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QGFL-TEEN: An Intelligent Hybrid Protocol for Energy-Efficient and Adaptive Routing in Wireless Sensor Networks

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ABSTRACT

Wireless sensor networks (WSNs) have emerged as a promising technology in modern wireless communication systems. These networks have been widely used in real-time applications that require reliable communication along with energy efficiency, which heightens the need for protocols that can provide both stable communication and reduced energy consumption. In essence, traditional hierarchical protocols, such as the threshold-sensitive energy-efficient sensor network (TEEN), have demonstrated effectiveness in lowering redundant transmissions. However, they often suffer limitations in adaptive energy management and the optimal selection of the cluster head (CH). Motivated by this fact, this paper proposes QGFL-TEEN. This new hybrid frame integrates reinforcement learning (RL), genetic algorithms (GAs), and fuzzy logic (FL) with the TEEN protocol to enhance energy efficiency, stability, and network lifespan. The obtained results have demonstrated that the proposed frame attains up to 87.55% improvement in network lifetime and 91.14% enhancement in stability compared to the standard TEEN protocol. Moreover, the framework maintains higher packet delivery rates and lower energy consumption across all simulation rounds, confirming its effectiveness for scalable and resilient WSN deployments.

Keywords:

Energy Efficiency; Reinforcement Learning (RL); Genetic Algorithm (GA); Fuzzy Logic (FL); Q-Learning, Sleep Scheduling; Intelligent Energy Management; Adaptive Clustering.

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1. INTRODUCTION

Wireless sensor networks (WSNs) have been exploited in intelligent monitoring and control for various applications, including environmental monitoring, industrial automation, medical care, and smart cities. These networks comprise numerous sensor nodes with limited battery life, computational resources, and communication capabilities. Consequently, designing energy-efficient protocols is essential to prolong the network's life and ensure stable performance. Thus far, hierarchical group protocols have been considered one of the most effective schemes for energy saving in WSNs. In essence, these protocols reduce communication overload by designating CHs that add and forward data to the base station. In particular, the network protocol for energy-sensitive sensors has shown effective performance in the critical applications of time due to its data transmission mechanism based on the threshold, which minimizes the communication of redundant data and retains energy [1]. However, the performance of the grouping protocols, such as TEEN, depends significantly on the optimal selection of the cluster head and the configuration of the network topology. These tasks are computationally complex and not deterministic [2]. To address these limitations, GAs, inspired by natural selection with fuzzy logic and reinforcement learning, offer a powerful solution for WSN optimization problems, including routing, CH selection, load balance, and sleep period management and duty cycles [3-5]. GAs' integration with FL evolves candidate solutions over generations, and RL allows each node to determine its appropriate sleep periods and duty cycles without missing important data, to optimize energy consumption and improve the general stability of the network. This study proposes the QGFL-TEEN framework, a hybrid model that integrates the TEEN protocol with a GA, FL, and RL to improve the energy efficiency and useful life of sensor networks [6]. The proposed framework intelligently selects optimal CHs and refines the routing routes using an aptitude function evaluated using FL based on residual energy, distance to the BS, and node density. Nodes enter sleep mode based on energy level, network density, and data urgency. The results of the simulation confirm that QGFL-TEEN significantly exceeds the traditional approaches of TEEN and other GA-based approaches in terms of energy consumption, network useful life, and data delivery rate. Recent research supports GAs, FL, and RL integration with protocols with energy knowledge to improve WSN performance.

Collectively, these articles illustrate a progressive evolution in the application of reinforcement learning and genetic-fuzzy methodologies, revealing their potential to revolutionize energy-efficient protocols in WSNs. The integration of these advanced techniques promises to enhance decision-making, adaptability, and overall network performance, paving the way for future research and development in this critical area.

1.1 Problem Context and motivation

The motivation for this research stems from the critical limitations observed in traditional hierarchical clustering protocols for WSNs, particularly the Threshold-sensitive Energy Efficient sensor Network (TEEN) protocol. While TEEN has demonstrated effectiveness in reducing redundant transmissions through its threshold-based data transmission mechanism, it suffers from significant shortcomings in adaptive energy management and optimal Cluster Head (CH) selection, which are computationally complex and non-deterministic tasks. The static nature of CH selection and fixed threshold parameters in TEEN creates rigidity that accelerates energy depletion, generates bottlenecks around cluster heads, and ultimately reduces network longevity, particularly in dynamic or heterogeneous deployment scenarios. To address these fundamental challenges, this research proposes a novel hybrid approach that integrates three complementary computational intelligence techniques: Reinforcement Learning (RL) for context-aware adaptive power management, Genetic Algorithms (GA) for exploring optimal CH configurations without exhaustive search, and Fuzzy Logic (FL) for interpretable multi-criteria decision-making that softens abrupt transitions in routing decisions. This integrated framework, termed QGFL-TEEN, represents a pioneering effort to unify these advanced techniques within the TEEN paradigm, delivering both adaptive power management and intelligent CH election under a single, lightweight protocol suitable for resource-constrained sensor nodes, thereby bridging a significant gap in existing WSN optimization approaches.

1.2 Contributions

Principal Contributions of QGFL-TEEN Framework

1. Hybrid protocol design: Embeds a Q-learning agent within each node to learn sleep durations and duty cycles, integrates a GA-driven, FL-evaluated mechanism for CH selection based on: residual energy, intra-cluster distance, CH-to-BS proximity
2. Modular framework architecture: Provides a formalized flowchart-guided framework that formalizes the interaction among RL, GA, and FL in a four-phase flow, creates a readily implementable solution that can be extended to other WSN scenarios
3. Comprehensive performance evaluation: Conducts extensive MATLAB simulations over 3,400 rounds, Benchmarks QGFL-TEEN against multiple protocols: LEACH, PEGASIS, TEEN, G-TEEN, GFL-TEEN, and Q-TEEN, Demonstrates significant improvements:
    - Up to 87.55% improvement in network lifetime
    - 91.14% enhancement in stability compared to baseline TEEN protocol
4. Practical implementation analysis: Provides open discussion of computational complexity and scalability considerations, analyzes computational overhead, memory footprint, and parameter sensitivity, outlines practical guidelines for real-world deployments
5. Novel integration achievement: First work to unify RL, GA, and FL within the TEEN paradigm Delivers both adaptive power management and intelligent CH election under a single, lightweight protocol suitable for resource-constrained sensor nodes, addresses the research gap where previous works either applied these techniques individually or in partial combinations
6. Holistic solution delivery by uniting RL, evolutionary optimization, and fuzzy inference in a lightweight package, QGFL-TEEN provides a comprehensive, adaptive, and energy-aware

solution for next-generation WSN applications that simultaneously addresses multiple critical challenges in WSNs.

The rest of the paper includes related works in Section 2, in Section 3, we discuss the methodology of the proposed protocol. Section 4, we discuss the results of the proposed protocol, and finally, in Sections 5 and 6, we present the conclusion, limitations, and future work.

2. RELATED WORKS

This section aims to review and analyze previous work relevant to the use of genetic algorithms, fuzzy logic and reinforcement learning for cluster head selection and power management in wireless sensor networks.

The exploration of energy-efficient protocols in wireless sensor networks has garnered significant attention, particularly with the emergence of advanced methodologies that integrate reinforcement learning and genetic-fuzzy systems. Oladimeji's article [7] provides a comprehensive general vision of critical challenges related to energy efficiency and longevity of the network in WSN. The author emphasizes that energy consumption remains a main concern in the design of the WSN protocol, especially given the typical deployment of numerous sensors in environments with limited resources. To address these problems, the article highlights the importance of grouping protocols.

G. Kaur et al. [8] provide a comprehensive examination of the critical challenges associated with routing in WSNs. The authors emphasize that routing processes are highly resource-intensive, depleting sensor node energy and thereby compromising network longevity and functionality. This issue underscores the importance of developing energy-efficient routing strategies that can prolong network lifespan while maintaining security and performance.

Ibrahim Alameri, Jitka Komarkova, and Tawfik al-Hadhrami [9] provide a comprehensive examination of the challenges associated with the establishment of effective routing within the wireless mesh networks (WMNs). The authors emphasize that the main obstacle is selecting routing protocols capable of adapting to dynamic network conditions and inaccuracies in the routing information. The work critically evaluates the benefits of diffuse-based routing, highlighting the improvements in energy efficiency, performance, packet delivery ratio, and reduced packet loss. These improvements are attributed to the system's ability to dynamically adjust routing policies based on real-time network conditions, thus maintaining optimal performance.

A critical aspect of the article is its focus on the deployment strategies utilizing metaheuristics like particle swarm optimization (PSO), multi-objective evolutionary algorithms (MOEA), multi-objective genetic algorithms (MOGA), and artificial bee colony (ABC). These techniques are evaluated for their effectiveness in addressing the relay node placement problem, which is important to prolong the network lifetime and ensure reliable data transmission. Mishra, Sen Gupta, and GUI [10] provide a comprehensive exploration of GA's application in adaptation to energy consumption within WSNs. Writers effectively highlight the role of GA as a discovery-based adaptation technique inspired by natural selection and genetics, emphasizing its suitability to address complex, real-world problems demanding long-term solutions, such as prolonging the network lifetime. The article depicts a systematic approach to integrating GA in the WSN routing protocol. The process begins with the codification of chromosomes efficiently, ensuring that genetic representation is aligned with the parameters and restrictions of the network. The selection mechanism prioritizes nodes with higher energy values, correlating directly with energy efficiency routing solutions, thus promoting the evolution of more optimal configurations in generations. The current discussion provides a solid foundation for understanding GA's role, but does not delve into hybrid frameworks that could potentially yield more adaptive and robust routing solutions.

Saleem et al [11] suggested the EEMCL protocol, which is dependent on splitting the network into layers to improve and optimize the balanced distribution of energy consumption. In every round, a main cluster head is determined in advance which has the highest energy. Thereafter, two secondary cluster heads are identified based on the proximity of the nodes to the main cluster head and the energy of the nodes. Non-CH nodes transmit their data to the secondary cluster head to reduce; the secondary cluster head compresses data and sends it to the base station. Secondary cluster head reduces transmission distance between non-CH nodes and the main cluster head and reduces load.

Alabady et al [12] proposed the LCPC protocol to enhance network performance in terms of packets sent to base station, end-to-end delay, and bit error rate. The mechanism uses coding technique does not involve complex computational operation thereby reduce energy consumption. The data split into equidistant samples and bits are inserted to create the encryption key. Upon decryption the syndrome vector (SR) computed if SR equal to one it means there is an error, an xor operation performed between the key and the error patterns table, which contains possible errors.

Basith and Shankar [13] provide an integral examination of energy management strategies within the WSN, emphasizing the importance of optimizing the operation of nodes and cluster training to improve the longevity and network safety. The authors recognize the inherent energy limitations faced by the sensor nodes, particularly in the context of package forwarding, which is a critical factor that influences the sustainability of the network. The center of its approach is the application of the Firefly algorithm to improve the selection process of cluster heads, an extension of the traditional leaching protocol. By taking advantage of the Firefly algorithm's capacity to perform efficient optimization, the authors demonstrate a reduction in energy consumption through a more effective cluster head selection, which contributes to the stabilization of the network based on power levels.

Behnam Ojaghi and Mohammad Mahdi Dehshibi [14] present a significant contribution to the domain of energy management within WSNs. The authors introduce an innovative active learning approach that strategically reduces the data required for critical node identification, thereby decreasing the computational complexity typically associated with such tasks. By integrating clustering and classification modules, the method iteratively refines the identification process, effectively balancing the trade-off between energy expenditure and network reliability.

Kubotani et al. [15] introduce RLTutor, an adaptive tutoring system that leverages reinforcement learning to model the learner's knowledge state. This framework demonstrates the potential of reinforcement learning to optimize instructional strategies, even with limited interaction data. The findings suggest that such systems can significantly improve lifetime networks, which could have implications for energy-efficient protocols that require adaptive learning mechanisms to optimize resource allocation in wireless sensor networks. The advance of Q-learning is explored more thoroughly by Zahmatkesh et al. [16], who apply it to the control of auto-landing in aviation. His work emphasizes the need for continuous state spaces and introduces a hybrid approach that combines fuzzy logic with basic Q-learning. This integration allows stronger decision-making in dynamic environments, indicating the potential of similar methodologies to improve decision-making processes in WSN. In a related vein, Li et al. [17] propose an innovative approach that progresses by combining TD3 and TEEN, focusing on joint policies to promote exploration in continuous control scenarios. This research underlines the importance of optimizing the interactions of agents and reward systems, which can be directly applicable to the development of energy-efficient protocols in WSN.

The article by Habeeb et al. [18] presents a convincing approach to managing energy resources on IoT devices through reinforcement learning, specifically using learning to adapt data transmission rates based on the availability of renewable energy. The authors effectively demonstrate how reinforcement learning can be used to balance compensation between the granularity of data and energy consumption. The evaluation, based on historical data of solar radiation, corroborates that this adaptive mechanism can increase data performance by up to 23%, while maintaining the continuous operation of the device, a significant achievement in the design of IoT, conscious of energy. Although the approach to Q-Learning provides a solid basis for energy management, the article does not explore the integration of more complex or hybrid reinforcement learning algorithms, which could offer better convergence or adaptability in highly dynamic environments.

Sathyan et al. [19] compare the Genetic Fuzzy System (GFS) and Q-learning within the context of collaborative control design. This study highlights the strengths of GFS in optimizing membership functions and rule bases without the need for ground truth data, while also illustrating the effectiveness of Q-learning in modeling nonlinear systems. The authors extend their analysis to energy-efficient wireless sensor networks, setting the stage for the integration of these methodologies in enhancing network performance.

Irmouli et al. [20] The current approach to hybrid reinforcement learning and genetic algorithms aims at improving the efficiency of genetic algorithms through the dynamic optimization of parent selection and mutation processes. Their findings reveal how reinforcement learning can enhance the performance of the genetic algorithm by adapting to the diversity of the population and improving the solution. This suggests that such adaptive mechanisms can lead to more efficient energy management in wireless sensor networks. Muthu Kumar et al. [21] introduced a multi-jump grouping strategy promoted by GA, while Patel and Eloocla [22], [23] developed a GA-based routing method that demonstrated extended node longevity. These studies affirm the potential of genetic algorithms to improve WSN operations when combined with energy efficiency protocols such as Teen. The authors, José M. Lanza-Gutiérrez et al., explore multiple strategies aimed at improving network performance metrics, such as energy efficiency, coverage, connectivity, and the cost of implementation, emphasizing the importance of balancing these often competing factors [24].

The article [25] by Xing Fu and Jeong Geun Kim offers a complete description of recent advances in energy-efficiency communication protocols within the WSN, emphasizing the integration of AI techniques. The authors emphasize that traditional research focused mainly on the routing schemes and communication protocols aimed at optimizing energy consumption, with sleep programming mechanisms such as EBM that play an important role by adapting sleep periods based on the positioning of nodes.

In addition, the article underlines the growing adoption of automatic learning and deep reinforcement learning techniques to improve network efficiency. For example, support vector machines (SVMs) have been used for proportional fair programming, while deep neural networks (DNNs) facilitate rapid channel allocation decisions. In particular, Deep-Q-Networks (DQN) are used for linkage programming in small base stations, illustrating the deep RL potential in the management of complex programming tasks in real time.

3. THE PROPOSED METHODOLOGY

To address the limitations of traditional TEENs based on static cluster selection and rigid energy management, this research introduces the QGFL-Teen protocol. This new hybrid approach synergizes the learning reinforcement (RL), GA, and FL within the framework of the proposed protocol. The justification of the design comes from the need to achieve intelligent, adaptive, and efficient energy in WSN, where sensors work under strict energy restrictions. RL integration allows dynamic decision-making for energy management based on environmental states such as residual energy and data urgency. Meanwhile, GA optimizes the CH selection, and FL improves the quality of this selection by evaluating the suitability of CH through a multiple aptitude function. This section details the methodology and workflow of the proposed protocol. The proposed framework, as illustrated by the flow diagram in Fig. 1, offers a modular and scalable design that facilitates the ease of implementation and expansion, with each component that goes from the behaviour of the sensor. The learning for the optimization of CH is delineated, which guarantees efficient purification and customization. The flow diagram not only helps visualize the interaction between algorithmic components but also demonstrates the perfect integration of RL, GA, and FL to achieve adaptive and conscious routing of the context in WSN. This structured methodology promotes the intelligent use of energy and the formation of robust clusters, which contribute to the superior performance metrics of the protocol.

3.1 QGFL-TEEN protocol

The Threshold-sensitive Energy Efficient Network (TEEN) protocol organizes nodes into clusters. Each cluster has a CH responsible for aggregating and forwarding data. TEEN introduces two thresholds:

- Hard Threshold (HT): minimum value beyond which the sensed data is considered significant.
- Soft Threshold (ST): the minimum change in the value since the last report.

Only when both thresholds are met does a node transmit, thus conserving energy by minimizing unnecessary transmissions. The objective of the proposed framework is to optimize CH selection and energy management in WSNs by combining the energy-aware behaviour of the TEEN protocol, the efficiency of the GA algorithm searches the gradient descent of FL, and the ability of RL to adapt to the environment through trial and error to automatically improve performance. The recommended approach consists of four phases as illustrated in Fig. 1: network initialization, Reinforcement Learning energy management, cluster head selection, cluster formation, and reinforcement learning energy phase.

3.2 Network initialization

Includes configuring the environment of the network and the initial parameters of all nodes, where X homogeneous nodes are randomly distributed at fixed locations in a two-dimensional area, and the BS is in the middle of the sensing area. Algorithm 1 illustrates that. The protocol relies on the radio energy model to calculate the remaining energy of each node after each round, where two basic models of propagation are used based on the transmission distance d. There are the free model and the multipath model. A common representation of sending *k-bit* data over a distance is

$$E_{Tx}(k,d) = \begin{cases} E_{elec} \times E_{mp} \times k \times d^4 & if\ d > d_o \\ E_{elec} \times E_{fs} \times k \times d^2 & if\ d \leq d_o \end{cases}, \quad 1$$

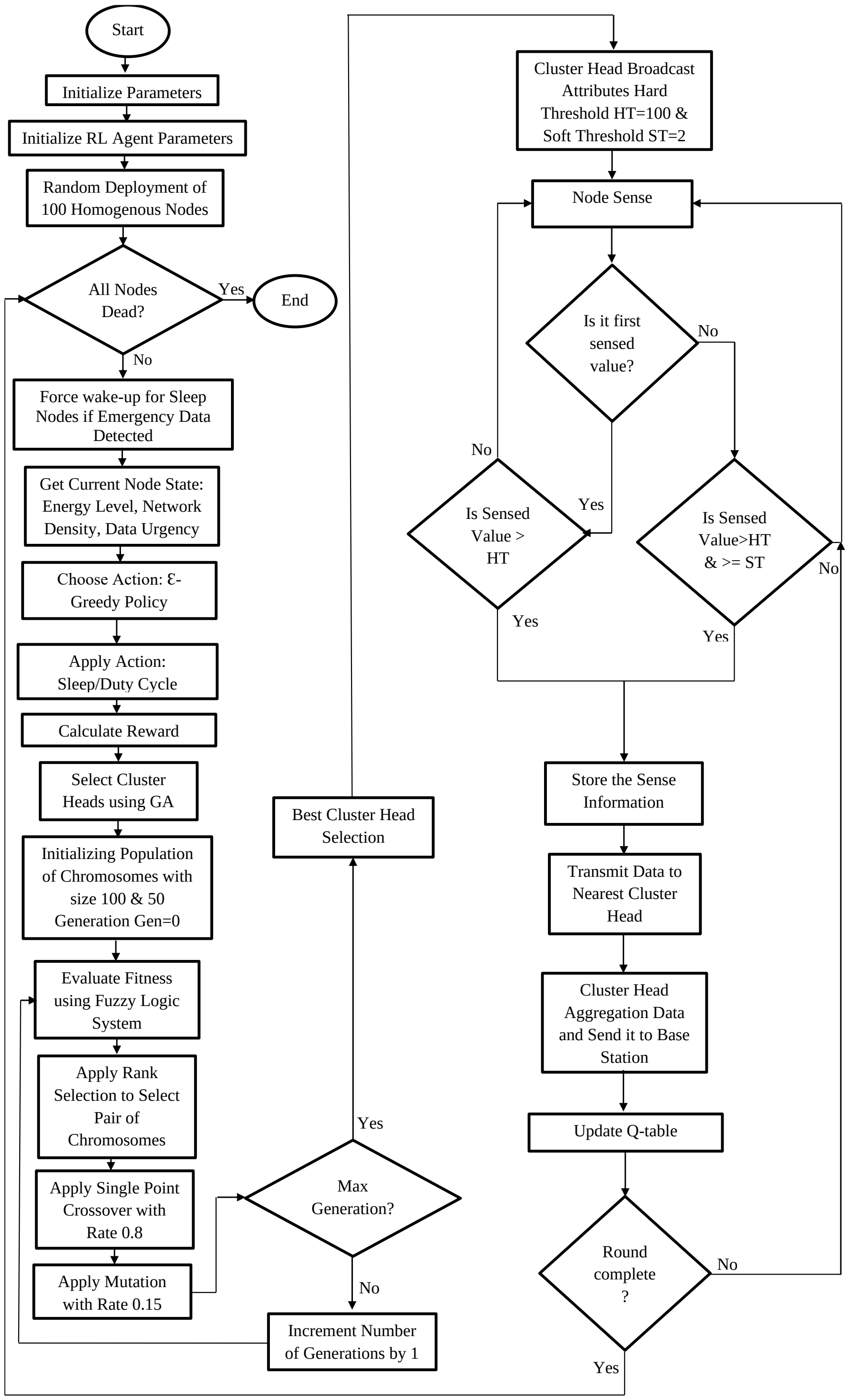

Fig. 1 Proposed Algorithm for QGFL-TEEN protocol

where the E_{elec} the energy consumed by the electronic circuit in a transmitter or receiver to process a single bit, regardless of the distance of the communication, E_{mp} denote the multipath amplifier coefficient, E_{fs} denote the free space amplifier coefficient, and d_o The threshold distance where models switch is given as

$$d_o = \sqrt{\frac{E_{fs}}{E_{mp}}}, \qquad 2$$

A common representation of sending k-bit data over a distance is

$$E_{Rx}(k,d) = E_{Rx} \times k. \qquad 3$$

The parameters of the reinforcement learning agent are set at this phase, where the learning rate, discount factor, and exploration rate are initialized, and the Q-table, in addition to the state space and actions for the reinforcement learning.

3.3 Reinforcement learning energy management

Each node in a WSN observes its current state in terms of energy level, network density, and data urgency, where there would be 27 states. Then, it chooses an action that determines how long the node will be asleep, and the activity levels of the node when it is active; there would be 9 actions. The action is chosen according to ϵ-Greedy policy that balances exploration and exploitation ϵ for exploration and 1-ϵ for exploitation at first knowledge of the network will be nonextant so exploration will be extensive which will choose an action with an unknown outcome to obtain more information about the environment discover energy-optimizing policies, and improve knowledge with the possibility of emergency response when there is a sudden change in data. After a while, Exploration will decrease due to the decay rate of exploration, so as not to be stuck in exploration, and increase exploitation with time that uses knowledge for better selection. After choosing an action, the reward is calculated as follows

$$R = w_1 \times E_{rew} + w_2 \times D_{rew} + w_3 \times ER_{rew} - w_4 \times U_{pen},$$

where E_{rew} is the energy of the node, D_{rew} is the density of the network, ER_{rew} is the response for emergency data, and U_{pen} is the data urgency. The reward evaluates the performance of a node after taking an action. The node receives a reward if it chooses an action that does not consume energy, and if it responds to emergency events, the selection of this action is increased in the next rounds. It receives a penalty if it is in a dormant state and loses important data. W values must be carefully chosen to ensure that reinforcement learning chooses decisions that improve energy consumption.

3.4 Cluster head selection and cluster formation

The head of the cluster is selected using GA integrated with FL, which operates as follows:

3.4.1 Chromosome Encoding

Each chromosome represents a possible CH configuration. It is encoded as a binary string of length N, where '1' indicates a node selected as CH and '0' indicates a normal node.

3.4.2 Fitness Evaluation based on Fuzzy Logic:

FL is an important tool to select intelligent decisions about CH selection and is used to evaluate the fitness of each individual, as illustrated in Fig. 2. FL inputs are based on:

- Residual energy of CHs.
- Average intra-cluster distance.
- Distance from CHs to BS.

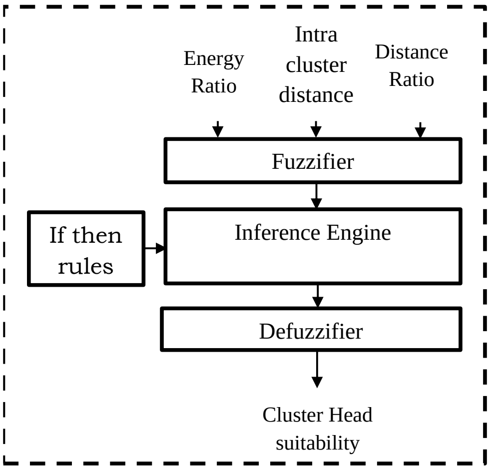

Fig. 2 Fuzzy inference system

Table 1. Fuzzy input function

Inputs	Linguistic variables		
Residual Energy of CHs	Low-Gaussian	Medium-Gaussian	High-Gaussian
Average intra-cluster distance	Close - trapezoid	Far - Gaussian	Medium - trapezoid
Distance from CHs to BS	Close - trapezoid	Far - trapezoid	Medium - trapezoid

Table 2. Defuzzifier Output Function

Output	Linguistic variables
Suitability of the CHs	Very Low
	Medium Low
	Low
	High
	Medium High
	Very High

Table 3. Some of the Fuzzy Logic rules

Inputs			Output
Residual energy of CHs	Average intra-cluster distance	Distance from CHs to BS	suitability of the CHs
Low	Far	Far	Very Low
Low	Medium	Close	Low
Low	Close	Medium	Medium Low
Medium	Close	Far	Medium
Medium	Close	Close	Medium High
High	Close	Medium	High
High	Close	Close	Very High

Membership function is defined for each of these inputs which determines the belonging of a certain value of the parameter to that group Trapezoidal membership function is assigned to the Distance from CHs to BS, Gaussian membership function assigned to Residual energy of CHs and combination of them as for the Average intra-cluster distance as show in Table 1. the output as show in Table 2. represent the suitability of the CHs the fitness of the solution depends on a set if fuzzy rules some of them are listed in Table 3. the fitness value is produced based on these rules the process of defuzzing is done to obtain crisp output value y using the weighted average method, which is given as

$$y = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}, \qquad 5$$

where yi (the degree of input affiliation) is represented by numeric values w, firing strength, n number of rules with an affiliation score, and i Index of fuzzy rule.

3.4.3 Selection, Crossover, Mutation

Selection: Rank selection method.
Crossover: Single-point crossover with rate 0.8.
Mutation: Bit flip mutation with rate 0.15.

The GA evolves the population over 100 generations to determine the optimal CH set for each round.

Nodes other than CH will look for the closest CH to associate with, and from a cluster, data from normal nodes is transmitted to CH only if it is beyond the thresholds; then the CH aggregates the data and sends it to BS.

ALGORITHM 1: TEEN PROTOCOL WITH FGA FOR CH SELECTION AND RL FOR POWER

Input: N, BS, HT, ST, λ, α
Output: Live/dead node statistics, cluster information, $k_{transmitted}$, and $E_{consume}$.

Initialization: E_o, E_{fs}, E_{mp}, E_{ele}, k, Q=zeros (s, a), **sleep-timer =** 0**, duty-cycles =** 1.
Random Deploy of **N** with $\mathbf{E_o}$
While $\mathbf{E_o} \neq \mathbf{0}$ for nodes
Read current data from the network
R = **0**
While not all **N** are dead
Begin
    Get **current-data**
    If current-data – **previous-data** ≥ **emergency- threshold** || **current-data** ≥ **critical-high** || **current-data** ≤ **critical-low**
    sleep-timer=**0**, **duty-cycles** = **1.0**
    Begin
        If Eo ≠ **0** for alive nodes, **then**
            Get the current state of nodes = (E, D, U)
            Choose action (sleep duration [0,1,2], duty cycle [0.8,1.0,1.2]) using ϵ-Greedy
            Calculate $\mathbf{R} = w_1 * E_{rew} + w_2 * D_{rew} + w_3 * ER_{rew} - w_4 * U_{pen}$
        End
    End
    Initialize **P** of CH candidates
    For **max G** iterations
    Begin
        Calculate **FF** for each solution using FL.
        Select Elite solution →Crossover →Mutation.
    End
    Select the best solution.
    For all non-CH and active **N**
    Begin
        If emergency - wake || **data** > **HT** && **Data - Change** ≥ **ST then**
            Find the nearest CH.
            Calculate E_{Tx} and transmit data.
        End
    End
    Update Q-table
    Decay Exploration Rate
    Update network statistics and increment **R**
End
End

3.5 Reinforcement Learning

After an action from the Q-table is executed based on a particular state of the node, the Bellman equation

$$Q(s,a) \rightarrow Q(s,a)+\alpha[R+\gamma \times max_{a'} Q(s',a')- Q(s,a)],$$

where $Q\ (s,\ a)$ is the present state of state s and action a, $Q\ (s,\ a')$ is the optimal value for the next state, and α is the learning rate that specifies how rapidly the algorithm updates its knowledge based on the Q table, and γ is the discount factor (prioritizes future rewards). Used to update the Q value in the table, this update allows nodes to gradually learn the optimal policy for state values and the actions the nodes take based on previous experiences and rewards they get from their environment. If the value is better, the confidence of this action increases, and if the value is worse, it decreases confidence and searches for better decisions.

Algorithm 1 illustrates the proposed algorithm's implementation step, which consists of four stages, starting with initializing the network parameters and RL parameters, then using RL to manage duty and sleep cycles while responding to emergency events, followed by cluster formation, and finally updating the action-state Q-table.

3.6 Methodological Justifications

To ensure the reliability, repeatability, and practical feasibility of the proposed QGFL-TEEN protocol, all algorithmic parameters were selected based on a combination of prior literature, sensitivity analysis, and empirical tuning under realistic simulated conditions. This section justifies the most critical parameters used in the RL, GA, and FL components.

3.6.1 Reinforcement Learning Parameters

The RL agent embedded in each node is governed by three fundamental hyperparameters: the learning rate (α), the discount factor (γ), and the exploration rate (ε). In our framework in the proposed framework, the parameters have been chosen to be lightweight and appropriate for the resource-constrained capabilities of the nodes, and are benchmark values commonly used in many reinforcement learning applications [26] [27]:

- **Learning rate (α = 0.1):** This moderate value ensures gradual learning without overreacting to single-time-step rewards. It was chosen to maintain a balance between stability and adaptability in dynamic WSN environments. When testing other values less than 0.1, the algorithm still makes random suboptimal decisions, which wastes energy and affects the number of packets delivered to the base station. When testing values higher than 0.1, the algorithm relied only on information from the current experiment and ignored previous knowledge, which directly affected the stability of the network.
- **Discount factor (γ = 0.9):** This value reflects the importance of future rewards in comparison to instant, appropriate for long-term energy management, where immediate energy savings may not always result in optimal lifetime extension. When values lower than 0.9 have been experimented with, the network lifetime has been reduced because the node will continue to seek instant rewards without concern for energy consumption.
- **Exploration rate (ε = 0.3) and decay (0.995):** Initial exploration helps the agent understand the action space. Values lower than 0.3 have been experimented with, resulting in higher energy consumption because the algorithm finds a suitable action at the beginning and continues to use it without exploring other actions that could consume less energy. When values higher than 0. 3 have been experimented with, they resulted in a reduced network lifetime and stability because the algorithm continues to learn new policies, which wastes more energy, while gradual decay encourages convergence to optimal actions. These values were validated through preliminary trials to avoid excessive exploration or premature convergence. A range of different values for each parameter has been tested individually, and the selected values had the best effect on network lifetime, stability, and the number of packets delivered to the base station.

3.6.2 Genetic Algorithm Parameters

The GA was designed to search for optimal CH configurations across multiple generations efficiently. The following parameter choices are justified as follows:

Population size (P = 50): Chosen to ensure genetic diversity while maintaining manageable computational overhead. Larger populations showed marginal gains at the cost of increased runtime. In contrast, a small population size is computationally fast but tends to fall into local solutions, leading to a reduction in network lifetime.

- **Number of generations (G = 100):** Empirically found to be sufficient for convergence to high-fitness solutions without overfitting. A large number of generations requires significant computational time, while a small number of generations will not explore the entire solution space and therefore will not contribute to improving the network lifetime.

- **Crossover rate (Pc = 0.8):** A high crossover probability promotes exploration of the solution space and encourages the combination of advantageous traits. Small values will not exploit the solutions sufficiently, leading to a waste of time and energy, which reduces the network lifetime.
- **Mutation rate (Pm = 0.15):** This moderate mutation rate introduces enough variability to avoid local optima while preserving solution quality. Lower mutation rates were observed to lead to premature convergence.
- **Selection method (Rank Selection):** Selected for its ability to maintain pressure towards fitter individuals while preserving diversity.

3.6.3 Fuzzy Logic Configuration

The fuzzy inference system evaluates cluster head suitability based on residual energy, intra-cluster distance, and distance to the base station:

Membership function types: Gaussian functions were used for continuous variables such as residual energy due to their smooth curves and better modeling of gradual transitions. Trapezoidal functions were used where abrupt classifications (e.g., distance proximity) are more practical.

Rule-based design: The fuzzy rules were defined manually, following domain knowledge, and validated using trial simulations. This design ensures interpretability and aligns with the physical characteristics of WSN operations.

3.6.4 General Considerations

All parameters were further refined through iterative simulation, observing their impact on network lifetime, stability, throughput, and energy consumption. Sensitivity testing confirmed that the selected values provide robust performance across a range of deployment scenarios without significant overfitting or brittleness.

4. RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed framework, a network simulation is conducted. Table 4 shows the parameters that are utilized.

Table 4. Simulation parameters

Output	Linguistic variables
Network area size	100*100 m^2
Number of nodes (X)	100
Base Station position (BS)	50,50
Initial energy of nodes (Eo)	0.5J
Energy required for running transmitter and receiver (E_{elec})	50 nJ/bit
Threshold distance (do)	87 m
Amplification energy required for a smaller distance d ≤ do (E_{fs})	10 pJ/bit/ m^2
Amplification energy required for a smaller distance d > do (E_{mp})	0.0013pJ/bit/ m^2
Energy consumption incurred while data aggregation (Eda)	5 pJ/bit/ m^2
Data packet size (k)	4000
Hard threshold (HT)	100
Soft threshold (ST)	2
Learning rate (α)	0.1
Discount factor (γ)	0.9
Exploration rate (ϵ)	0.3
Exploration Decay	0.995
Population Size (P)	50
Number of Generations (G)	100
Crossover rate (Pc)	0.8
Mutation rate (Pm)	0.15
Type of crossover	Single Point
Selection method	Rank Selection Method

4.1 Energy Efficiency assessment and Network lifetime

To assess the efficiency of the proposed framework QGFL-TEEN, it was benchmarked with LEACH, PEGASIS, TEEN, G-TEEN using GA to optimize CH as given

$$FF = w_1 \times Res + w_2 \times Dis + w_3 \times Avg\ ICD \quad 7$$

where Res is the residual energy of CHs, Dis is the distance from CHs to BS, and $Avg\ ICD$ is the average intra-cluster distance. To evaluate fitness, GFL-TEEN uses GA to optimize CH selection and FL to evaluate fitness, Q-TEEN, with RL for power management, uses the metrics of stability, network lifetime, Throughput, and Average Energy Consumption.

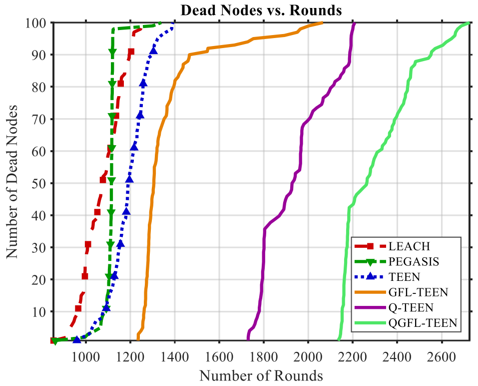

Fig. 3 Comparison of Dead nodes vs. rounds of QGFL-TEEN with other protocols

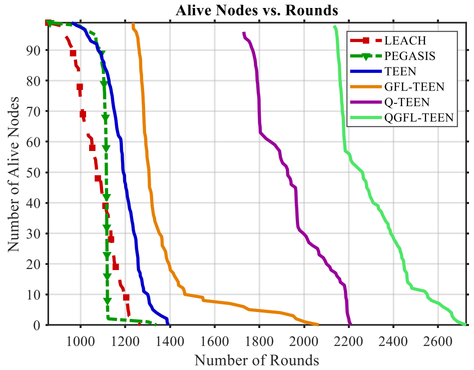

Fig. 4 Comparison of Alive nodes vs. rounds of QGFL-TEEN with other

Table 5. Performance Comparison between the proposed framework and other protocols

Protocols	Stability	Network lifetime	Final packets to BS
LEACH [28]	954	1342	20305
PEGASIS[28]	958	1358	1358
TEEN [25]	960	1390	21280
G-TEEN	1126	1983	57534
GFL-TEEN	1235	2066	53679
Q-TEEN	1725	2208	26597
QGFL-TEEN	1835	2607	71825

- **Stability**

The number of rounds before the first node lost its energy in QGFL-TEEN was 1835 rounds compared to 954, 958, 960, 1126, 1235, and 1725 rounds in LEACH, PEGASIS, TEEN, G-TEEN, GFL-TEEN, and Q-TEEN, as illustrated in Fig. 3 and Table 5. It is obvious that it exhibits better stability.

- **Network Lifetime**

The round in which the last node lost its energy. Fig. 4 and Table 5 illustrate the superiority of the QGFL-TEEN protocol in extending the overall lifetime of the network, where the network lasted for 2607 rounds before all nodes exhausted their energy, significantly outperforming the LEACH, PEGASIS, TEEN, G-TEEN, GFL-TEEN, and Q-TEEN protocols, which lasted for 1342, 1358, 1390, 1966, 2066 and 2208 rounds, respectively.

- **Throughput (number of packets successfully arriving at the BS)**

As illustrated in Table 5, the QGFL-TEEN protocol outperformed the network in terms of throughput, sending 71825 data packets to the BS successfully. Comparison to the performance of other protocols was lower LEACH 20305 packets, PEGSIS 1358 packets, and TEEN 21280 packets. G-TEEN 53592 packets, GFL-TEEN 53679 packets, and Q-TEEN 26597 rounds. This increase is due to the selection of optimal CH and RL, which extends the lifetime of the network and allows nodes to send data for a longer period, significantly enhancing overall throughput.

- **Average Energy Consumption**

Fig. 5 illustrates that the proposed framework is more efficient in terms of energy consumption compared to the LEACH, PEGASIS, TEEN, G-TEEN, GFL-TEEN, and Q-TEEN protocols, as it consumes less energy. This difference becomes more pronounced as the number of rounds increases.

4.2. Tuning the simulation parameters

To optimize the proposed framework, different values of the w coefficients used to calculate the reward formula 3 for a given node action were tried. Fig. 6 shows that when using equal values, the longest network lifetime and the optimal packet delivery were obtained.

The reward function has been tested on a different scenario, where the base station is located at position 0, 0 instead of position 50, 50. Assigning more weight to energy results in lower energy consumption and, therefore, a higher network lifetime and stability. This means that the weights of the reward function are not constant and vary depending on the scenario, but what fits the network scenario shown in Table 4 is that the weights are equal.

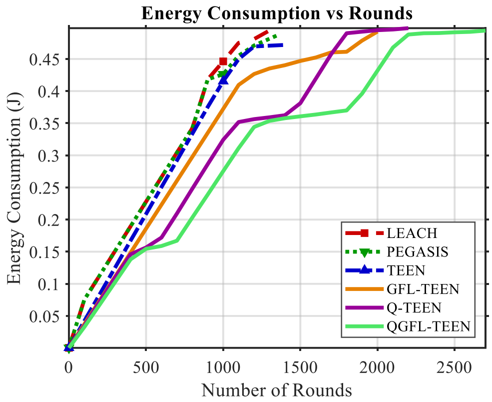

Fig. 5 Comparison of Average Energy Consumption vs. rounds of QGFL-TEEN with other protocols

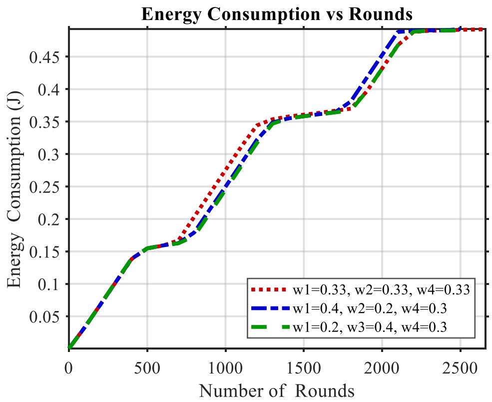

Fig. 6 Comparison of Energy Consumption vs. rounds of QGFL-TEEN with different weights for the Reward function

Table 6. Compare the performance of the QGFL-TEEN and TEEN protocols in terms of stability and network lifetime

Protocols	TEEN		QGFL-TEEN	
	Stability	Network Lifetime	Stability	Network Lifetime
Mean	938	1409	2042	2856
Standard Deviation	14.1	23.8	78.6	84.0

The mean and standard deviation have been computed for ten experiments. As illustrated in Table 6, the QGFL-TEEN protocol clearly surpasses the TEEN protocol in terms of stability and network lifetime with a statistically significant difference p-value < 0.0001, which means that the difference is genuine and not due to coincidence. Still, it is more sensitive to initial conditions.

5. CONCLUSION

This paper presented QGFL-TEEN, a novel and intelligent hybrid routing protocol designed to enhance energy efficiency, stability, and scalability in WSNs. By integrating the TEEN protocol with RL, GA, and FL, the proposed framework addresses key challenges in cluster head selection and adaptive energy management.

The QGFL-TEEN protocol enables sensor nodes to autonomously manage their power states based on network context—such as residual energy, node density, and data urgency—using a Q-learning agent. Simultaneously, GA optimizes cluster head selection, while FL enhances decision accuracy by evaluating fitness based on multiple network parameters. This combined approach allows the network to adapt to dynamic conditions, reduce redundant transmissions, and extend operational lifespan.

Comprehensive simulation results confirmed that QGFL-TEEN significantly outperforms several benchmark protocols, including LEACH, PEGASIS, TEEN, G-TEEN, GFL-TEEN, and Q-TEEN. The framework achieved up to 93.55% improvement in network lifetime and demonstrated superior performance in stability, throughput, and energy conservation. Future work will focus on reducing the computational overhead associated with integrating GA and RL, optimizing fuzzy rule selection, and validating the framework in real-world WSN deployments or IoT environments. The QGFL-TEEN model serves as a promising foundation for the development of intelligent, energy-aware communication protocols in next-generation wireless sensor applications.

6. LIMITATIONS AND FUTURE WORK

While the proposed QGFL-TEEN framework demonstrates significant improvements in energy efficiency, stability, and network lifetime over traditional clustering protocols, several limitations must be acknowledged to guide future research and practical deployment.

6.1 Limitations

- **Computational Complexity:**

The integration of Reinforcement Learning (RL), Genetic Algorithms (GA), and Fuzzy Logic (FL) introduces additional computational overhead, particularly in resource-constrained sensor nodes. To illustrate the computational complexity of each round, assume that:

N total number of sensor nodes.
S number of states in the RL.
A number of actions in the RL.

G number of generations in the GA.
P Population Size.

Reinforcement learning energy management

- The initialized of Q table of S, A → O (N × S × A) where S and A are constant values.
- Each node in each round computes its current state based on three parameters: energy of the node, density of the network, and data urgency → O(N).
- Select an action from the Q table → O (A × N).
- Calculate the reward for each action → O(N).
- Update the action state table for each round → O (S × A × n).

Genetic algorithm for CH selecting

- Initialize the chromosome → O (P × N) where P is a constant number.
- Evaluate the fitness of each generation using fuzzy logic based on 3 metrics: remaining energy, distance to the base station, and intra-cluster distance → O (P × n) for all generations → O (G × P × N) where G is a constant number.

Transmit data based on thresholds

- Each node performs threshold checks → O(N) in each round.
- Nodes that exceed the thresholds only transmit data → O(N).

Table 7 summarizes the computational complexity of each phase. This additional computational complexity per round remains suitable for small and moderate-scale deployment, but reinforcement learning may need improvements for large networks by adding pruning techniques or policy-based pruning to remove actions that are never chosen in the optimal policy. The genetic algorithm with fuzzy logic remains suitable for large networks. The data transfer phase adds minor overhead, as this additional processing is traded off against reducing redundant transmissions and improving the overall lifespan of the network by 87.55% compared to TEEN, making the trade-off between overhead and gains favorable.

- **Memory Constraints:**

The Q-learning mechanism requires maintaining a Q-table that grows with the number of state-action pairs. As the number of observable states increases—especially in heterogeneous networks—the Q-table can become prohibitively large for low-power sensor hardware.

Table 7. Summary of computational complexity and impact for QGFL-TEEN phases

Phase	RL for energy management	Genetic-Fuzzy Logic (GFL) CH Selection	TEEN Threshold-based Data Transmission
Major processes	An intelligent energy management system that adapts node behavior based on environmental conditions and performance feedback	Hybrid optimization approach combining genetic algorithms with fuzzy logic for intelligent CH selection and network optimization	A conditional data transmission system that activates communication only when specific performance thresholds are exceeded
Complexity	O (S *A* N)	O (G* P* N)	O(N)
Impact on Energy Efficiency / Lifetime	Very High – Significantly reduces energy waste through intelligent scheduling	High – Optimizes cluster head selection for better network stability	Very High – eliminates redundant transmissions, reduces network congestion

- **Parameter Sensitivity:**

The performance of the protocol is influenced by hyperparameters such as the learning rate, exploration rate, population size, and fuzzy membership function shapes. Although these were carefully selected, suboptimal tuning in different environments may degrade performance.

- **Simulation Environment:**

The evaluation was conducted using MATLAB simulations in an environment that simulates real-world deployments involving environmental noise, node mobility, packet dropouts and irregular terrain—all of which affect protocol behavior.

6.2 Future work

To address the above limitations and enhance the adaptability of the framework, future work will focus on:

- **Scalable RL Techniques:**

Replacing Q-learning with more scalable alternatives such as Deep Q-Networks (DQN) or Policy Gradient methods, which can generalize across larger or continuous state spaces without the need for exhaustive Q-tables.

- **Online Adaptation and Transfer Learning:**

Enabling sensor nodes to transfer learned policies between similar network environments or to adapt online to changes in topology, traffic, or energy dynamics.

- **Hardware-In-The-Loop Testing:**

Implementing QGFL-TEEN on real embedded sensor platforms to evaluate runtime performance, memory usage, and robustness under actual environmental conditions.

- **Security and Fault Tolerance:**

Extending the framework to incorporate secure cluster formation and resilience mechanisms against node compromise or communication failures.

- **Energy Harvesting Integration:**

Investigating the integration of energy harvesting models into the learning and clustering processes, where node behavior adapts not only to consumption but also to dynamic energy availability. By exploring these directions, QGFL-TEEN can evolve into a more robust, scalable, and deployable solution for intelligent energy management in next-generation WSN and IoT environments.

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