FOA-IT2FLS+QL: An Adaptive Energy-Efficient Clustering and Routing Protocol for IoT-enabled Wireless Sensor Networks

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Abstract
This research paper suggests a hybrid energy-efficient clustering and routing method inspired by the Fruit Fly Optimization Algorithm (FOA) and Interval-Type-2 Fuzzy Logic System (IT2FLS) and Q-Learning for Internet of Things (IoT) - Wireless Sensor Networks (WSN). First, FOA is applied to decide the best set of Cluster Heads (CHs) and then an IT2FLS is used to judge the candidate's fitness in the uncertain network based on distance to BS (Base Station), Residual Energy and node degree. Optimized CHs are then used for a Q-Learning routing algorithm, which is able to create secure multi-hop communication paths. The routing mechanism adds residual energy and distance progress to the reward function to enhance reliability, and prevent the formation of hotspot. The IT2FLS optimizes cluster formation and routing jointly to achieve the best results. The proposed technique compared with well-known algorithms; LEACH, DEEC and BOA+ACO and performs best with regard to energy efficiency, packet delivery, throughput and network lifetime.

Keywords: IoT, WSN, CH, FOA, Q-learning, IT2FLS, Energy efficiency.

1. Introduction

WSNs have become one of the most promising enabling technologies for the monitoring and data collection in physical environments. A WSN is a group of a huge number of miniature sensor spread throughout a geographic area for measuring phenomena like temperature, humidity, pressure, vibration, light levels, and motion [1,2,3]. These sensor nodes work together to collect information about the environment, and then send the data back to a centralized BS for processing and decision making [4][5]. WSNs have been a key part of the latest IoT application because it has the ability of autonomous sensing and wireless communication.

The ability of WSNs to be used in a wide variety of real-world applications, and the low deployment costs are the primary drivers behind their use. They have been widely used in numerous different applications for examples environmental monitoring [6], precision agriculture, forest fire detection, industrial automation [7], healthcare monitoring [8], smart homes, military surveillance [9], disaster management [10], smart transportation, structural health monitoring [11], and smart city infrastructures. In such applications, nodes are usually placed in the inaccessible or unfavourable surroundings where replacement of batteries and manual maintenance are difficult, expensive, or even impossible. Thus, long-term operation of networks while maintaining reliable communication is a major design goal.

Although WSNs have many potential applications, they have a number of inherent problems caused by the low capability of sensors. The sensors have limited memory, processing capability, battery power and the communication range. In these constraints, energy is regarded as the most significant constraint since sensors are typically battery generated with non rechargeable batteries. When the battery energy is depleted, the involved node is non-functional and causes coverage holes, connectivity degradation, reduced sensing capability and ultimately reduces the overall network lifetime [11] [12]. Hence, it is crucial to make the most efficient use of the available energy resources to maintain network performance.

In WSNs, the energy consumption can be caused by various activities that sensor nodes undertake. During wireless communication, a lot of energy is expended, especially when sending and receiving data packets. Extra energy is used when sensing is required, when signals must be processed, when data must be aggregated [13], when packets collide or when there is an interference in the channel, when control packets are exchanged, and when routes are established frequently. Furthermore, nodes near to the Base Station may be subjected to too much forwarding load, causing an unbalanced energy consumption and resulting in premature death of nodes. All these factors contribute to battery depletion and greatly diminish network stability and lifespan [11][14].

To design efficient energy routing protocols has been an active investigation field in WSNs due to the energy constraint. The primary goal of energy-efficient routing is to reduce unnecessary transmissions, to stable the energy usage between the sensors, to lessen the communication overhead, and to extend the network's working lifetime. The routing protocol should be efficient enough so that the data can be delivered reliably while the energy is conserved, the network does not become congested and the heavily used nodes do not die early [15][16]. Thus, in practice, a network that has the capacity to adjust to changing network conditions is needed.

The different routing methods were compared and it was found that cluster-based routing is one of the finest techniques for achieving energy efficiency and expandability. In a cluster-based architecture, as seen in the below Figure 1, sensors are assembled into clusters, and the CH is selected to supervised the interaction between the sensors within the cluster. All the member nodes will send their sensed data only to the CH to which they belong, and the CH will aggregate the data for eliminating the redundant data and send the compressed data to the Base Station [17][18][19]. This hierarchical communication helps to lessen the amount of long distance communications, overcome the communication overhead, increase bandwidth utilization and increase network scalability. In addition, data aggregation at the CH decreases duplicated packet transmissions, which helps to save useful energy resources.

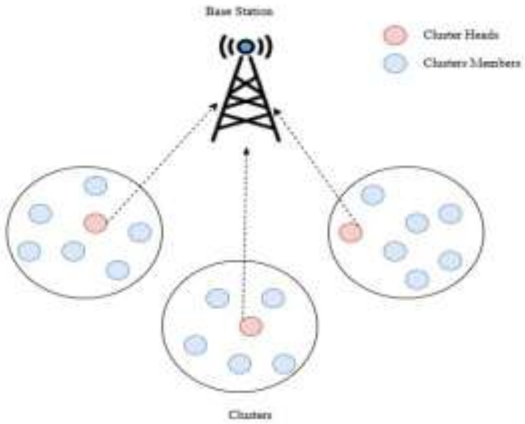

Figure 1: Framework of Clusters in WSN

However, the effectiveness of cluster-based routing heavily depends on the appropriate choice of CHs. Choosing inappropriate CHs based on the remaining energy, communication distance, node connectivity information and the network dynamics will lead to unequal energy consumption and frequently failure of CHs, higher packet loss and shorter network lifetime. Probabilistic methods are not always useful for adapting to the continuously dynamic conditions of a network, and deterministic methods may not consider uncertainties in node characteristics. Thus, intelligent CH selection methods that can cope with uncertainty and dynamically adapt their routing decisions are crucial to realize energy balance and extend network life.

1.2 Motivation

In the recent years, several studies have turned their interest to embedding fuzzy logic, metaheuristic optimization and reinforcement learning techniques in cluster-based routing protocols to tackle drawbacks. Fuzzy logic is used to contract with the uncertainty of multiple decision parameters; metaheuristic algorithms are used to explore for best CH candidates from big solution spaces and reinforcement learning continuously enhances the routing decision by interacting with the network environment. These intelligent techniques when integrated into the routing mechanism, can provide adaptive and energy-aware routing, which results in a balanced energy usage, better packet delivery, better throughput and much longer network lifetime. Therefore, it is necessary to build a new effective and useful routing protocol to eliminate the above-mentioned drawbacks. This work suggests a hybrid cluster head selection method depend on the intelligent concept of combining ITFLS, FOA, and Q-learning to attain efficient and adaptive energy management in WSNs with the advantages of the aforementioned methods.

1.3 Contribution of the work:

- A new hybrid cluster head selection algorithm is presented by combining IT2FLS-FOA approach.
- IT2FLS is designed to use residual energy, distance and node degree to tackle uncertainty and provide CH suitability score.
- FOA is integrated to optimize the candidate solutions generated by IT2FLS and guarantees to provide optimized CH and balanced energy consumption.
- Q-learning is integrated to dynamically update the routing decisions in accordance with the network condition, which results in an adaptive path selection and avoids unnecessary energy loss.
- The proposed approach is tested through extensive simulations using MATLAB, which clearly point out that the proposed technique provides better network lifetime, stability period, throughput, residual energy and packet delivery performance than existing clustering protocols.

1.4 Organization of Paper

This paper presents the clustering and routing review of recent research papers i.e. discussed in Section 2. A detailed study about clustering using FOA-IT2FLS and routing using Q-learning are discussed in Section 3. A discussion of the performance of the purposed study and its comparative analysis is included in Section 4. The conclusion and future scope of this study is available in last Section 5.

2. Related Work

Energy efficiency is a critical concern for IoT-enabled WSNs because nodes have limited resources. The integration of IoT capabilities into WSNs has significantly increased their usefulness in smart applications. Nevertheless, load balancing, scalability, and energy management provide additional challenges. Clustering and routing algorithms are often utilised to tackle these challenges, with the leading of extending network lifetime by optimising energy consumption. The most recent publications on clustering and routing algorithms are reviewed here.

2.1 Hierarchical Clustering

This multi-tier architecture, introduced by D. Gupta et al. [11] incorporates division strategies for effective long-distance communication and load balancing, and optimises energy-aware routing through selection of cluster heads based on multiple criteria function. The aim of RHECR is to prolong network lifetime by minimizing long distance communication and spreading the load of the network evenly among all the nodes.

Heterogeneity management and energy conservation are some of the objectives of existing probabilistic routing protocols like SEP, DEC, LEACH and PEGASIS mentioned in the study: D. Sharma, et al. [20]. To this end, not only the existing protocol is reviewed but also a new multi-tier protocol for agricultural predicated on DECs is presented which optimizes the selection of the CH and raises energy efficiency. Performance comparisons show that this new strategy provides a better energy allocation efficiency.

To prolong the life of a network, an M2M routing protocol was proposed by W. Twayej, et al. [21] which is an M2M routing protocol based on a smart sleep mode structure that uses IPv6 LoWPAN. The monitoring field is split into four parts with two location sinks, and different CHs. The execution of MLCMS methods is assessed and compared using MODLEACH protocol. The energy efficiency is 75% higher with MLCMS than with MODLEACH. The proposed model 6LoWPAN is then analyzed using the NS3 simulator.

M. Al-Jumaili, et al. [22], suggested to use an adjustable hierarchical clustering and routing technique. The basis of this clustering and routing technique is the greater bottleneck energy routing, where the energy is minimized along the routes from the node towards the sink. This differs from the nearest node with the most energy; this technique favours the route with more energy. MBER reduces the likelihood that a node may die while transmitting a packet to the sink. MBER's hierarchical nature allows for the use of data fusion in many ways and depending on the application, more data can be passed from each node to the sink at multiple levels. It can be modified to accommodate different node-to-node transmission ranges.

2.2 Swarm Intelligent Method

M. R. Rami Reddy and colleagues [23] recently developed an improved version of the GWO algorithm, known as the EECHIGWO algorithm, aimed at optimizing energy-efficient CH selection. The method improves the network stability when compared to the other existing protocols, considering the CH selection parameters, such as sink distance as well as residual energy. Using this technique reduces energy usage, resulting in reduced convergence time and prolonging network lifetime.

To solve the issues of clustering and routing in the WIoT-based WBAN, M. Y. Arafat, et al. [24] proposed a two hop based clustering and routing protocol DECR for WBAN. During the cluster building phase, every node in DECR is provided with information about nodes within two hops. The CH selection and routing are done using the modified GWO technique. The CH in each cluster was determined by both residual energy and node connection. In order to minimize the total number of transmissions, they also developed an analytical model to get the ideal number of clusters by taking intra- and inter-cluster transmission distances into account. The outcome of this simulation demonstrated its ability to see the recommended DECR operates significantly better than the existing clustering and routing.

The novel algorithm, AHCS-GWO by M. H. Rangappa, et al. [25] is a combination of conventional clustering with nature-inspired optimization techniques, for efficient event localization and minimum energy consumption. It was evaluated on a network size ranging from 100 to 200 nodes, and proved to be superior in terms of various factors including residual energy, energy consumption, PDR, end-to-end delay, etc. when compared to some of the existing algorithms.

In [26] S. Sankar, et al., presented an innovative selection of CHs and cluster construction algorithm. There are two divisions for the process. The optimization algorithm used to select the CH is the SOA which is based on the Swarm Intelligence algorithm. Second, the cluster is created by the Euclidean distance. The NS2 simulator is used for running the simulation. A comparison of the SOA with HCCHE, EPSOCT, and IABCOCT is done.

A LOA for selecting CH in RPL was presented by S. Sennan et al. [27]. LOA-RPL consists of three steps: route establishment, cluster construction, and CH selection. A cluster is created using the Euclidean distance. The choice of a CH is done using LOA. The route is constructed based on information of residual energy. The nS-3 is used to do a comprehensive simulation for many attributes such as throughput, PDR, power consumption, network longevity, etc.

M. K. Roberts, et al. [28] proposed an improved two-phase routing paradigm in WSNs for cluster based, energy efficient routing. It handles the pivotal issue of striking a stability between dependable network execution and energy usage. The proposed framework is supplemented with two meta-heuristic algorithms: SFO and SHO. That combination strategy makes use of SFO's quick exploration to identify the best CH and cluster effectively. In addition, SHO's advanced exploitation techniques optimize routing routes.

The study by S. Bharany et al. [29] intends to provide underwater sensor networks and enhances the energy usage by the suggested algorithm, named SSGSO, and compares the outcomes with those of other algorithms, such as ACO, GWO, MFO, and Leach. Energy consumption, PDR, and cluster lifetime parameters are the parameters used to obtain the results. The suggested algorithm outperformed ACO with regards to energy efficiency, cluster longevity, and PDR when evaluating the clustering, according to the results.

N. Meena et al. [30] suggested an optimized Hierarchical Clustering Algorithm called FOHCA for energy efficient network lifetime in WSNs. The method is based on cluster formation and CH selection using the FOA to minimize the energy usage in data transmission. FOHCA lowers power consumption and stabilizes networks by optimizing the selection of CH. Through simulation, it was shown that FOHCA was more energy-efficient and longer lifetimes than traditional methods such as GA based methods.

E. Srivastava et al. [31] suggested PSO based secure and energy-efficient routing protocol in WSNs. The protocol is based on PSO heuristic learning mechanism to detect the reliable routing path and has also developed a light-weight security mechanism to secure data transfer from malicious attacks. Further, a traffic exploration mechanism is employed to find out the route maintenance. The results showed that the suggested methodologies could be significantly better than the existing ones in respect of throughput, packet drop ratio, delay, energy consumption.

2.3 Hybrid Optimization Method

To prolong network lifetime and reduce energy consumption, P. Maheshwari, et al. [16] tried to optimize the lifetime of networks and reduce the total energy usage, routing and clustering techniques have been mainly used in WSNs. In this work, the best CH was selected from the nodes using the BOA. ACO in which the path selection relies on the cluster head to base station distance, residual energy and node degree help to establish the path between the cluster head the base station.

J. A. I. Syed Masood, et al. [32], suggested a privacy-preserving strategy utilizing multipath routing and secret key concepts for healthcare applications depending on WSNs. Several routes to the sink calculated using ECSO method. ECSO-suggested algorithm is used to determine the best routes, based on the distance and traffic rate of the routes. Path selected is be utilized for sending encrypted data to the sink.

N. K. Shinde, et al. [33] introduced a novel cluster-based routing model with the two steps of routing and CH selection. The TICOA, a hybrid optimisation model, was recommended as Phase 1 of selection of the optimal CH based on security, energy, trust, latency and distance restrictions. Subsequently the routing process was followed and even the Trust and Quality of Link requirement was adhered to, which extended the life of the WSN.

N. Kumar, et al. [34], suggested the use of a hybrid WAOA for WSN routing that is energy-efficient. The ACO is used to search the optimum path from the source cluster sensors to the cluster head within the predefined space, whereas the proposed WAOA is designed to locate the optimal CH in the defined search space using the WOA. Linear programming architecture is used to construct optimization problems related to CH selection and the search of routes.

2.4 Learning Based Approaches

M. U. Younus et al. [35], optimized the routing path of SDWSN with the help of RL. All the needed network quality of service and energy efficiency were included in a proposed reward function. The SDWSN controller tried the previous experience to refine the route that was to be taken, and the agent was rewarded and went along the route. However, the whole network was controlled remotely with the help of the Internet. The execution of the RL-based SDWSN was differentiated to traditional SDN, energy-aware SDN, QR-SDN, TIDE and non-SDN-based strategies such as RL-based routing.

In order to maintain energy balance in WSNs, Z. Zhaohui et al. [36] proposed a special semi-fixed algorithm named SFC-QL-IACO. The proposed system was implemented with semi-fixed clustering to spread out cluster nodes for initial load balancing and optimizing the ant colony to produce data transmissions. The clusters were modified dynamically to reach the energy equilibrium when the energy gap passed a given threshold. The cluster head was rotated when needed and a dynamic energy threshold was applied to save disruptions to the network due to the energy depletion of the cluster head.

This literature review focuses on the construction of energy efficient cluster-based routing protocol for IoT based WSN, which shows the enormous progress achieved in the field. Although some progress has been made on the energy efficiency, network lifetime and data transmission, there is still a scope for further improvement in the energy domain to tackle issues of scalability and heterogeneity in the IoT environments.

3. Proposed Methodology

The suggested method is using two algorithms; one is for the selection of CH and the other is for the routing. Optimal CH is selected by incorporating hybrid approach FOA with IT2FLS. In the first step, only the alive sensor nodes with remaining energy of 20% or more of the initial energy are treated as CH candidates because these nodes have more energy to remain alive and, thus, avoiding low energy nodes in the optimization search space. The overall process of work is shown below in Fig 2.

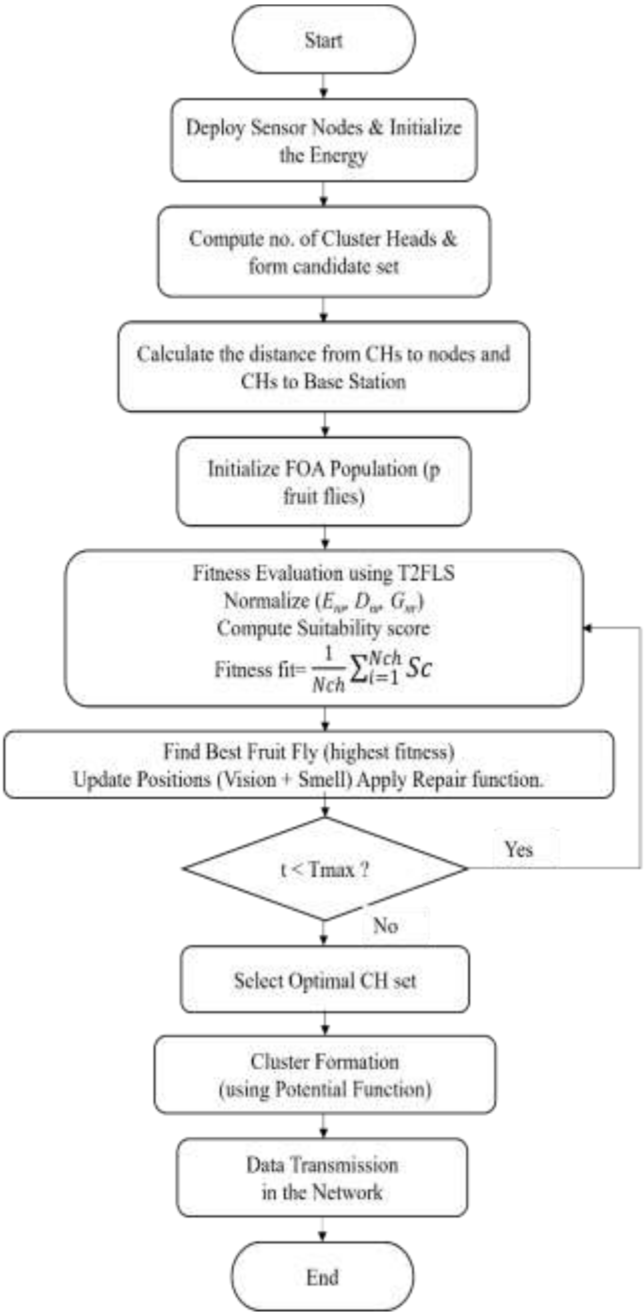

Figure 2: FOA-IT2FLS based CH Selection

3.1 Fruit Fly Optimization Algorithm

FOA is an optimization method based on swarm intelligent population behaviour that is studied from the food search behaviour of fruit flies. Fruit flies have very acute sense of smell and sight, allowing them to find their food effectively. All the fruit flies correspond to one possible solution, for the full list of candidate CHs. Assuming that there are N_{ch} required number of Cluster Heads, then the i^{th} fruit fly is represented as mention in Eq. (1). Next, FOA samples a population of fruit flies where each fruit fly is a complete set of candidate CHs. Normalized residual energy of each Cluster Head, which is computed using Eq. (2), normalized distance to the Base Station computed using Eq. (3) and normalized node degree computed using Eq. (4), of each Cluster CH are calculated and fed to the IT2FLS.

$$X_i = [x_1, x_2, x_3 \dots\dots\dots, x_{Nch}] \tag{1}$$

$$E_n = \frac{E_i}{E_{init}} \tag{2}$$

$$D_n = \frac{d_{BS}}{d_{max}} \tag{3}$$

$$G_n = \frac{N_j}{N_{alive}} \tag{4}$$

3.2 IT2FLS Fitness Evaluation

The input parameters (E_n, D_n, G_n) are acquired by the input normalization process which ensures all the input variables are within range (0-1) in the proposed IT2FLS. In the equation (5), input variables are normalized. In the next stage, the Interval Type-2 fuzzification, the normalized inputs are processed, and each one of these inputs is modeled by a pair of upper and lower triangular membership functions to take into account the uncertainty caused by the dynamic network conditions.

$$x = (E_{nr}, D_{nr}, G_{nr}) \tag{5}$$

The resulting interval valued membership grades are then evaluated with a set of pre-defined fuzzy rules (Table 4.1) with the firing strength of each rule obtained by multiplying the upper (w_i^U) and lower (w_i^L) membership value with product T-norm operation. In inferred interval fuzzy outputs, the fuzzy outputs are transformed to crisp interval values on the type reduction stage by computing weighted average of the upper and lower firing strength as depicted in Eq. (6), Eq. (7). Finally, the Cluster Head Suitability Scores given by the upper and lower type-reduced sets are merged via the defuzzification process to give one CH Suitability Score which is used as the fitness value of each candidate CH in the FOA and is expressed as in Eq. (8).

$$S_U = \frac{\sum w_i^U y_i}{\sum w_i^U} \quad (6)$$

$$S_L = \frac{\sum w_i^L y_i}{\sum w_i^L} \quad (7)$$

$$S_c = \frac{S_U + S_L}{2} \quad (8)$$

3.3 Final FOA Fitness Function

The fitness of the fruit fly belonging to each solution is calculated based on the average suitability score of all Cluster Heads in that solution. In each iteration for the realization of the FOA, the fruit flies use a smell search strategy or a vision search strategy to update their position and, in the end, the candidate solution that maximizes the fitness is chosen as the optimum CH set. Last, each non-CH node is linked to the CH with the greatest energy-to-distance potential for communications. The fitness function is given in Eq. (9). Distance of CH to BS and other nodes is calculated by Euclidean formula.

$$\text{Fitness} = \frac{1}{N_{CH}} \sum_{i=1}^{N_{CH}} S_C \quad (9)$$

3.4 Q-Learning Optimal Route Process

The algorithm proposed by Q-learning routing periodically interacts with the network environment to learn the best forwarding policy in each training episode. The learning process starts with randomly choosing a Cluster Head to be the first routing state. The initial state is selected as given in Eq. (10), where N is the total number of Cluster Heads in the current communication round.

$$S_0 \in \{CH_1, CH_2, CH_3 \ldots\ldots\ldots\ldots, CH_{N_{CH}}\} \quad (10)$$

The agent at the current routing state s determines all possible forwarding node$s$, it can choose from that will meet the routing constraints. A CH that is alive and not visited during the current episode and is different from the current CH is a valid forwarding CH. Also, the BS is always available in the list of routing destinations. So, the valid set of actions is described in Eq. (11).

$$A(s) = \{CH_j \mid Alive(CH_j = 1, Visited(CH_j) = 0, CH_j \neq CH_i\} \cup \{BS\} \quad (11)$$

Once the set of valid actions are identified, the routing agent chooses the next forwarding action according to the greedy policy. After the forwarding action is chosen, the routing agent will assess the quality of the action by determining the immediate reward for that action. The residual energy and the distance progress towards the BS are taken into consideration for the reward function. The immediate reward is given as shown in Eq. (12)

$$R = w_E E_r + w_D D_r \quad (12)$$

Once the reward is calculated Q-table is upgraded using the Bellman optimality equation, which is a combination of the immediate reward and the future reward of the next routing state. The Q-value's update is provided in Eq. (13)

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R + \gamma \max Q(s',a') - Q(s,a)] \quad (13)$$

After the Bellman update, the routing agent changes its routing state to the next one in the routing state machine based on the chosen forwarding action. The state transition is represented by Eq. (14) and final route is expressed as in Eq. (15)

$$S_{t+1} = a_t \quad (14)$$

$$R = \{CH_1, CH_2, \ldots\ldots CH_n, BS\} \quad (15)$$

The above sequence of state selection, determining validity of action, greedy action selection, reward computation, Bellman Q-value update, and state transition are repeated until one of the termination conditions are met. The training episode ends when Base Station is reached, no available Cluster Head for forwarding or when the maximum number of hops is exceeded.

4. Evaluation Matrices

Various cluster-based routing performance metrics such as dead nodes, alive nodes, average energy consumption, throughput are used to analyse the performance standards of cluster-based routing. The following explanation of the performance measures is provided:

- Network Lifetime: Dead node tracking directly affects network longevity. Important information on network resilience and energy stability is revealed by the course of node failure.
- Alive nodes: The quantity of nodes in the network that are still operational. When there are more active nodes in the network, its performance improves.
- Dead Nodes: Dead nodes in WSNs are sensors that are totally inert due to hardware failure or battery exhaustion.
- Residual energy: It is the average energy used by every node in every iteration.

- PDR: The total number of packets sent to BS.
- Throughput: The quantity of bits sent to BS via WSN is known as the throughput. Units of measure for throughput are bits per second.

4.1 Simulation Setup

Experimental setup and performance of proposed method is discussed in this section. A routing protocol that is energy efficient is proposed and validated in MATLAB R2021a. The initial sensor deployment is chosen randomly to be 300 nodes distributed throughout the sensing area of 200m × 200m and BS is located at the centre position. In the following Table 1, the details of the various simulations taken for the experimentation are presented.

4.2 Simulation Parameters

Table 1: Simulation Parameters

Parameters	Description	Value
A	Network Area	200*200 m^2
N	Number of Nodes	300
Ei	Initial Energy	2.0 J
L_BS	Location of BS	(100,100)
pkt_size	Packet Size	4000 bits

As shown in below Figure 3, BS is located in the centre of the network field with the aim of providing uniform distance between sensor nodes and the sink. This deployment is used to test the performance of the proposed routing protocol in a uniformly distributed WSN environment.

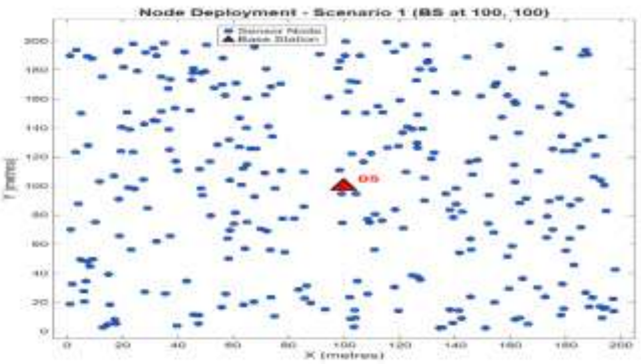

Figure 3: Node deployment Scenario

The number of alive sensor nodes shown in Figure 4 with number of rounds in the simulation for the three algorithms LEACH, DEEC and BOA+ACO. At first, the four protocols begin with 300 live sensor nodes, meaning that each node has its full initial energy level. From the above observation, it can be seen that the suggested algorithm keeps all the sensor nodes alive for a much longer time as compared to the existing ones. The alive-node curve of the proposed method is relatively stable until round 2250 of the simulation, which shows that the number of nodes that fail in the alive state is low. On the other hand, BOA+ACO starts to suffer from node deaths much sooner than the others, while LEACH and DEEC start to lose alive nodes in early stages of simulation.

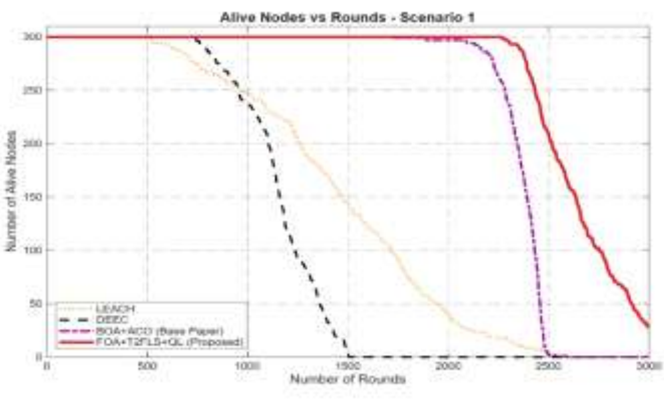

Figure 4: Alive Nodes

In the case of LEACH, the number of dead nodes gradually grows and all the 300 nodes die around 2500 rounds. But in DEEC, the number of dead nodes fastly rises and the nodes die off completely around round 1600. Once node deaths start, though, In, BOA+ACO rapidly becomes an increasingly broken network with 300 dead nodes around 2500 rounds and only about 30 nodes alive at 3000 rounds even then. Therefore, the proposed method extends the stability period and whole network lifetime as shown below in Figure 5.

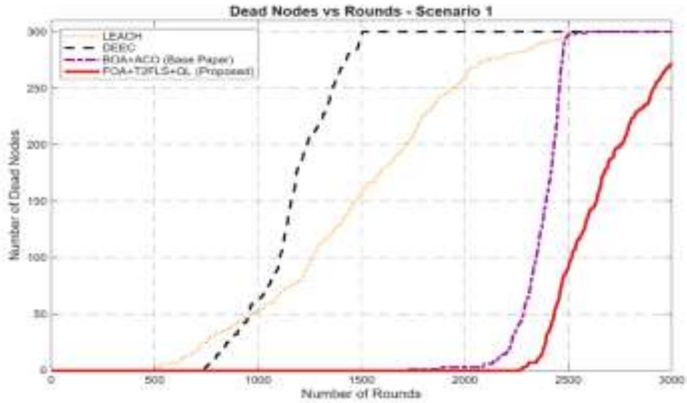

Figure 5: Dead Nodes

The PDR performance of all the protocol is shown in Figure 6. The proposed method always yields the best PDR throughout the simulation with values close to 0.98–0.99 for most of the network life cycle. This means that most of the packets created are able to be passed on to the base station, which is a sign of good communication and effective routing decisions. The performance of LEACH and FOA+ACO is moderate, their PDR values are between 0.92 and 0.95, but worse performance can be observed as the nodes consume their energy. DEEC achieves the lowest PDR among the protocols compared, and suffers a sudden death at almost 1550 rounds because of a complete failure of the network.

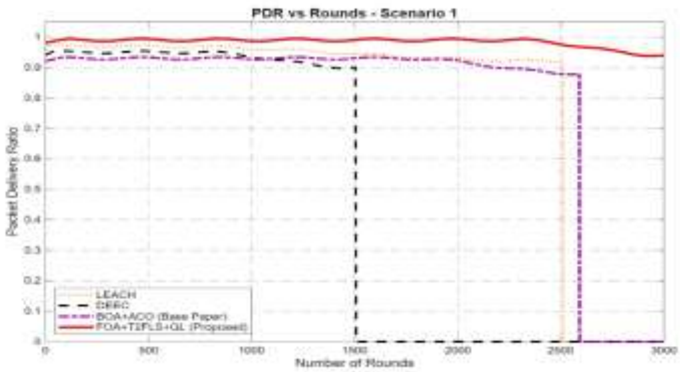

Figure 6: Packet Delivery Ratio

The residual energy results for protocols are shown in figure 7. All protocols start with a network energy of 100%, but their energy consumption is not the same during the simulation time. DEEC displays the highest depletion of energy, which is left almost depleted by rounds 1,600, leading to the conclusion of low energy utilization and low network lifetime. While DEEC shows a faster decay, LEACH still uses a significant amount of energy until about 2,200 rounds, when virtually all energy is used up. FOA+ACO yields better energy conservation, with higher residual energy levels for longer and close to zero energy by 2,500 rounds. The proposed protocol shows the most balanced energy consumption pattern, keeping more energy reserve at the end of the simulation and keeping a noticeable energy reserve after 2300 rounds.

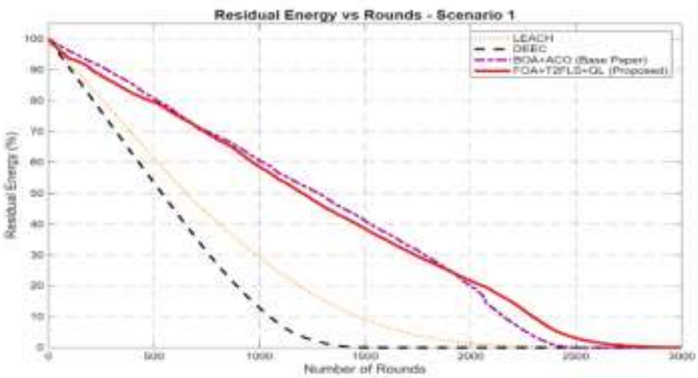

Figure 7: Residual Energy

The comparative study shows that the proposed FOA+IT2FLS+QL scheme has the best energy conservation, packet delivery performance and network longevity. The proposed approach is able to effectively trade energy usage among sensor nodes and make flexible routing decisions so as to considerably prolong the working life of the network while guaranteeing data transmission reliability. Thus, the proposed protocol is an energy-efficient and powerful routing mechanism for next-generation WSNs applications based on IoT technology.

Conclusion & Future Scope

This research suggested an energy-efficient routing method which is combination of FOA + IT2FLS + Q-Learning for WSNs in the IoT environment. The proposed method was shown to enhance the network performance by prolonging the network lifetime, decreasing the nodes mortality, increasing the PDR, and achieving energy balancing in the network compared to the other three methods LEACH, DEEC, and FOA+ACO through the simulation results. Optimization, fuzzy decision making and reinforcement learning are integrated to select the CHs and adaptive routing, which improves the reliability and energy efficiency.

The protocol developed here is expected to be validated in future works in large-scale and dynamic WSN-IoT networks with mobile sensor nodes and variable traffic parameters. In addition, real world implementations and testing in smart city and healthcare and industrial IoT applications can be discussed.

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