step 4. After reaching the destination, calculate the loss of pheromones.

The proposed algorithm is

Algorithm ACO-SA

Input: $S_{\max}, \mathrm{Ant_{num}}, t = 0$

Output: Return best path

Step 1. Let consider $g = (1, \ldots, \mathrm{Ant_{num}})$

Step 2. initialize the pheromone $\mathrm{ph_{tau}}$, $\mathrm{uv_{nodes}}$, $\mathrm{best_{score}}$

Step 3. $\mathrm{best_{score}} \rightarrow$ computed by using SA

Step 4. For $t = 1$ to $S_{\max}$

Step 5. For $g = 1$ to $\mathrm{Ant_{num}}$

Step 6. While destination is not arise, do

Step 7. Select the next node in unvisited nodes by using

Step 8. $\mathrm{argmax}\left[ph_{\mathrm{tau}}(K,U)^{\alpha} * \mathrm{eta}(K,U)^{\beta}\right]$, rand $<$ s0

Step 9. $\mathrm{cumcom}\left[\frac{\mathrm{ph_{tau}}(K,U)^{\alpha} * \mathrm{eta}(K,U)^{\beta}}{\sum \mathrm{ph_{tau}}(K,U)^{\alpha} * \mathrm{eta}(K,U)^{\beta}}\right]$, rand $\geq s0$

Step 10. Where $\mathrm{eta}(K,U) = \frac{1}{|\mathrm{dist_{cp\_uc}} - 93.65|}$

Step 11. End while

Step 12. Compute the best score

Step 13. If score $< \mathrm{best_{score}}$

Step 14. $\text{best}_{\text{score}}$= score
Step 15. End if
Step 16. $\text{ph}_{\text{tau}}(K,U) = \text{ph}_{\text{tau}}(K,U) + \frac{1}{\text{score}}$
Step 17. End for
Step 18. $\text{ph}_{\text{tau}}(K,U) = (1-\sigma) * \text{ph}_{\text{tau}}(K,U)$
Step 19. End for
Step 20. Return best path

There ph_{tau} is the pheromone between the present position and unvisited nodes; eta stands for human-made expectation, $\text{dist}_{\text{cp\_uc}}$ stands for a range between the current position and unvisited nodes; cumcom selects the upcoming node by using roulette, s0 is a parameter to compute chance for about selecting argmax; $S_{\max}$ stands for maximum step iteration.

4.2.1. ACO

The first ACO is Dorigo's first philosophical ant technique (AS) to solve the TSP (T… S… P…) problem [39, 40]. It involves the pheromone accumulated on the ground to figure out the best way. In AS, on the routes followed, both ants construct the corresponding route and inject the appropriate pheromone. The probability of a C_{ij} ant, Ant_{num} moving from town i to town j is described as follows:

(11) $$C_{ij} = \begin{cases} \frac{\text{ph}_{\text{tau}}(i,j)^{a}.\text{eta}(i,j)^{\beta}}{\sum_{l \in \text{Rn}_i} \text{ph}_{\text{tau}}(i,j)^{a}.\text{eta}(i,j)^{\beta}} & \text{if } j \in \text{Rn}_i. \\ 0 & \text{otherwise.} \end{cases}$$

Here: Rn_i denotes the number of nodes that can be reached in the region *i*; $\text{ph}_{\text{tau}}(i,j)$ refers to the accumulation of pheromones between towns i and j; $\text{eta}(i,j) = 1/\text{dis}_{ij}$ is the heuristic knowledge in which dis_{ij} is the time window between town i and j. The parameters a and β specify the relative strength of pheromone eta and heuristic detail, respectively. The pheromone modification law is achieved after the creation of the routes as follows:

(12) $$\text{ph}_{\text{tau}}(i,j) = (1-p).\,\text{ph}_{\text{tau}}(i,j) + \sum_{v=1}^{z} \Delta\,\text{ph}_{\text{tau}}(i,j)^{v},$$

where $p \in (0, 1)$ is the evaporation rate that governs the accumulation of pheromones on the path, $\text{ph}_{\text{tau}}(i,j)^{v} = \frac{K}{T_L}$ is the pheromone deposited by the ant *v*, where T_L is the duration of the ant *k* tour found in the current iteration and *K* is a constant.

The successive subtype is the Elitist strategy for the Ant System (EAS), which by adding extra pheromone [41] reinforces the best-so-far route. The different AS updating pheromone is shown as follows:

(13) $$\text{ph}_{\text{tau}}(i,j) = (1-p).\,\text{ph}_{\text{tau}}(i,j) + \sum_{v=1}^{z} \Delta\,\text{ph}_{\text{tau}}(i,j)^{v} + \text{ph}_{\text{tau}}(i,j)^{\text{bs}}.$$

Here $\text{ph}_{\text{tau}}(i,j)^{\text{bs}} = \partial\,\frac{K}{T_{L\,\text{bs}}}$ is the pheromone deposited with the best-so-far ant and where it represents the best-so-far ant count. A preferable ACO version, called MAX–MIN Ant System (MMAS), suggested by S t ü t z l e and H o o s [42] improves ACO's efficiency. MMAS has some excellent features to solve the TSP problem, which applies the pheromone modification as follows:

(14) $$\text{ph}_{\text{tau}}(i,j) = (1-p).\,\text{ph}_{\text{tau}}(i,j) + \Delta\ \text{ph}_{\text{tau}}(i,j)^{\text{bs}},$$

where $\mathrm{ph}_{\mathrm{tau}}(i,j)^{\mathrm{bs}}=1/T_{L\ \mathrm{bs}}$ is the pheromone released by the best-so-far or iteration-best ant. To stop instability of mathematical formula, the pheromone concentration is restricted to an interval [$\mathrm{ph}_{\mathrm{tau}}$ min, $\mathrm{ph}_{\mathrm{tau}}$ max] and to expand at first the search space of solutions, the initial pheromone is set to $\mathrm{ph}_{\mathrm{tau}}$ max with a low evaporation rate.

Ant Colony System (ACS) also produces impressive results for TSP as it uses global and local pheromone warnings as well as two search frames [40]. The ACS defines a pseudo-random proportion rule as follows: the likelihood of moving an ant k from cities i to j depend on a random q variable and a q_0 parameter. All q and q_0 allocate 0 to 1, i.e., $q \in [0, 1]$, q_0 [0, 1] equally. q_0 is a key factor in improving ACS performance. If $q > q_0$, the description of the city i's visit is the same as that of AS. If $q \leq q_0$ is used, the formula is defined as $j = \underset{l\in \mathrm{Rn}_i}{\mathrm{argmax}}\{\mathrm{ph}_{\mathrm{tau}}(i,j).\mathrm{eta}(i,j)^{\beta}\}$.

The modification of global pheromone is as follows:

(15) $$\mathrm{ph}_{\mathrm{tau}}(i,j) = (1-p).\mathrm{ph}_{\mathrm{tau}}(i,j) + p\ \Delta\ \mathrm{ph}_{\mathrm{tau}}(i,j)^{\mathrm{bs}}.$$

The ACS makes only the latest pheromone changes so far, and other pathways stay invariant. The update of the local pheromone is shown as follows:

(16) $$\mathrm{ph}_{\mathrm{tau}}(i,j) = (1-\varphi).\mathrm{ph}_{\mathrm{tau}}(i,j) + \varphi\mathrm{ph}_{\mathrm{tau}\ 0},$$

where $\varphi \in (0, 1)$ is the coefficient of pheromone decrease and where $\mathrm{ph}_{\mathrm{tau}\ 0}$ is the original pheromone value.

4.2.2. Simulated Annealing (SA)

SA is a well-known global heuristic approach to optimization prompted by the physical process's strong annealing. The SA Algorithm is based on the Metropolis Monte Carlo framework to establish the set of molecules in equilibrium at a specific temperature. The standard Monte Carlo algorithm only acknowledges travel to a decreased-energy state, while a higher-energy state is also likely to be taken seriously by the Metropolis procedure [43]. The probability of acceptance from the current X_a solution point of the X_{a+1} test solution is indicated as

(17) $$P = \begin{cases} 1 & \text{if } f(X_{a+1}) \leq f(X_a), \\ e^{-\Delta f/W} & \text{else,} \end{cases}$$

where f is the objective function, $\Delta f = f(X_{a+1}) - f(X_a)$, and W is the regulate parameters that are referred to as temperature by comparison. The temperature term of the SA algorithms is the control parameter. The same thing we said as weights. The temperature of our paper represents the weights. The reduction in temperature significantly reduces the probability of approval.

Throughout the SA protocol, the step-length vector is generally used to recognize at least 50% of the measurements [44]. If δ_j is the ratio of the number of movements accepted to the number of tests for each variable, the disturbance can be written as

(18) $$X_{\mathrm{trail}} = X_{\mathrm{current}} + C\ (-1,1) * V,$$

where $C\ (-1,1)$ is the random number of the phase length vector between -1 and 1, and V. The elements of the step width vector are determined by adding the V_{bi} of the difference between the top and bottom limits as half of the difference for each dimension,

(19) $$V_a = V_{\text{bi}} * \begin{cases} \left(1 + 2(\delta_j - 0.6)/0.6\right) \text{ if } \delta_j > 0.6, \\ \left(1 + 2(0.4 - 0.6)/\delta_j\right) \text{ if } \delta_j < 0.4. \end{cases}$$

Theoretically, it's been shown that the probability of getting a global minimum will approximate 1 while using a very slow rate of temperature decrease [45]. Several cooling schedules are implemented using linear, logarithmic, and exponential functions [46, 47]. The most famous temperature drop rule is as follows:

(20) $$W_{a+1} = C_w w_0,$$

where w_0 is the initial temperature and C_w is a positive constant generally taken at 0.8-0.999 intervals.

5. Performance analysis

MATLAB is being used to enforce the recommended protocol and equate the suggested protocols with traditional protocols such as Enhanced LEACH [48], Improved SEP [49]. In EISEP, the estimation of the probability of selecting the cluster heads was optimized by taking the energy factors into account. The threshold was also modified similarly as EISEP [50] and ACO-PSO [20].

Table 1. Setup parameter for simulation

Parameter	Description	Value
prob_i	In a particular round, the desired fraction of cluster heads	0.1
E_{init}	Normal Nodes initial energy	0.5 J
E_{elec}	Dissipated power in data transmission	50×10^{-9} J per 1 bit
E_{elec}	Dissipated power in data reception	50×10^{-9} J per 1 bit
φS_f	Amplifier dissipated energy in transmission	10×10^{-12} (J per 1 bit)/m^2
φP_M	Energy amplifier used in transmission	1.3×10^{-15} (J per 1 bit)/m^4
$E_{\text{data\_ag}}$	Data aggregation energy	10×10^{-9} J per 1 bit
N_{side}	The nodes were distributed in a defined area of $100 * 100$	100
M_{size}	Size of the message	4000 bits

In our implementation, we consider a square network area with a length and width of 100 units and randomly place 100 sensor nodes in the network geographical area. The base station (sink) is fixed in the middle of the field. The parameters for the simulation configuration have been defined as in Table 1.

5.1. Throughput

The throughput appears to be the number of packets enacted to the sink effectively. Fig. 3 compares the research methods suggested with current technologies. The figure demonstrates a significant improvement in the performance of the proposed technique. The results indicate that 85% of strengthened percentage throughput especially in comparison to LEACH, 16.91% higher percentage throughput particularly in contrast to EISEP, 58.47% higher percentage throughput especially in contrast to ISEP, 22.80% higher percentage throughput particularly in comparison to ACO-PSO.

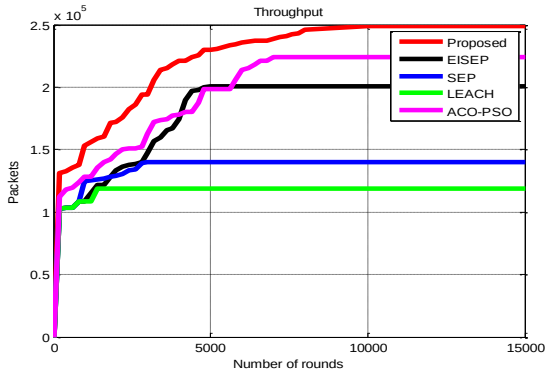

Fig. 3. Comparative analysis for throughput

5.2. Network Lifetime

The network life expectancy is described as when the entire length at which the first and last node in the network dies. Fig. 5 is a correlation between the new framework with the established techniques. The statistic is simple, demonstrating a significant change in the network existence of the proposed methodology. According to the current protocols, the network lifetime of the new methodology is substantially higher than the established accessible technique. Fig. 4 expresses the dead node count.

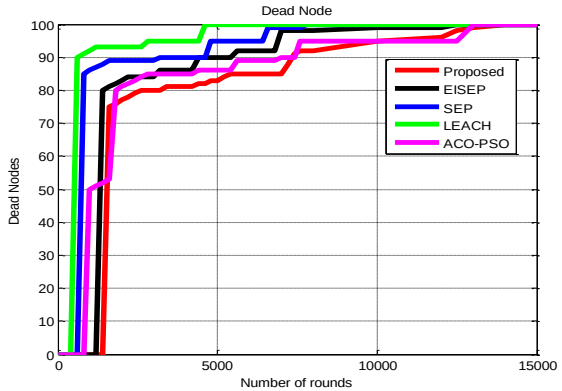

Fig. 4. Comparative analysis for Dead Node

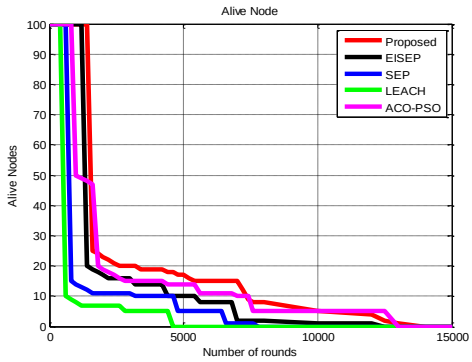

Fig. 5. Comparative analysis for Alive Node

5.3. Execution time

The Table 2 points out the time between both the ACO and the proposed methodology. Equated to ACO, our execution time methodology decreased by 45.59%.

Table 2. Comparison of Execution time

Methodology	Execution time
ACO-PSO	23.71 s
Proposed	12.90 s

5.3.1. End to end delay

The end-to-end delay is described as the time the sink receives a packet on the sensor. The end-to-end distribution time lag of the packet is indeed equal to the local distribution delay and is between the time it is delivered and the time the sink receives it. In Fig. 6 compared to the traditional policies and procedures, it is acknowledged that the delay of the envisaged technique is compatible and minimized too though known protocols are available.

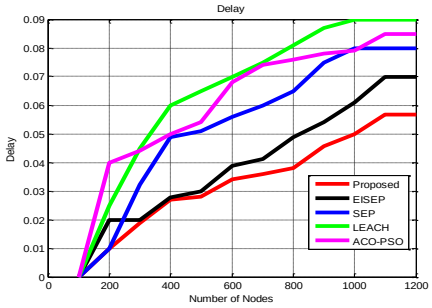

Fig. 6. Comparative analysis for delay

5.4. Residual energy

The residual energy of the network is the interval after the last node in the network dies. In Fig. 7 the envisaged technique is contrasted with the available technique. The

estimate is accurate and shows a massively improved performance in the residual energy of the suggested technique. Compared to the standard protocols, it is often acknowledged that the proposed strategy's residual energy is appropriate and significantly increased as well-known protocols are applicable.

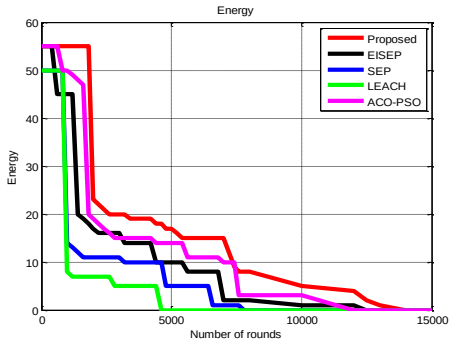

Fig. 7. Comparative analysis for Energy consumption

6. Conclusion

In this article, we have put in place two methodologies, notably Improved Resampling based Genetic Algorithm, to choose the best Cluster Head, other is Ant Colony Optimization based Simulated Annealing for routing. Our IRGA will discover an appropriate solution while selecting the best cluster head. This strategy eliminates the current genetic algorithm drawback and effectively identifies the cluster head. The MACS optimization analyzes the shortest path between the sink and the cluster header. It, therefore, reduces the delay and time of execution of the routing algorithm. Compared to the current methods, our solution's lifespan and residual resources are significantly improved; the execution time and the end-to-end delay are minimized. Experimental results indicate that 85% of increased percentage throughput than LEACH, 16.91% higher percentage throughput than EISEP, 58.47% higher percentage throughput than ISEP, 22.80 % higher than ACO-PSO.

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