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A Modified LEACH Protocol Using Multi-Hop Mechanism and Neural Networks for IoT Applications

Hamdy H. El-Sayed, Elham M. Abd-Elgaber*, E. A. Zanaty, and Samy S. Bakheet

Faculty of Computers and Artificial Intelligence, Department of Computer Science, Sohag University, Sohag, 82524, Egypt

**E-mail:* elham3.mohamed@gmail.com

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Abstract: The wireless sensor network is a big field for researchers because it has a lot of applications. One of these applications is IoT. IoT has a lot of applications in agriculture, Traffic Monitoring, smart homes, smart cities...etc. WSN has the challenge to reduce the consumed energy through it over time because sometimes it is hard to change the sensor nodes in the network that may be in different environment conditions in applications like forest detection, military battlefield, and other extreme environments. Therefore, it is critical to prolong the network's lifespan and conserve the power as much as possible. Hierarchical routing efficiently reduces consumed energy by aggregating and fusing data. It reduces the transmissions to the base station (BS). LEACH (Low Energy Adaptive Clustering Hierarchy) is one of the hierarchical protocols that cluster sensor nodes and aim to prolong the lifetime of the network. In this paper, we aim to produce LEACH in a modified form by using Multi-hop LEACH and Neural networks. We used MATLAB environment to simulate the proposed protocol that we called NNMH_LEACH and to make all the comparisons that prove that the proposed method is enhancing the network's lifespan and decreasing the consumed energy by nodes all over the rounds. LEACH and Multi-hop LEACH are outperformed by the suggested protocol. The simulation and all of the results are discussed in this publication.

Keywords: Wireless sensor networks; LEACH; Multi-hop LEACH; Neural Networks.

1. Introduction

The wireless sensor network (WSN) consists of tiny sensor nodes with little memory and power. These nodes are deployed to aggregate data from different environments that have different conditions such as pressure, noise, temperature, vibrations, populates ...etc. In every network, there is at least one sink (base station), and sensor nodes transmit their sensed data to this base station. This base station acts as a connector between users and networks [1].

Many protocols were presented by researchers to limit the energy consumed by sensor nodes during the network's lifetime. Every node in the wireless sensor network is outfitted with one or more sensors, a small microcontroller, a radio receiver, and an energy source. In WSN, energy has an important role because the battery is the source of energy in most wireless sensor network applications, and when a wireless sensor network routing protocol is created, conserving the consumed energy by every sensor node should be important [2].

LEACH is a common protocol in wireless sensor networks. LEACH considers that the network is made up of clusters of sensor nodes. In every cluster, there is a cluster head and some normal sensor nodes. These sensor nodes collect data by sensing the environmental conditions around them and then transmit them to the sink. LEACH considers the base station to be both remote and static from the sensor nodes. LEACH sensor nodes can be conserved with one another and with the sink [3].

The algorithm of LEACH includes multiple phases (rounds), each with two parts:

(A) Setup phase. (B) Steady-state phase.

In every cluster, the cluster head will be chosen during the setup process. The steady-state phase is slightly longer than the setup phase and is primarily concerned with data aggregation at cluster heads and sending the collected data to the base station. The setup phase has three fundamental steps which are: cluster head advertisement, cluster setup, and creation of transmission schedule.

In the first step, each cluster will have a cluster head by giving every node a random number between 0 and 1, then the threshold T (n) will be calculated using equation.1. If the given number for any node is less than T (n), this node will be assigned as a cluster head. Each cluster head will announce that it became a CH by sending an advertisement packet to the other nodes. The regular nodes will then receive this advertisement and issue a join request to the nearest cluster head, informing them that they are now members of this cluster under that cluster head. Finally, each CH generates a transmission schedule for each of its member nodes. That enables every node to transmit its data in its allocated time.

$$T(n) = \begin{cases} \dfrac{P}{1 - P[r * \bmod(1/P)]} & if \ n \in G \\ 0 & otherwise, \end{cases} \quad (1)$$

Where P stands for the required proportion of CHs, n represents the given node, G represents the set of nodes that were not CH in the previous 1/p rounds, and r represents the current round.

The acquired data will be transferred from the normal nodes to the cluster heads during the steady phase. Each cluster's normal nodes only connect with the cluster head via a single hope broadcast. The cluster head then sends all aggregated data to the sink, either directly or via another cluster head. Then, the network returns to the setup phase after the predefined time [4].

There are several reasons why LEACH is used in WSNs such as:

- **Energy Efficiency:** LEACH aims to minimize the energy consumption of sensor nodes by employing a hierarchical clustering structure. By rotating the role of CH among nodes using probabilistic methods, LEACH balances the energy load across the network, reducing the energy drain on individual nodes.
- **Self-organization:** LEACH allows sensor nodes to self-organize into clusters without relying on centralized control or global knowledge. This self-organizing capability simplifies network deployment and management, making LEACH suitable for dynamic and resource-constrained environments.
- **Data Aggregation:** LEACH facilitates data aggregation within clusters, where the CH collects and processes data from member nodes before transmitting it to the base station. This aggregation reduces redundant transmissions and conserves energy by minimizing the amount of data sent over long distances.

As the LEACH protocol has its advantages it also has some limitations which highlight the challenges in energy consumption, network stability, scalability, and data aggregation that the LEACH protocol faces such as:

- **Uneven Energy Consumption:** The LEACH protocol leads to uneven energy consumption among sensor nodes, causing network imbalance and reduced network lifetime.
- **Early Exhaustion of Cluster Heads:** Cluster heads in LEACH experience increased energy consumption, leading to frequent cluster reorganization and network instability.
- **Limited Scalability:** LEACH's clustering approach becomes less efficient as the network size increases, resulting in significant overhead and reduced scalability.
- **Lack of Adaptive Cluster Head Selection:** LEACH's static cluster head selection approach does not consider dynamic changes in network conditions and node energy levels, leading to suboptimal cluster head selections.
- **Inefficient Data Aggregation:** LEACH's single-hop communication for data transmission from cluster heads to the base station results in increased energy consumption, especially in large-scale networks.

Addressing these limitations is crucial for improving the performance and efficiency of wireless sensor networks. There are a lot of approaches that have addressed LEACH's limitations and we will mention some of them in the related work section. The concept of the Internet of Things (IoT) revolves around the ability to connect and monitor various objects from anywhere through the Internet. Wireless technology plays a crucial role in achieving this connectivity. Wireless Sensor Networks (WSNs) act as a virtual layer, bridging the gap between the physical and virtual worlds by transmitting data from the real world to the Internet. WSNs serve as the eyes and ears of the IoT [5].

In the future, IoT systems are expected to facilitate communication between numerous devices in various settings, such as homes, offices, agriculture, industries, transportation, and even battlefields. This will lead to a significant increase in the demand for infrastructure. WSNs, consisting of wireless sensing nodes, play a vital role in IoT systems. These nodes sense different physical characteristics and transmit the collected data to a central base station for processing, analysis, and sharing over the Internet. As the IoT expands, the number of sensing nodes will exponentially grow, posing challenges such as the need for more communication spectrum, enhanced data security, and higher energy requirements. Energy is a fundamental requirement for sensing nodes, but recharging or replacing batteries is not feasible in remote or hazardous environments. Therefore, energy conservation becomes crucial [6].

Routing protocols significantly impact energy usage, especially when energy efficiency is a primary consideration. Cluster-based routing protocols are known for their energy-saving capabilities and are commonly used in sensor networks to extend their lifespan. Clusters consist of sensor nodes, with one node acting as the cluster head (CH) responsible for data collection and transmission to the base station. Cluster-based approaches improve scalability and reduce radio transmissions, ensuring reliable sensor operation. Selecting the appropriate CH is vital for system performance, and criteria such as energy level and position are often used [7].

Researchers focus on improving WSN protocols to extend network lifespan and reduce energy consumption. In this paper, we propose a new method that utilizes neural networks and the multi-hop mechanism to enhance cluster head selection and conserve energy. Machine learning refers to algorithms and tools used to create prediction models. It allows computers to learn from data and make predictions for new situations. Supervised, unsupervised, and reinforcement learning are the three main categories of machine learning algorithms. Supervised learning involves using predefined data inputs and known outputs to build a model that represents the relationship between inputs, outputs, and system parameters. Our proposed algorithm incorporates neural networks (NNs) to enhance the ILEACH protocol. NNs are supervised learning algorithms that mimic a simplified model of the brain, consisting of interconnected decision units known as neurons. These neurons are linked through weighted connections called neural connections, connecting the input layer to the output layer [8, 9].

In the recent decade, machine learning processes have been widely employed in domains such as bioinformatics, spam detection, speech recognition, fraud detection, computer vision, and advertising networks for tasks such as regression, classification, and density estimation. Algorithms and approaches are drawn from a variety of fields, including mathematics, statistics, computer science, and neuroscience. There are three kinds of machine learning based on their model structure. They are classified as either supervised, unsupervised, or reinforcement learning. Predefined inputs and known outputs characterize supervised learning. They are extensively utilized in WSN competitions. K-nearest neighbor (K-NN), support vector machines (SVMs), decision trees (DT), and neural networks (NNs) are examples of supervised learning methods [10].

Neural networks can be defined as networks of neurons that are interconnected by weighted associations known as neural connections. These neurons are based on a greatly simplified model of the brain [8]. The rest of this document will look like this: section 2 will talk about wireless sensor networks, Multi-hop LEACH, and neural networks, section 3 will talk about the related work, and section 4 will talk about the proposed scheme and the experimental results.

2. Background:

2.1. Wireless sensor networks (WSNs)

Computer networks are data transmission networks that enable computers to exchange information. Data links transport data from one computer to another. Wired or wireless media create these connections between nodes and these nodes can be hosts like PCs, servers, phones, or networking hardware. The wireless sensor network (WSN) is a collection of dispersed nodes (sensors) that are able to track environmental or physical factors such as sound, temperature, and pressure. The data gathered would then be sent to a central location.

The wireless sensor network is built of a set of sensor nodes and each sensor node consists of some components like a microcontroller, radio transceiver with a built-in or external antenna, a source of power which usually be a battery, and an electronic circuit to interface the nodes with the source of energy [11].

The WSN can consist of several sensor nodes which may reach thousands of nodes, these sensor nodes have limited power, computational capabilities, and memory. Many different areas have wireless sensor network applications such as forest detection, military battlefields, as well as other severe environments. In these conditions, it is so hard to change the nodes that are dead as a result of drained energy and put new nodes with limited energy to keep exchanging data through the system. To prolong the network's lifespan, we have the challenge of making the sensor nodes work as long as possible [12]. In WSN, the sensor nodes gather and send their perceived data to the base station which acts as an interface between the network and the users. We can get the required information by injecting queries then the results will be gathered from the base station.

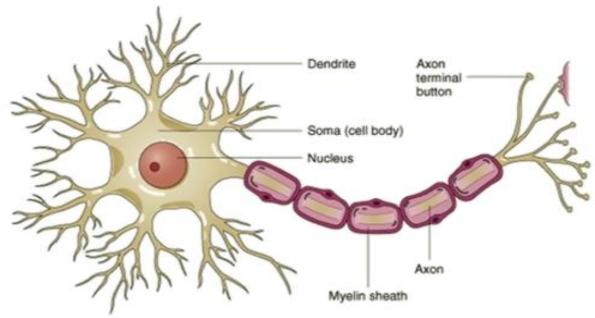

Figure 1: Biological neurons [13].

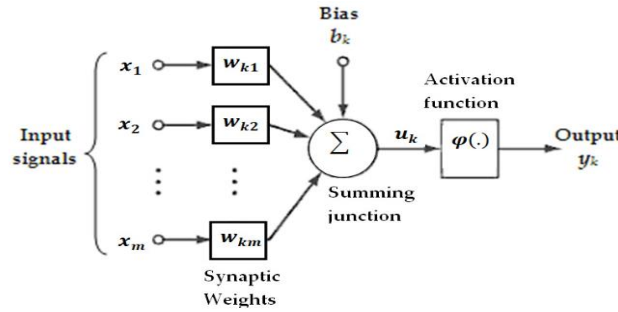

Figure 2: Artificial Neuron [14].

The lifespan of the wireless sensor network depends on the rate of power consumption by the tiny nodes that build the network [15]. We can split routing in wireless sensor networks into three forms according to the network structure: data-centric routing (flat-based routing), hierarchical-based routing, and location-based routing. In hierarchical-based routing, nodes in the network play diverse roles. The basic purpose of hierarchical routing is to preserve sensor node energy usage as efficiently as possible by integrating them in multi-hop communication within a single cluster. To limit the number of messages sent to the sink, data aggregation and fusion are conducted here. During the cluster time, any node can become the cluster head. For wireless sensor networks, LEACH (Low Energy Adaptive Clustering Hierarchy) is a common dynamic clustering hierarchical routing technique [16].

The LEACH protocol divides the sensor nodes into groups called clusters, and each group has a sensor node chosen as the cluster head (CH). CH receives sensed data from neighboring sensor nodes and transfers it to the sink. Typically, the first nomination of the CH is random, and every node can be a CH at least one time during its lifetime [17].

2.2. Multi-hop LEACH

WSNs use two types of interaction patterns of behavior: single-hop and multi-hop communication. In the case of single-hop communication, it was discovered that the farthest nodes or cluster heads would be expected to consume their energy faster than the other nodes in the network. In other words, because of the long-distance connection, the most distant nodes have a greater energy burden in single-hop. As a result, in the single-hop case, where data packets are delivered directly to the cluster head or base station without a relay, the nodes may perish first. To address this issue, we can employ multi-hop communication [18].

Multi-hop LEACH employs two forms of communication: intra-cluster communication and inter-cluster communication. In the first mode, nodes send collected data to the associated cluster head, which then forwards it to the base station via a chain of cluster heads. The second option happens when the detached node requests that the connected node serves as the cluster's temporary head. Because of this technique, multi-hope LEACH is more energy efficient than LEACH. However, due to the random selection of the cluster heads, the problem of unbalanced cluster size persists [11].

2.3. Artificial neural networks

Artificial intelligence (AI) is the science of simulating human intelligence by programming machines to perform tasks normally performed by humans and to mimic human actions. There are numerous major subfields of AI, including machine learning (ML), expert systems, natural language processing (NLP), and so on.

Machine learning (ML) is a branch of artificial intelligence (AI). It investigates how computers can learn from themselves by following these steps:

- It pays attention to the examples.
- It then comprehends the relationship between input and output values.
- Then, for new examples, it makes better decisions.

The majority of machine learning algorithms fall into one of three categories: supervised learning, unsupervised learning, or reinforcement learning. Supervised learning builds a system model by combining predefined inputs and known outputs. This model depicts the connection between input, output, and system parameters.

There is no output vector in unsupervised learning. Its goal is to produce a classification for a sample set into different groups by examining their similarity. Reinforcement learning makes use of a sensor node (agent) to interact with and learn from its surroundings. Using its experience, this sensor node will learn how to take the best actions to maximize its rewards over time.

Neural networks (NNS): A neural network (NN) is a human brain model that can inspire and be used to get a solution for many complex apps like pattern recognition, computer vision, video games ... etc. The human brain is a sophisticated neural system. 1011 neurons are wholly linked. The cell body (Soma) is in charge of sending a pulse or signal. The axon transmits the outcome rather than the inputs. Dendrites transport signals, while synapses serve as points of contact.

The artificial neural networks consist of some neurons with weighted connections to connect between them and allow the input layer to be connected with the output layer by a function that is a transfer function of the sum of the products of the inputs and their weights. Neural networks don't need data storage because they stores information. The model of artificial neural networks was made up of four elements.

The training process is classified as supervised learning because it learns from labeled examples. Classification and prediction are accomplished using neural networks [9, 10].

Fig.1 shows the biological neurons, and Fig.2 shows the artificial neurons.

3. Related work

Many researchers work in the wireless sensor networks field and they do their best to make enhancements to it by developing protocols such as the LEACH protocol, to prolong the network lifetime and decrease the consumed energy by the sensor nodes over the network.

D.Singh and S. Kumar [19] produced a reactive protocol called EMODLEACH (Enhanced Modified LEACH), which was implemented in a homogeneous network model. They applied the ECHR (Efficient Cluster Head Replacement scheme) concept and the DTP (Dual transmitting power level) of MODLEACH with the (Efficient Intra Cluster transmission scheme of TEEN) concept.

EMODLEACH relies on the probabilistic selection of cluster heads, which can lead to uneven energy consumption and reduced network lifetime. Its use of fixed transmission power levels may not be optimal for varying distances between nodes. In our paper, we addressed the problem of the random selection of the cluster heads by using neural networks This allows for more accurate and efficient cluster head selection compared to traditional approaches that rely on simplistic criteria. Also, we used the multi-hop mechanism to improve the overall energy efficiency of the network by reducing the energy consumption required for long-range transmissions.

B.A.Sabarish and R. Lavanya [20] proposed a modified version of the LEACH protocol in which cluster formation and data routing are entirely based on energy. As a result, the proposed system first identified the cluster heads and then formed the clusters based on the distance measure. Data is also transmitted via the most energy-efficient path. They simulated the LEACH protocol over the existing system and showed the performance improvement attained through the proposed LEACH protocol. This protocol proposes a distance-based clustering approach with energy-aware routing to improve network longevity. While this approach shares some similarities with our work on neural network-based cluster head selection and multi-hop routing, it relies on static cluster heads and fixed transmission power levels, which can lead to limitations in energy efficiency and scalability. This paper proposes a novel approach using neural networks for dynamic cluster head selection and multi-hop routing, aiming to overcome these limitations and achieve improved network performance compared to existing clustering protocols.

I.Daanoune et al [21] proposed an improved leach to reduce energy consumption and increase network lifetime by selecting the cluster head method based on remaining power, balancing the number of the sensor nodes in the clusters, they determined abandoned nodes to transmit their data to the sink, and then the CHs should select the best path for the sink. While it is comparable to our work on neural network-based cluster head selection and multi-hop routing, its use of static methods and probabilistic selection may not result in optimal energy allocation. This research provides a novel technique for dynamic cluster head selection utilizing neural networks, to overcome these restrictions and improve network performance as compared to existing clustering protocols.

S.Anada et al [22] introduced a method called MaximuM-LEACH that gives a solution by even load balancing the number of nodes by fixing the average value N, thereby increasing the network's lifetime.MM-LEACH presents a centralized approach where the base station calculates the average energy of nodes and selects cluster heads based on a predefined threshold. While MM-LEACH effectively balances cluster sizes, its static threshold and reliance on average energy limit its adaptability to dynamic network conditions. Additionally, the centralized selection process incurs communication overhead.

Our proposed protocol, in contrast, utilizes a distributed, neural network-based approach for cluster head selection. This allows us to consider factors beyond average energy, such as remaining energy leading to more adaptive cluster head choices. Furthermore, our protocol leverages multi-hop communication for data transmission, potentially reducing energy consumption compared to single-hop approaches.

One significant effort is the LEACH technique presented by Heinzelman et al. [23]. LEACH selects cluster heads randomly in each round; however, it does not take into account cluster heads' energy levels. This random selection might cause energy imbalances within clusters and the potential energy depletion of cluster heads, resulting in a loss of connectivity to the base station. In contrast, our suggested technique, NN_MHLEACH, uses neural networks to improve cluster head selection. By training the neural network with previous data, we hope to make more educated decisions about energy levels, enhance the selection process, and minimize energy imbalances.

Another interesting effort is the ILEACH methodology proposed by Youssef et al. [24]. ILEACH includes an energy threshold (Eth) to help reduce the selection of low-energy cluster heads. However, it still uses random selection, which may not result in ideal cluster head choices. In our suggested system, we extend the notions of LEACH and ILEACH by introducing a novel approach that uses neural networks to choose cluster heads. This methodology assures that the most acceptable cluster heads are chosen, addressing the constraints of random selection methods.

According to the previous literature we need to explain that: Firstly, our proposed scheme leverages neural networks, specifically supervised learning algorithms, to improve the cluster head selection process. By training the neural network with predefined data inputs and known outputs, we can model the relationship between various parameters such as energy level, position, and other relevant factors in the selection of optimal cluster heads. This allows for more accurate and efficient cluster head selection compared to traditional approaches that rely on simplistic criteria.

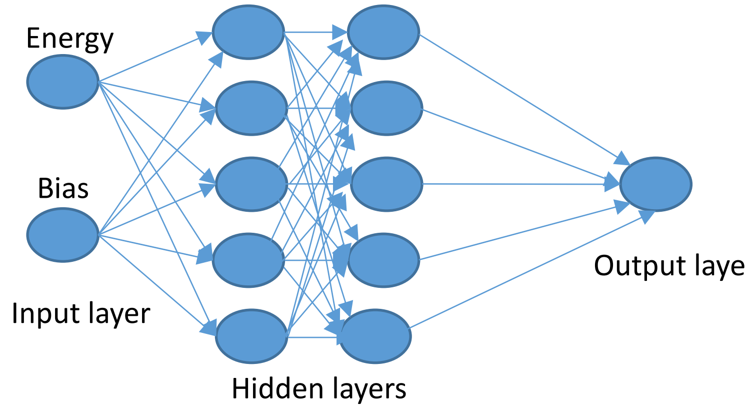

Figure 3: Structure of proposed NNS.

Secondly, we introduce the multi-hop mechanism, which enables sensor nodes to communicate with the cluster head through intermediate relay nodes. This multi-hop communication extends the network coverage, improves energy efficiency, and enhances load balancing. Unlike previous approaches that primarily focused on single-hop communication, our scheme takes advantage of the relay nodes to enable longer communication ranges and more flexible routing paths.

By combining neural networks and the multi-hop mechanism, our proposed scheme offers several distinct advantages. It improves the overall energy efficiency of the network by reducing the energy consumption required for long-range transmissions. It also enhances the network's coverage area, particularly in large-scale deployments or areas with sparse node distribution. Additionally, the multi-hop mechanism provides fault tolerance and load balancing, ensuring reliable data transmission and avoiding congestion at the cluster head.

In summary, our proposed scheme differentiates itself from previous literature by integrating neural networks and the multi-hop mechanism into the cluster head selection process. These novel elements address the limitations of existing approaches and offer improved energy efficiency, extended coverage, and enhanced network performance.

4. Proposed scheme:

In Leach, the process of selecting a cluster head is random based on the random number that is given to every node, then Eq. 1 should be calculated, and the clusters are formed according to the advertisement message sent by the CH. Random selection may not always lead to the optimal clustering solution. It is also inefficient for large datasets. In this paper, we used Neural networks to get an optimum selection for the cluster heads.

Firstly, we generate our data set to use in our model training process using LEACH and by recording the energy as an input for our model and the type of the node will be recorded as the label (0 if the node is normal and 1 if it is a cluster head). Random samples of the used dataset are recorded in Table 1. Then, we trained our model using the generated data set:

Table 1: A random sample of our generated data set.

Energy	Type
5.000000e-01	0
4.903436e-01	1
4.911188e-01	1
4.679864e-01	0
4.666652e-01	0
3.851017e-01	0
3.598775e-01	1
3.680846e-01	1
3.454089e-01	1
3.208926e-01	0
2.641142e-01	0
2.182186e-01	1
1.922036e-01	0
2.020595e-01	1
1.819310e-01	0

Table 2: Simulation parameters.

Symbol	Description	Value
X_m	Distance at X-axis	200
Y_m	Distance at Y-axis	200
N	Number of nodes	500
E_{TX}	Transmitter energy	50*0.000000001
E_{RX}	Receiver energy	50*0.000000001
E_{fs}	Energy dissipation: free-space model	10*0.000000000001
E_{mp}	Energy dissipation: Receiving	0.0013*0.000000000001
E_{DA}	Energy dissipation: aggregation	5*0.000000001
Rmax	Number of rounds	2500
L	Packet size	4000
E_o	Initial energy	0.5j/node

As shown in Fig. 3, the neural network architecture and training parameters. The neural network has two hidden layers with five neurons in each one. The training data is divided into 85% training data and 15% validation data.

$$\tanh(x) = (\exp(2x) - 1) / (\exp(2x) + 1) \qquad \textbf{(2)}$$

Where (x) is the input value

We also used the tansig (hyperbolic tangent) activation function which is defined as: The tanh activation function is a versatile and powerful tool for introducing non-linearity into neural networks. It is a popular choice for a variety of tasks, including classification, regression, and sequence processing.

We faced a challenge in using neural networks in this case for the classification process because the data set that we generated by the LEACH protocol has a class imbalance. After all, the number of normal nodes is greater than the number of cluster heads. This imbalance can lead to biased predictions from the neural network, as it may overfit the more prevalent class (non-leaders) and perform poorly on the minority class (leaders). Therefore, we assigned weights to the leader and non-leader samples for two primary purposes:

1. Addressing Class Imbalance.
2. Balancing Misclassification Costs:

The weights assigned to the leader and non-leader samples reflect the relative costs of misclassifying each type of sample. Misclassifying a non-leader as a leader is likely less costly than misclassifying a leader as a non-leader. By assigning a higher weight to leader samples, the training algorithm is incentivized to minimize the error rate for this more important class. In essence, weighting the samples helps to address the class imbalance and ensure that the neural network pays more attention to the minority class (leaders); thereby improving the overall classification accuracy.

This technique is commonly used in machine learning when dealing with imbalanced datasets. We also strengthen our proposed protocol by using the multi-hop mechanism which is a routing technique used in wireless sensor networks (WSNs) to transmit data from sensor nodes to the base station (BS) when direct communication is not possible due to the limited transmission range of individual nodes. In a multi-hop network, sensor nodes relay data packets from other nodes closer to the BS, forming a chain of hops. This allows data to be transmitted over longer distances by utilizing the collective range of multiple nodes.

We implemented a pathfinding algorithm to find the shortest path from each node in a network to a base station. then, we utilized a loop to iterate through each node and calculated the shortest path to the base station using a combination of distance checks and hop count limitations.

The distance between the current node i and each of the other nodes is calculated using the Euclidean distance formula:

Len = sqrt ((S(i).xd-(S(j).xd))^2 + (S(i).yd-(S(j).yd))^2)

If the calculated distance len is less than the hop distance limit (do), where do=sqrt(Efs/Emp), Efs is the amplification coefficient of free-space signal, Emp is the multi-path fading signal amplification coefficient, and the current node j is not the same as the source node i, the following actions are performed:

1. If the current node j is the base station (j==(n+1)), the variable l is updated to the base station's index, effectively terminating the pathfinding process.
2. If the distance to the current node j is less than the minimum hop distance encountered so far, the variables (min_hd: This variable stores the minimum hop distance encountered so far.) and (l: This variable stores the index of the next node in the shortest path) are updated accordingly.
3. After the distance checks, the hop count f is incremented, and the index of the current node i is added to the (short path (i,f): This array element stores the index of the current node in the shortest path at the current hop count.) array at the current hop count, indicating the next node in the shortest path.
4. Finally, the temporary source node i is updated to the next node in the path.

The multi-hop mechanism is used in the LEACH protocol to extend the network's coverage area and improve energy efficiency. In wireless sensor networks, sensor nodes typically have limited transmission ranges due to power constraints. By leveraging intermediate nodes as relays, the multi-hop mechanism enables data to be transmitted over longer distances by hopping through multiple nodes. This helps to mitigate the effects of signal attenuation and reduces the energy consumption required for long-distance communication. Additionally, the multi-hop mechanism can enhance the network's fault tolerance and enable more flexible network topologies.

4.1. Proposed algorithm:

1. Start.
2. Deploy sensor nodes into the WSN randomly with an initial energy of 0.5j/node.
3. Loop to count the alive and dead nodes:
   If s(i).E=<0 ➔dead=dead+1, alive=alive-dead.
4. Cluster head selection using neural networks. This step involves a lot of steps as follows:
   1. Generating the data set that we will use to train our neural network model by recording the energy level as an input and the type of the node if it is a normal node (0) or a cluster head (1) as a label after running the LEACH.
   2. Data preprocessing by loading the document that we used to record the generated data set. then, separate the input features and labels from the loaded document. After that, we identified the indices of the leader nodes (where the target label is 1) and assigned them an energy value of 2 in the Ew array. Similarly, assign an energy value of 1 to the non-leader nodes.
   3. Network architecture consists of 4 layers, the input layer, the 2 hidden layers which include 5 neurons in each one, and the output layer.
   4. Data set division, we divided the data set into training and validation sets.
   5. Finally, the training process.
5. Calculation of energy dissipated in all nodes involved in multi-hop transmission.
6. Counting the number of cluster heads.
7. Association of normal nodes with cluster heads (formation of cluster).
8. Counting for packets that are sent to BS and CH.
9. If the lifetime ended stop. Else go to 3.

According to the mechanism of LEACH, if the node's place is far from the sink, that means more energy consumption by the cluster head for the transmissions. In this paper, we used the multi-hop mechanism to save the consumed transmission energy. The multi-hop protocol allows using an optimal path between the cluster head and the sink. According to the distance from the BS point, the MH-LEACH determines an upper and lower CH. The data is transmitted from the lower CH to the upper CH, and from the uppermost CH to the BS. To set up wide-area networks, MH-LEACH must allow data transmission between CHs.

In wireless sensor networks (WSNs), the multi-hop mechanism is employed to enable energy-efficient data transmission over long distances by utilizing intermediate nodes as relays. Instead of directly transmitting data from a source node to a destination (e.g., base station), the data is relayed through a series of intermediate nodes, forming a multi-hop path. This approach helps to conserve energy by reducing the transmission power required for long-distance communication and mitigating the negative effects of signal attenuation. The multi-hop mechanism typically involves the following components and steps:

- **Cluster Formation:** WSNs often employ clustering algorithms to organize sensor nodes into groups or clusters. In these clusters, one or more nodes are selected as cluster heads responsible for managing and coordinating the activities of the cluster members. Cluster formation helps to improve network scalability, reduce energy consumption, and enable efficient data aggregation.

- **Data Aggregation:** Within each cluster, nodes collect data from their sensing environment. Instead of transmitting raw data individually, nodes can perform local data aggregation by combining and summarizing the collected information. Data aggregation reduces the amount of data to be transmitted, further conserving energy.

- **Routing:** Once data is aggregated within each cluster, the multi-hop mechanism comes into play. Each cluster head acts as a relay node, receiving data from its member nodes and forwarding it toward the base station or another designated destination. This forwarding process occurs in a hop-by-hop manner, where data is relayed from one node to the next until it reaches the destination. Intermediate nodes along the path store and forward the data packets, ensuring reliable and efficient transmission.

- **Path Selection:** The choice of the optimal path for data transmission is crucial in multi-hop communication. Various routing algorithms and protocols are employed to determine the best path based on factors such as energy levels, link quality, distance, or network traffic. The goal is to find paths that minimize energy consumption, avoid congested or faulty nodes, and maintain a reliable connection between the source and destination.

- **Data Delivery:** The data is transmitted hop-by-hop along the selected path until it reaches the destination, typically the base station or a sink node. At each hop, the receiving node checks the integrity of the received data and retransmits if necessary. This process continues until the data successfully reaches its final destination.

By leveraging the multi-hop mechanism, WSNs can achieve longer communication ranges, improve network coverage, and conserve energy compared to direct single-hop communication. The use of intermediate relay nodes reduces the transmission power required for long-distance communication, enabling efficient and reliable data delivery in resource-constrained sensor networks. Fig.4 and Fig.5 show the difference between LEACH and MH-LEACH (Multi-hop LEACH) mechanisms [25].

5. Simulation results and discussion:

In the simulation, we used a 200*200 network that has 500 nodes distributed through it randomly with limited initial energy. This simulation was made using the MATLAB environment and the parameters that are shown in Table 2.

We made a comparison between NN_MH LEACH and LEACH. This comparison showed the progress made by our proposed protocol (NN_MH LEACH) over its counterpart. We conducted simulations to evaluate the performance of the proposed NN_MH LEACH protocol in comparison to the traditional LEACH protocol. The simulations were performed using a wireless sensor network (WSN) environment.

5.1. Simulation Setup

- **Sensor node deployment:** Sensor nodes were randomly deployed in the WSN with an initial energy level of 0.5j/node.
- **Network architecture:** The WSN consisted of a base station (BS) or sink node and multiple sensor nodes.
- **Data collection:** We collected data on energy levels and node types (normal node or cluster head) by running the LEACH protocol to generate a dataset for training the neural network model.

5.2. Performance Metrics

We evaluated the performance of the protocols based on the following metrics:

1. **Network Lifetime:** The duration until the first node depletes its energy and becomes inactive.
2. **Energy Consumption:** The total energy consumed by the network during the simulation.
3. **Packet Delivery Ratio:** The ratio of successfully delivered packets to the total number of packets generated.

5.3. Results

Figs. [6-13] Compare the performance of LEACH and NN_MH-LEACH mechanisms in terms of network lifetime, energy consumption, and packet delivery ratio. The results demonstrate the superiority of the proposed NN_MH LEACH protocol over the traditional LEACH protocol.

- **Network Lifetime:** The NN_MH LEACH protocol significantly prolongs the network lifetime compared to LEACH. This improvement is attributed to the effective selection of cluster heads using the neural network approach, which optimizes energy utilization and extends the lifespan of the network.
- **Energy Consumption:** The proposed protocol exhibits lower energy consumption compared to LEACH. By leveraging the multi-hop mechanism, the NN_MH LEACH protocol reduces the energy consumed for long-distance transmissions, leading to overall energy savings in the network.
- **Packet Delivery Ratio:** The packet delivery ratio of the NN_MH LEACH protocol outperforms that of LEACH. The multi-hop approach improves data transmission reliability by utilizing intermediate nodes as relays, mitigating the negative effects of signal attenuation and enhancing the successful delivery of packets to the base station.

5.4. Limitations and Challenges

During the simulations, we encountered a few limitations and challenges that should be acknowledged. such as the performance of the proposed NN_MH LEACH protocol, which heavily relies on the accuracy of the neural network model for cluster head selection. The training of the neural network requires a representative dataset, and the performance may vary based on the dataset's quality and diversity.

As we mentioned before the class imbalance may be considered one of these challenges that we addressed in the paper. The simulation results validate the effectiveness of the proposed NN_MH LEACH protocol in improving the network performance metrics. The protocol demonstrates a prolonged network lifetime, reduced energy consumption, and improved packet delivery ratio compared to the traditional LEACH protocol.

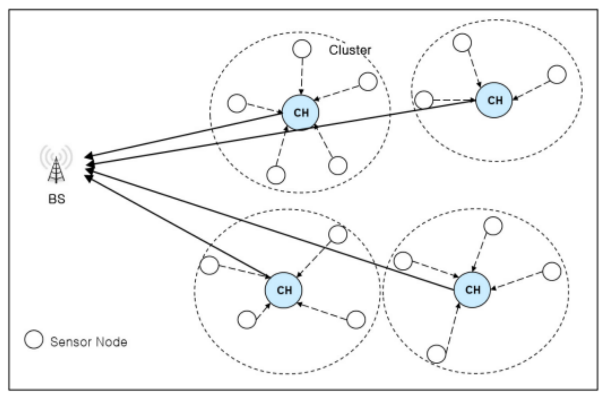

Figure 4: Steady-state phase of LEACH [5].

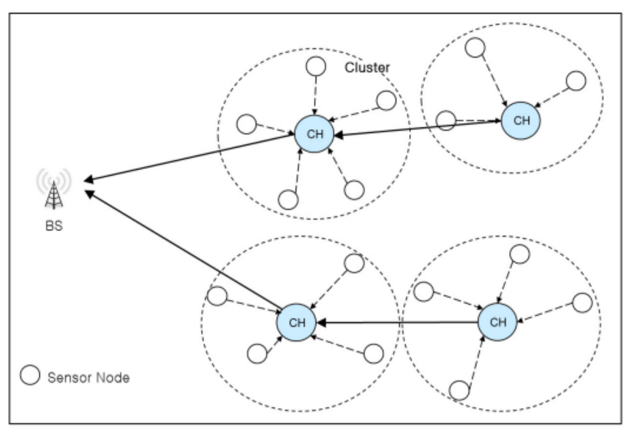

Figure 5: Steady-State phase of a multi-hop LEACH [5].

Table 3: Energy Statistics for LEACH and NN_MH LEACH

	No of rounds	Mean	Std. Deviation	Std. Error Mean
LEACH	436	94.3317	75.08867	3.5961
NN_MH LEACH	1454	37.0428	60.67093	1.5911

Table 4: Packet delivery ratio Statistics for LEACH and NN_MH LEACH

	No of rounds	Mean	Std. Deviation	Std. Error Mean
LEACH	2501	0.7001	0.00508	0.0001
NN_MH LEACH	2501	0.7	0.0036	0.00007

Table 5: Throughput Statistics for LEACH and NN_MH LEACH

	No of rounds	Mean	Std. Deviation	Std. Error Mean
LEACH	437	299.643	71.95864	3.44225
NN_MH LEACH	1455	133.6426	120.70349	3.16438

Table 6: T-Test for Energy in LEACH and NN_MH LEACH

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
LEACH	26.232	435	0	94.33171	87.2638	101.3996
NN_MH LEACH	23.281	1453	0	37.04277	33.9217	40.1639

Table 7: T-Test for Packet delivery ratio in LEACH and NN_MH LEACH

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
LEACH	6894.53	2500	0	0.70015	0.6999	0.7003
NN_MH LEACH	9733.51	2500	0	0.69997	0.6998	0.7001

Table 8: T-Test for Throughput in LEACH and NN_MH LEACH

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
LEACH	87.049	436	0	299.64302	292.8776	306.4085
NN_MH LEACH	42.233	1454	0	133.64261	127.4354	139.8498

These findings highlight the benefits of incorporating the multi-hop mechanism and neural network-based cluster head selection in WSNs. The NN_MH LEACH protocol presents a promising solution for achieving energy-efficient and reliable data transmission in wireless sensor networks.

In Tables [3-5], the statistical results comparing the LEACH and NN_MH LEACH protocols demonstrate the superior performance of the NN_MH LEACH protocol across all parameters.

Regarding energy consumption, the NN_MH LEACH protocol exhibits a significantly lower energy Std. Error Mean of 1.59110 compared to LEACH's value of 3.59610. This indicates that the enhanced protocol achieves better energy efficiency, as it consumes less energy on average per node.

Furthermore, in terms of packet delivery ratio, the NN_MH LEACH protocol outperforms LEACH with a lower packet delivery ratio Std. Error Mean of 0.00007 compared to LEACH's value of 0.00010. This implies that the enhanced protocol achieves a higher rate of successful packet delivery, ensuring more reliable data transmission in the network.

Additionally, the throughput results also favor the NN_MH LEACH protocol. It exhibits a throughput Std. Error Mean of 3.16438, whereas LEACH has a higher value of 3.44225. A lower value in this case indicates that the NN_MH LEACH protocol achieves higher data transfer rates, resulting in improved network performance.

These statistical results provide strong evidence supporting the superiority of the NN_MH LEACH protocol over LEACH in terms of energy consumption, packet delivery ratio, and throughput. The reduced energy consumption and improved packet delivery and throughput metrics highlight the effectiveness of the enhanced protocol in optimizing cluster head selection and enhancing overall network performance.

To assess the statistical significance of the observed differences between LEACH and the NN_MH LEACH protocol, appropriate statistical tests were conducted. We utilized a T-test to determine the significance levels, considering a confidence interval of 95%. The results in tables [6-8] revealed that the performance improvements achieved by the NN_MH LEACH protocol were statistically significant, reinforcing the validity and reliability of the findings

6. Conclusion

Due to its ability to regulate and collect data from many locations with various conditions, wireless sensor networks (WSNs) have difficulty of preserving the sensor node's energy for as long as possible, making it difficult to replace the sensor nodes. Therefore, it is crucial to increase the network longevity. Using multi-hop-LEACH and neural networks, we present a modified LEACH (Low Energy Adaptive Clustering Hierarchy) algorithm in this research (NNs).In this paper, we proposed the NN_MH LEACH protocol, which integrates the multi-hop mechanism and neural network-based cluster head selection to enhance energy efficiency and prolong the network lifetime in wireless sensor networks (WSNs).

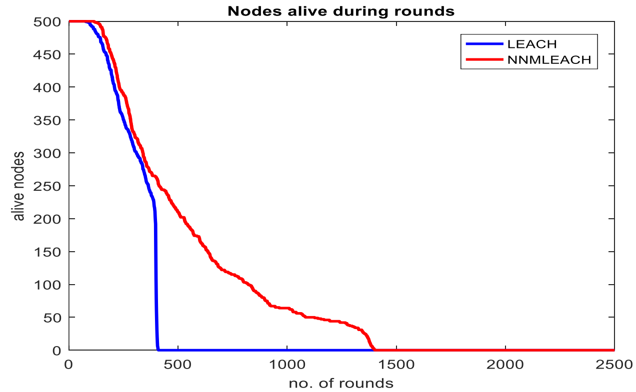

Figure 6: Alive nodes over the rounds.

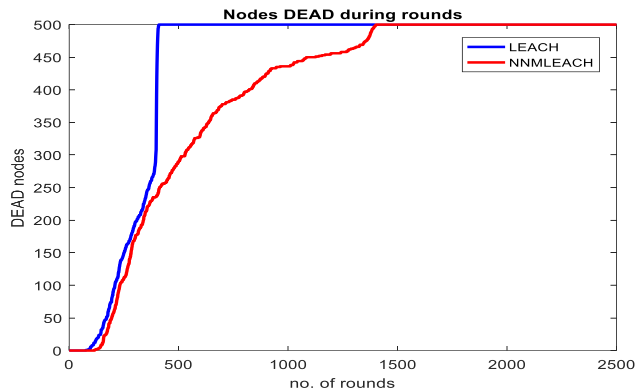

Figure 7: Dead nodes over the rounds.

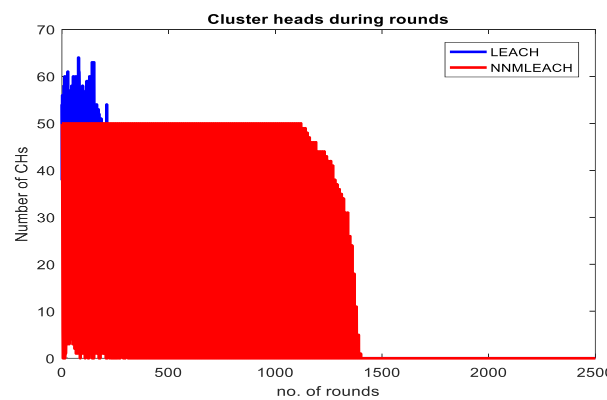

Figure 8: Number of Cluster heads.

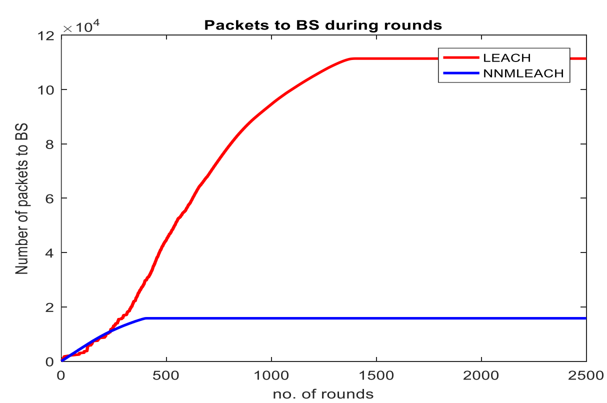

Figure 9: Number of packets sent to BS.

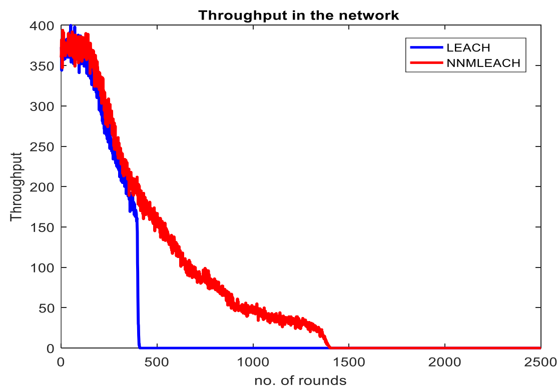

Figure 10: Throughput.

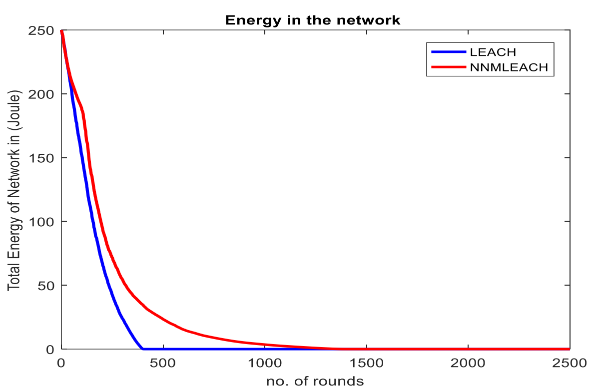

Figure 11: Energy in the network.

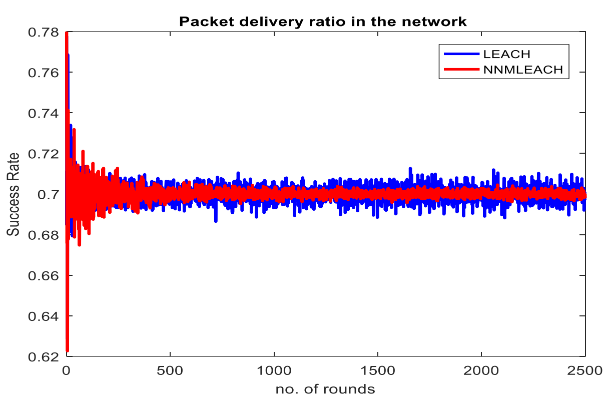

Figure 12: Packet delivery ratio.

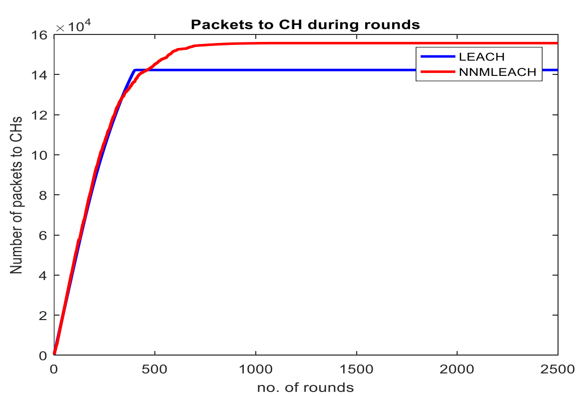

Figure 13: Number of packets sent to CHs.

Through extensive simulations and performance evaluations, we have demonstrated the superiority of the proposed protocol over the traditional LEACH protocol in terms of network lifetime, energy consumption, and packet delivery ratio.

The findings of this study have significant implications for the design and optimization of WSNs. By leveraging the multi-hop mechanism, the NN_MH LEACH protocol reduces energy consumption by utilizing intermediate nodes as relays for long-distance data transmission. This energy-efficient approach extends the overall network lifetime, making it particularly suitable for large-scale WSN deployments where energy resources are limited. The neural network-based cluster head selection in the proposed protocol optimizes the energy utilization within the network.

By considering factors such as energy levels and node types, the neural network model achieves a balanced distribution of energy consumption, mitigating the risk of premature energy depletion in individual nodes. This contributes to a prolonged network lifetime and improved data transmission reliability.

However, it is important to acknowledge the limitations of the proposed NN_MH LEACH protocol and identify areas for future research. Firstly, the effectiveness of the protocol heavily relies on the accuracy and generalizability of the neural network model for cluster head selection. Further research should focus on enhancing the training process and investigating advanced neural network architectures to improve the model's performance and adaptability to varying network conditions.

Additionally, the performance of the multi-hop mechanism can be influenced by factors such as network topology, node density, and communication range. Future studies should explore the impact of these factors on the protocol's performance and develop adaptive mechanisms to optimize the multi-hop routing for different network configurations.

Furthermore, the proposed protocol should be evaluated in real-world WSN deployments to validate its performance under practical conditions. Field experiments can provide valuable insights into the protocol's scalability, robustness, and energy efficiency in diverse environmental settings.

Lastly, the proposed protocol focuses primarily on energy efficiency and network lifetime. Future research should consider other performance metrics, such as network latency, fault tolerance, and security, to develop a more comprehensive and holistic approach to WSN design and optimization.

CRediT authorship contribution statement:

Methodology, Elham M. Abd-Elgaber.; Data curation, Elham M. Abd-Elgaber, and Hamdy H. Elsayed.; Writing—review and editing, Elham M. Abd-Elgaber, Hamdy H. Elsayed, E.A. Zanaty, and Samy S.Bakheet. supervision, Hamdy H. Elsayed.; All authors have read and agreed to the published version of the manuscript.

Data availability statement

The data used to support the findings of this study are available from the corresponding author upon request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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