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Artificial neural networks-based improved Levenberg–Marquardt neural network for energy efficiency and anomaly detection in WSN

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Abstract
One of the key goals in the design of the networks is to increase the lifespan of wireless sensor networks (WSNs). Using different models of intelligent energy management could help designers achiseve this objective. By reducing the number of sensors required to collect data on the environment, these models can achieve higher levels of energy efficiency without sacrificing the quality of the readings. When battery power is an issue, wireless sensor networks (WSNs) are often employed for applications such as monitoring or tracking. Several routing protocols have been developed in the last several years as possible answers to this problem. Despite this, the issue of extending the lifetime of the network while considering the capacities of the sensors remain open. As a result of applying neural networks, Low-Energy Adaptive Clustering Hierarchy (LEACH) and Energy-Efficient Sensor Routing (EESR) can be improved in terms of their overall efficiency as well as their level of dependability, as is shown in this research EESR. Energy-Efficient Sensor Routing (ESR) and Low-Energy Adaptive Clustering Hierarchy (LEACH) are the names of the two protocols that are being utilized here EESR. The system incorporates a refined version of the Levenberg–Marquardt Neural Network (LMNN), which serves to enhance the efficiency with which it uses energy. The ability of an Intrusion Detection Systems (IDS) based on an artificial neural system to detect anomalies has also been proven. Anomalies can be identified using this system's optimum feature selection. Simulations showed that the proposed ANN-ILMNN model worked better, as shown by these results.

Keywords ILMNN · EESR · Network lifetime · Low-energy adaptive clustering hierarchy (LEACH) · ANN

1 Introduction

Wireless sensor networks (WSNs) are a kind of wireless communication network in which device bulges serve as the core backbone. When it comes to the configuration of their sensors, WSNs can have either homogeneous or heterogeneous sensors, and the number of such sensors can range anywhere from hundreds to thousands. The vast majority of wireless sensor networks are designed to fulfil the requirements of a particular application, and the sensor nodes that make up these networks often provide core capabilities such as sensing, processing, computation, and communication. The majority of message between neighboring nodes is carried out through the use of electromagnetic signals that are broadcast on radio frequency.

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Aside from that, a wireless sensor network (WSN) will typically have a base station (BS) installed at a particular location so that it may serve as a centralized node through which the sensor nodes can broadcast the data that they are monitoring. WSNs are application-based message systems, which implies that sensors are placed in the intensive care ground and a message system is formed based on the application. This type of network is known as a wireless sensor network. WSNs are often installed in open places so they can watch and track the surrounding environment [1]. A few examples of monitoring applications are the intensive care of patients' health, the monitoring of hazardous gases in the chemical sector, and the intensive care of rubber manufacture. WSN technology may also be put to use for tracking applications such as the monitoring of domesticated animals, wild animals, and even individuals. Micro-electromechanical systems (MEMS) are a relatively new kind of hardware that has recently been available [2, 3]. WNS knowledge has seen significant development over the past few years, which has resulted in the creation of more cutting-edge communication network platforms that are both economical and efficient.

The monitoring field is equipped with sensors, and a communication network is established. Wide-area sensor networks (WSNs) are typically placed in open areas for the purposes of both monitoring and tracking. Patient monitoring, harmful gas monitoring in the chemical industry, and rubber monitoring are all examples of monitoring applications. WSN technology can also be used for tracking purposes, such as tracking pets, tracking wildlife, and tracking people. Recently released hardware includes micro-electromechanical systems (MEMS). As WNS technology has evolved in recent years, more cost-effective and efficient communication networks have become possible. It is possible for sensor nodes (SNs) to pick up, decode, and transmit radio frequency data. Base station (BS) nodes are scarce in WSNs. Among its many applications are climate nursing, front-line tracking, material identification for multiple fume examinations, and clinic intensive care (for patients who are in danger). Additionally, WSNs can be beneficial in places where human intervention is either impossible or impossible, such as in hostile or inaccessible environments, for monitoring and tracking purposes. Tracking animals and people is used to check and track them, as are observations of gaseous tension and mixture vapour.

The overall design of the WSNs used in our research is depicted in Fig. 1. This illustration shows the architecture for protocols that are based on hierarchical clustering. Device bulges in the free colour scheme serve as cluster heads (CHs), whereas sensor nodes in the yellow colour scheme serve as basic data collectors. Non-cluster head bulges are also recognized as elementary nodes (N–CH). The BS and cluster head nodes are connected through blue dotted lines.

The BS is the central node from which all sensor data is pooled. In general, the CH and N–CH node configurations produce a additional effectual system with a longer lifespan than competing architectures [4]. Typically, radio waves are used to communicate, ensuring that all nodes are accessible. All nearby nodes listen to the signals that are sent, but devices solitary reply if the message contains the bulge ID; otherwise, the message is ignored. Coordinating protocols can be considered the core of all functions, such as detection information, combining information, regulatory expenses, controller and administration of mails, and query creation.

- Proposed ground techniques include artificial neural networks (ANN). The LEACH and EESR procedures were embedded with an Improved-Levenberg–Marquardt neural network (ILMNN), i.e., ANN-ILMNN, in order to improve their energy efficiency.
- A sub-cluster LEACH procedure is suggested and incorporated with an Improved-Levenberg–Marquardt neural network to further increase the LEACH protocol's performance (ILMNN).

2 Literature survey

Khan et al. [5] proposed a distance-aware PR-LEACH routing schemes can be used to optimise energy consumption in an IoT network. By applying routing protocols, this study aims to reduce energy use. In comparison to the original, the proposed technique performs significantly

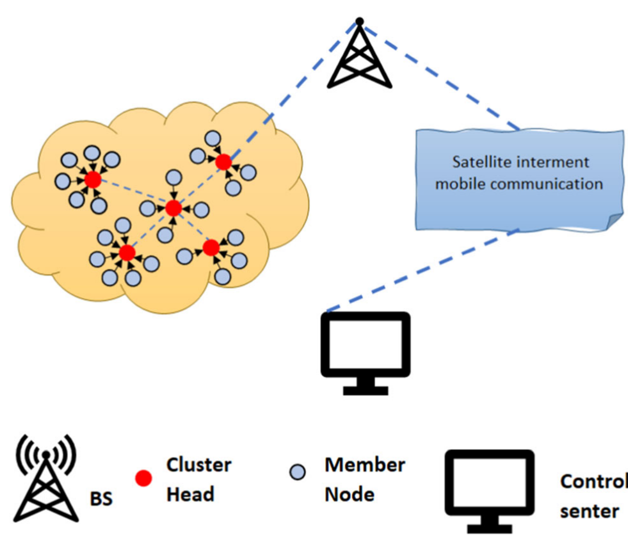

Fig. 1 For clustering-based protocols, the basic architecture of wireless sensor networks

better. Because it differs from its predecessor in terms of the threshold calculation mechanism, the suggested protocol will be implemented locally instead of globally. This add-on is used in order to make the chosen protocol more dynamic and effective [6, 7]. The quantity of vigor required to connect among device bulges and the cloud has been reduced because of improvements in IoT network protocols.

El-Sayed et al. [8] devised a new CH selection method for wireless device systems. According to the information provided in this page, it is the first hierarchical energy adaptive protocol, also known as LEACH. In wireless sensor networks, LEACH is a hierarchical routing technique that increases the network lifetime. A single node among these nodes serves as the cluster head in the LEACH protocol, which groups sensors into clusters. This protocol extends the network's lifespan. Hierarchical routing protocols based on clustering algorithms are also discussed in this article. An unexpected outage can be avoided using LEACH's cluster head rotation approach. Rajakumar et al. [9] used the grey wolf optimization to create energy-efficient clusters in a radiocommunication device network. This study used the Grey-Wolf Optimization (GWO) algorithm to find the best possible cluster heads in terms of efficiency. The 'is algorithm has high leadership capabilities and hunting techniques, but it is lacking in exploration and exploitation, which leads to poor clustering in WSN when it is used. This is the case despite the fact that it has great hunting methods. The suggested method incorporates a tuning option in order to address the issue with WSNs. Results from the experiments show that the proposed strategy outperforms the current one

Liu et al. [1] Clustering protocols for wireless sensor networks based on genetic algorithms There were certain modifications made to this protocol in an attempt to get a improved reply and to increase the system life span. It is possible to use artificial intelligence to enhance the LEACH protocol's performance. The LEACH process can be made more energy efficient by including a genetic algorithm (LEACH-GA) into it. It is possible to implement a preparatory phase for this protocol during the first round of competition. Selecting the CH nodes with the best probabilities helps in this phase. All three steps are completed in every round. To aid in the assortment of the CH bulge for the following rounded, an end optimum value is computed after each iteration of the algorithm. This is how LEACH-GA reduces vigor ingesting by selecting the CH bulge from all N–CH bulges respectively rounded.

Xu et al. [2] proposed LEACH protocols for WSN. As far as network longevity and reliability are concerned, it's an excellent choice. It uses minimum variance in energy betweenness calculation to increase the clustering performance of LEACH-EB. Individually device bulge in the system consumes the same amount of power when using this technique. Because of this, each cluster has a consistent N–CH count because of which the CH selection process is done in a more distributed manner. This makes it possible for the CH node to experience a consistent rate of energy loss; alternatively, certain CH nodes lose their energy more rapidly as a result of more thoughtful N–CH nodes, and the total energy levels of the N–CH nodes are balanced. When compared to the LEACH approach, this procedure has a much higher energy efficiency.

Salim, A. et al. [3]: The LEACH-E protocol uses a technique called a minimum spanning tree to increase the total lifespan of the network. In terms of performance, the LEACH-E protocol is superior to the LEACH protocol. Within LEACH-E, one of the most essential criteria for selection is the CH's residual energy. Another method that is easy to use and is good for the environment is called IBLEACH [10].

Feng et al. [11] It works well to increase the longevity and dependability of networks. For better clustering performance, LEACH-EB calculates energy betweenness with a low variance. This aids in balancing the network's sensor nodes' individual energy consumption. As a consequence, this produces a type of CH selection that is more distributive, in which each cluster comprises a predetermined number of N–CH nodes. In contrast, the total amount of available energy in the CH and N–CH nodes is maintained in a state of equilibrium despite the fact that certain CH nodes lose their stored energy relatively rapidly due to the presence of more easily accessible NCH nodes. This helps the CH node deplete its energy at a more consistent rate after each round it has completed. When compared to the LEACH method, the energy efficiency has seen a rather significant improvement. Additionally, the LEACH-E protocol employs the least-spanning tree technique to extend the total network lifetime.

Anand et al. [12] The LEACH procedure is outperformed by LEACH-E. The CH's residual energy is a crucial selection factor in LEACH-E. Additionally, IBLEACH is presented as an additional energy-efficient approach. The pre-stage phase, which is an additional phase, is inserted between two other phases. Between the collection arrangement stage and the stable stage, it is inserted. This stage aims to significantly lower vigor use. LEACH-EX is a modified version of LEACH-E [13].

Ravishankar et al. [1] improve response and further extend network period, the inventors of this procedure attempted to change the threshold function. The LEACH procedure can be applied with artificial intelligence methods for improved performance [14]. To create a more energy-efficient approach, LEACH-GA incorporates a genetic algorithm. In this protocol, the execution of the first round includes an additional step known as the preparation phase. This stage aids in the choice of CH nodes by providing the best values for each CH probability. All three phases are carried out during each round. The end ideal value is determined after each round, which aids in choosing the CH node for the following one. To reduce energy consumption, LEACH-GA optimizes the choice of the CH bulge from among all N–CH nodes in respectively circular.

3 Proposed system

There is a new neural network model for the selection of CHs, as well as a clustering method that utilizes this model, in this section. WSN's CH elections are influenced by a variety of factors. The CH has more responsibilities in a WSN with a hierarchical structure. It maintains the sensors in its cluster and communicates with other CHs in addition to the BS. As a result, selecting CHs is an important step in network configuration. A CH might be the access point for an infiltration and a power outage that causes the network to vanish. The majority of CH election methods concentrate on energy, yet network security is one of the most frequent causes of failure, leaving the network open to exploitation of computing power and data modification by intruders. As a result, the optimal selection requires the appropriate combination of these factors. Intrusion detection systems (IDS) are a kind of anomaly detection system (IDS). It enables the combination of all input characteristics in a way that indicates the effectiveness of each in the selection of CH. There are many elements that can influence the outcome of an organization's board of directors (Board of Directors) election, so it is imperative that a successful ANN model be built with the right combination of rules and the right design for each ANN set [15].

3.1 Artificial neural network

One of the most frequent EAs is one that generates an Artificial Neural Network (ANN). The concepts of ANNs are based on biological neural networks, or brains, in the sense that ANNs are formed of interconnected nodes (neurons) that create outputs based on the weighted connections between them. Multilayer perception is the most well-known form of artificial neural networks (ANNs) and is comprised of one input and output layers as well as one or more hidden layers. Nodes known as "input" are used to feed information into a neural network's output. Game AI input nodes collect data directly from the game world in the form of numerical data, like the distance to a wall, the distance to an adversary, or the current health of a character. Deterministic and nondeterministic behavior are the two main categories of game AI approaches. Deterministic performance or behavior is predetermined and predictable and have no uncertainty. A basic chasing algorithm is an example of deterministic behavior. Deterministic behavior is the inverse of nondeterministic behavior. A certain measure of uncertainty and unpredictability appears in nondeterministic behavior. An ANN's output is generated by one or more output nodes, which are used to identify the best course of action. In Fig. 1, the input nodes are on the left, and the output nodes are on the right; this is an example of a network diagram.

Each node performs some operation on the values it receives from one or more inputs before sending the result to the node's output. A node's output can be used by any number of nodes as an input. A value is propagated through the network until it reaches the output nodes in this manner. Dynamic system models can be built using artificial neural networks. Various modelling tools and models are incorporated into this system. Using dynamic systems modeling (DSM), it is possible to define and predict how different parts of a phenomenon will interact over time. It focuses on the mechanisms through which the system's elements and components change over time. DSM enables researchers to investigate communication phenomena at a range of sizes that might not be well represented in survey research or that are difficult to monitor in experiments [16]. There are many advantages to using this method instead of other modelling techniques. When sparse training data is needed and the network must generalize well, ANNs are an ideal choice because they can operate with nonlinearly separable data without a hitch in applications like machine condition monitoring. Figure 2 for instance, neural networks have been used to identify and classify problems in a variety of condition monitoring applications. Applications for artificial neural networks include speech recognition, machine translation, image identification, and medical diagnosis [17]. An important benefit of ANN is that it learns from sample data sets. Random function approximation is the most frequent use of ANN [18]. Haykin [19] and Rojas provide an excellent introduction to neural networks.

Classifying data was done using ANNs based on the multilayer perceptron (MLP) architecture. Equation 1 shows that a logistic beginning purpose activates the hidden layer while a lined beginning purpose activates the output layer.

$$\varphi(w) = \frac{1}{1 + \exp(-w)} \tag{1}$$

$$\varphi(w) = w \tag{2}$$

The sum of the weighted outputs is V. We experimented with various hidden layer sizes. The output layer was set to have a size of dual neurons for this specific use. The ANN

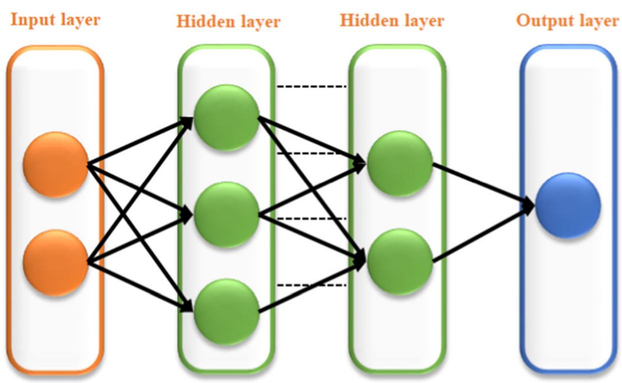

Fig. 2 Architecture of an Artificial Neural Network

systems are trained using the Levenberg–Marquardt procedure (explained in Sect. 3.2). The training and validation sets are used to build the network, and a different set of test features are used to test it.

Its performance is measured by how well it is able to classify unknown information in the examination set. Gradually reducing training time occurs as the organization accuracy of authentication data begins to deviate from that of the exercise data (a condition known as "overtraining"). The fully connected feed forward network with 100 hidden layers is the architecture of the neural network. Figure 3

After processing, WSN sensor node data is transmitted to the LEACH protocol module. LEACH has the capacity for self-organization, adaptation, and clustering [20]. According on the characteristics of the sensors and base station, LEACH has a hypothesis. LEACH is established over the round concept, and each round contains two stages: a setup stage and a steady-state stage. As a result, a cluster head in the LEACH protocol is not stable. The setup stage is divided into the cluster setup and the advertisement setup, and the stable stage involves the construction of a schedule and data transfer. Wireless sensor networks (WSNs) are networks that screen physical or ecological characteristics but do not require an underlying infrastructure to function. LEACH is a hierarchical procedure in which the vast majority of nodes connect with cluster leaders, who then aggregate the data and compress it before transmission it to the base station (sink). Following that, the information is sent to the ANN architecture module so that it can be optimized. When designing an artificial neural network, it is helpful to take into account both the construction and the purpose of a organic neural network. Similar to the neurons found in the brain, ANN is composed of neurons grouped in numerous layers [21, 22].

The data is further improved using the ILMNN (Improved Levenberg–Marquardt neural network) method, and its superior performance over current approaches with multiple performance metrics is proven. The Levenberg–Marquardt algorithm (LMA) is a well-known trust region algorithm that determines the minimum of a function, whether it is linear or nonlinear, across a set of parameters. Essentially, a trustworthy part of the objective function is internally represented with some function, such as a quadratic [23].

3.2 Improved Levenberg–Marquardt neural network fundamentals

Its update rule, which is resulting from the sharpest ancestry technique and the Newton procedure, is

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \tag{3}$$

w stands for mass vector, I for identity matrix, and = combination coefficient. These are the definitions of the Jacobian matrix and mistake vector, correspondingly,

$$J = \begin{bmatrix} \frac{\partial e_{11}}{\partial w_1} & \frac{\partial e_{11}}{\partial w_2} & \cdots & \frac{\partial e_{11}}{\partial w_N} \\ \frac{\partial e_{12}}{\partial w_1} & \frac{\partial e_{12}}{\partial w_2} & \cdots & \frac{\partial e_{12}}{\partial w_N} \\ \cdots & & \cdots & \\ \frac{\partial e_{1M}}{\partial w_1} & \frac{\partial e_{1M}}{\partial w_1} & \cdots & \frac{\partial e_{1M}}{\partial w_1} \\ \frac{\partial e_{P1}}{\partial w_1} & \frac{\partial e_{P1}}{\partial w_1} & \cdots & \frac{\partial e_{P1}}{\partial w_1} \\ \frac{\partial e_{P2}}{\partial w_1} & \frac{\partial e_{P2}}{\partial w_1} & \cdots & \frac{\partial e_{P2}}{\partial w_1} \\ \cdots & & \cdots & \\ \frac{\partial e_{PM}}{\partial w_1} & \frac{\partial e_{PM}}{\partial w_1} & & \frac{\partial e_{PM}}{\partial w_1} \end{bmatrix} \tag{4}$$

where P stands for the total amount of exercise patterns, M for the number of productions, and N for the number of masses in their entirety. s is used to calculate individual components of the mistake vector.

$$s_{PM} = a_{PM} - n_{PM} \tag{5}$$

where a_PM and n_PM are the chosen and real productions at network production m for training design p, correspondingly.

As is common, before multiplying the Jacobian matrix to update the weight, as is common, it is first constructed and stored in (3). Small or medium-sized training patterns may benefit from this method. The Jacobian technique, also known as the Jacobi method, is one of the iterative approaches of estimating the solution to a system of n linear equations in n variables. The Jacobi iterative technique is an iterative procedure used in numerical linear algebra to determine the solutions to a system of linear equations that is diagonally dominant. Jacobian matrix J storage is limited for large-scale designs, though.

There are 60,000 training patterns in the MNIST handwritten digit database: 784 inputs and 10 outputs for the

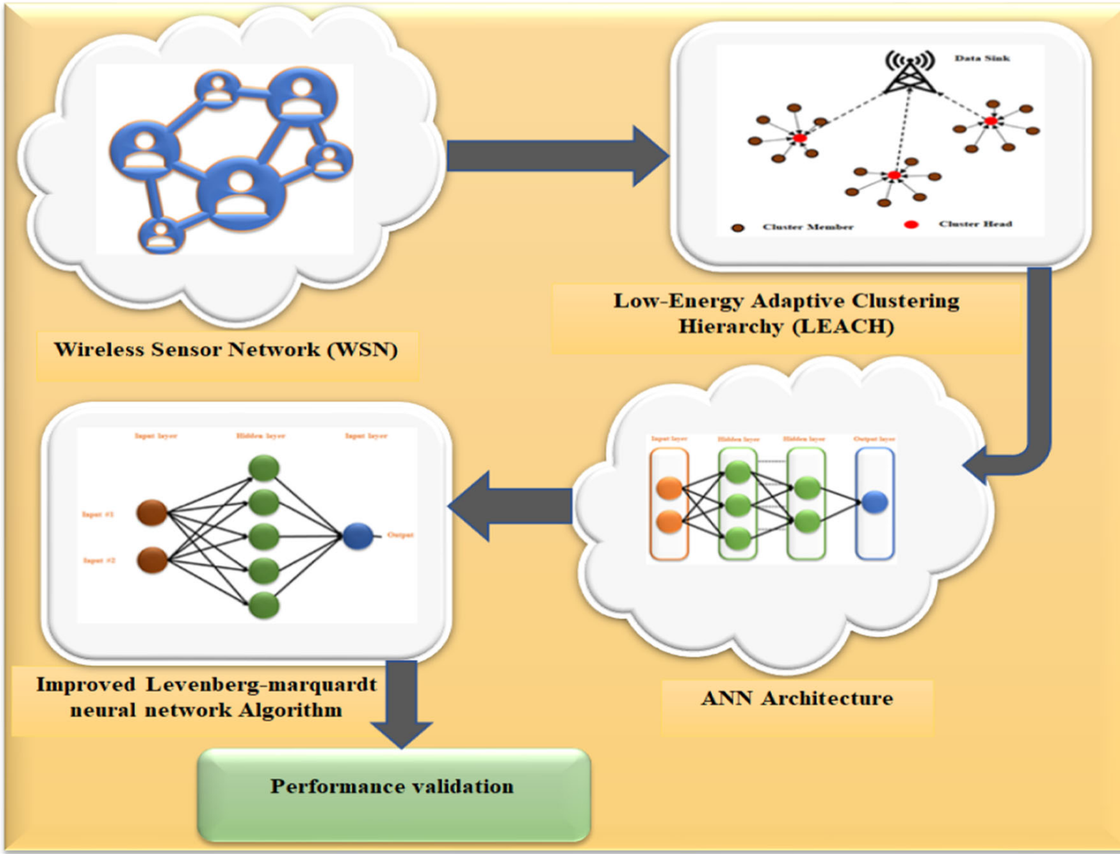

Fig. 3 Architecture of ANN-ILMNN method

pattern recognition issue. The remembrance rate of the entire Jacobian matrix storage is approximately 35 gigabytes, even when using the simplest and most likely neural system, which consists of ten neurons (one neuron for each output). This substantial quantity of memory cannot be accessed because 32-bit Windows compilers can only hold 3 GB of information in a single array at a time. The LM approach is clearly ineffective in cases where there are a lot of patterns to deal with. The Levenberg–Marquardt (LM) is a hybrid method that corresponds to the optimal method using both the Gauss–Newton and steepest descent techniques. It has been utilized for parameter extraction of semiconductor devices. The Levenberg–Marquardt method's core principle is that it performs a hybrid training process: in the neighborhood of complex curvature, it shifts to the steepest descent approach until the local curvature is suitable for a quadratic approximation; at that point, it roughly transforms into the Gauss–Newton technique, which can substantially speed up the convergence.

3.3 Flow work of proposed system

Explanation in detail of the Artificial Neural Network (ANN) that makes use of the LMNN technique that was suggested. The recommended flowchart for the technique can be found in Fig. 4. It is proposed in this document that ANN-LMNN be modified in order to reduce the network's overall energy consumption and the latency from beginning to end. Energy efficiency is the most important requirement for developing routing protocols for wireless sensor networks, as the system's lifetime is dependent on the lifetime of each sensor node. Another possibility for a routing protocol is data centricity. As seen in Fig. 4, the first few phases are quite similar to those in the ANN-LMNN approach that was used before. The most important improvement that this method has made is the incorporation of CH selection into sub-clusters. Following the selection of CH nodes by the Levenberg–Marquardt neural network, the main concept is to make the assumption that all CH nodes may select one or two more nodes in their neighborhood. Clustering is an effective technique for increasing network energy efficiency. Every single cluster has a Cluster Head, which is one of the sensor nodes (CH). The CH node prepares a registration request message that contains both its ID and the ID of the gateway (GW) node, together with a secret key. This is done with the expectation that this will occur. Subcluster CH nodes are the ones that provide assistance for the major CH node. To ensure

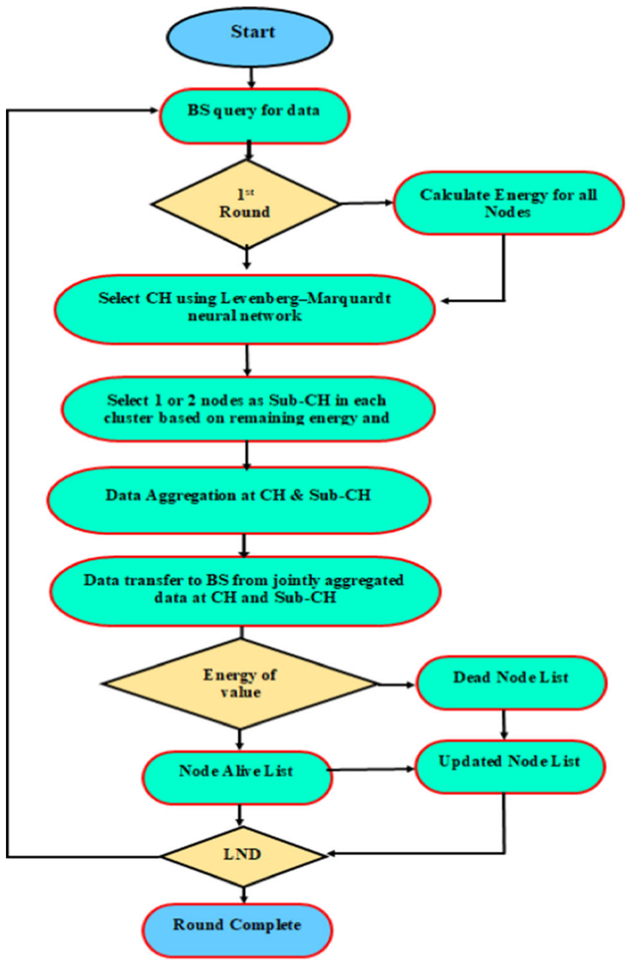

Fig. 4 A flowchart that illustrates the protocol for the sub-cluster LMNN being carried out in consecutive order

the cluster's dependability and efficiency, at least three nodes are required. Every cluster consists of a master node, which serves as the cluster's main endpoint, and a minimum of two worker nodes. To perform operations, all of these nodes interact with one another across a common network. These nodes have such role. For example, if a cluster contains 10 nodes, only one of those nodes will function as a CH node, while the other nine may perform the duties of N–CH nodes. These nine N–CH nodes will communicate their control messages, data, and other relevant information to a single CH node in the very first stage of the proposed method. In the Levenberg–Marquardt neural network, one or two additional nodes are chosen to serve as sub-cluster CH or Sub-CH nodes in order to lessen the weight of this responsibility. N–CH nodes are categorized as either CH or N–CH according to their distance from the CH root node. A link quality parameter is utilized in the calculation of the distance. As a result, data will be transferred from some nodes to the CH node in their cluster by others, while some nodes will transmit data to the sub-CH nodes. Following the completion of the data aggregation process, the sub-CHs will send their data to the CH node, which will subsequently send it to the BS in combination with the CH node.

3.4 Improved Levenberg–Marquardt neural network computation

The sum squared error (SSE) is utilised to assess exercise in the following derivation

$$E(v) = \frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{pm}^{2} \tag{6}$$

Training pattern p, specified by e_{pm}, produces an error at output m, which is defined as (5).

[H] is the hessian matrix OF N * N

$$H = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\ \frac{\partial^2 E}{\partial w_2 \partial w_1} & \frac{\partial^2 E}{\partial w_2^2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_N} \\ \frac{\partial^2 E}{\partial w_N \partial w_1} & \frac{\partial^2 E}{\partial w_N \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_2^2} \end{bmatrix} \tag{7}$$

The number of weights is N. It is possible to derive elements of the Hessian H matrix as follows by combining steps 6 and 7

$$\frac{\partial^2 E}{\partial w_i \partial w_j} = \sum_{p=1}^{P}\sum_{m=1}^{M}\left(\frac{\partial s_{PM}}{\partial w_i}\frac{\partial s_{PM}}{\partial w_j} + \frac{\partial s_{PM}}{\partial w_i \partial w_j} s_{PM}\right) \tag{8}$$

where the weight indices are I and j. (8) can be estimated using the LM technique as [10, 11].

$$\frac{\partial^2 E}{\partial w_i \partial w_j} \approx \sum_{p=1}^{P}\sum_{m=1}^{M}\left(\frac{\partial s_{PM}}{\partial w_i}\frac{\partial s_{PM}}{\partial w_j}\right) = q_{ij} \tag{9}$$

where q_{ij} is the row i and column j quasi-Hessian matrix element.where Q is the row I and column j quasi-Hessian matrix element.

$$H \approx Q = J^T J \tag{10}$$

$N \times 1$ gradient vector d is

$$d = \left[\frac{\partial E}{\partial w_1}\frac{\partial E}{\partial w_2}\cdots\frac{\partial E}{\partial w_N}\right]^T \tag{11}$$

Inserting (6) into (10), Gradients can be calculated as a series of numbers.

$$d_i = \frac{\partial E}{\partial w_i} = \sum_{p=1}^{P}\sum_{m=1}^{M}\left(\frac{\partial s_{PM}}{\partial w_i}\partial s_{PM}\right) \tag{12}$$

The link between the gradient vector d and the Jacobian matrix J can be deduced from (4) and (11).

$$d = J^F e \tag{13}$$

The LM algorithm's update rule can be expressed as (10), (13), and 3 when they are all put together.

$$\Delta w = (X + \mu I)^{-1} d \tag{14}$$

People often think that the amount of exercise designs and outputs is directly related to the number of weights in a network and the gradient vector d.

There are no differences in weight updates when using Eqs. (3, 13), and (14). In (13), quasi-Hessian matrices and slope matrices are calculated directly instead of a Jacobian matrix being calculated and stored.

Table 1 Initial parameters for the network

S. no.	Parameters	value
1	Field Dimensions	100 m × 100 m/ 200 m × 200 m
2	Count of nodes	**100**
3	Base Station	50 m × 50 m/100 m × 100 m
4	Battery energy	0.5 Joules
5	Energy model parameter	1 × 10 −11
6	Energy model parameter	1.3 × 10 − 15
7	Electronics Energy	50 nJ/bit
8	Data packet length	**4000 bits**
9	Control packet length	**200 bits**

4 Result and discussion

4.1 Experimental results

The results for the LEACH, LEACH-LMNN, EESR-LMNN, and LEACH-ILMNN sub-clusters In this section, we will discuss one of the concepts that was investigated in this study, as well as the simulation setup and the results obtained from it. MATALB (2009b) was utilized during the construction of the network, and Table 1 contains information regarding the network's startup parameters. The necessary energy model is shown in Fig. 5, which contains the energy computations. This image illustrates the energy that is lost by both the transmitter and the receiver during the transmission process. The reduction in power level, such as the optical, electrical, or acoustic power level, that takes place (a) within a component, (b) from the output of one component to the input of another component, or (c) from one point to another in a propagation medium, during the transmission of a signal from one location to another is called transmission loss. Equations (15) and (16) show how much energy is used to send a packet of K bits over a detachment of d.

$$TX = \begin{Bmatrix} K * E_{elec} + K * E_{gh} * f^2 : f \leq f_0 \\ K * E_{elec} + K * E_{oe} * f^4 : f > f_0 \end{Bmatrix} \tag{15}$$

where f_0 is evaluated as $f_0 = \sqrt{E_{gh}/E_{oe}}$

$$E_{RX} = K * E_{elec} \tag{16}$$

Existing clustering and routing protocols like LEACH, EESR, LEACH-LMNN, and EESP-LMNN are compared to the suggested method. There are 120 nodes employed in contrast to other ways in order to calculate system vigor ingesting, throughput, End-to-End-delay, accuracy, packet delivery ratio (PDR), and packet loss ratio (PLR)… In these simulations, there are 100 sensor nodes and nine cluster head nodes in a 1000 × 1000 m^2 area. PDR, throughput, packet loss ratio (PLR), total energy, and accuracy were all simulated using the proposed data gathering scheme to evaluate network performance[24].

4.2 End-to-end delay

The endwise interruption is the total amount of time that the system has taken to complete a deal. Figure 6 and Table 2 represent a judgement of the endwise suspension of different methods like LEACH, EESR, LEACH-LMNN, and EESP-LMNN. The ANN-ILMNN procedure has a delay of only 95.23 ms from end to end. In contrast, the previous procedures, such as LEACH, EESR, LEACH-LMNN, and EESP-LMNN, take 143.28 ms, 132.34 ms, 125.32 ms, and 99.23 ms, respectively, as time delay. Similarly, for 600 data points from a dataset, the delay of the ANN-ILMNN method is only 97.56 ms while it is 148.66 ms, 136.89 ms, 128.95 ms, and 121.78 ms for LEACH, EESR, LEACH-LMNN, and EESP-LMNN, respectively. Analyses have shown that the ANN-ILMNN procedure only delays decisions by a small amount compared to the other procedures.

4.3 Accuracy

Table 3 and Fig. 7 illustrate a comparative accurateness examination of the ANN-ILMNN approach with additional approaches. The picture reported that the machine learning approach has resulted in higher performance with more accuracy. For example, with 100 data points, the ANN-ILMNN method has an accuracy of 95.21% while the existing methods like LEACH, EESR, LEACH-LMNN, and EESP-LMNN techniques have obtained an accuracy of 82.33%, 85.39%, 88.24%, and 91.19%, respectively. However, the ANN-ILMNN model has shown maximum performance with the highest accuracy of 97.85% for 600 data points, whereas the LEACH,

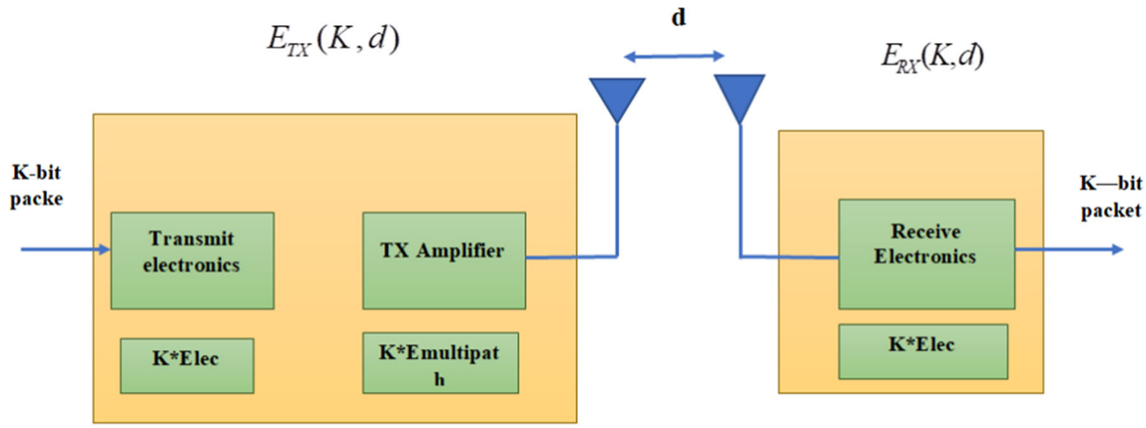

Fig. 5 Energy dissipation at transmission and receiver

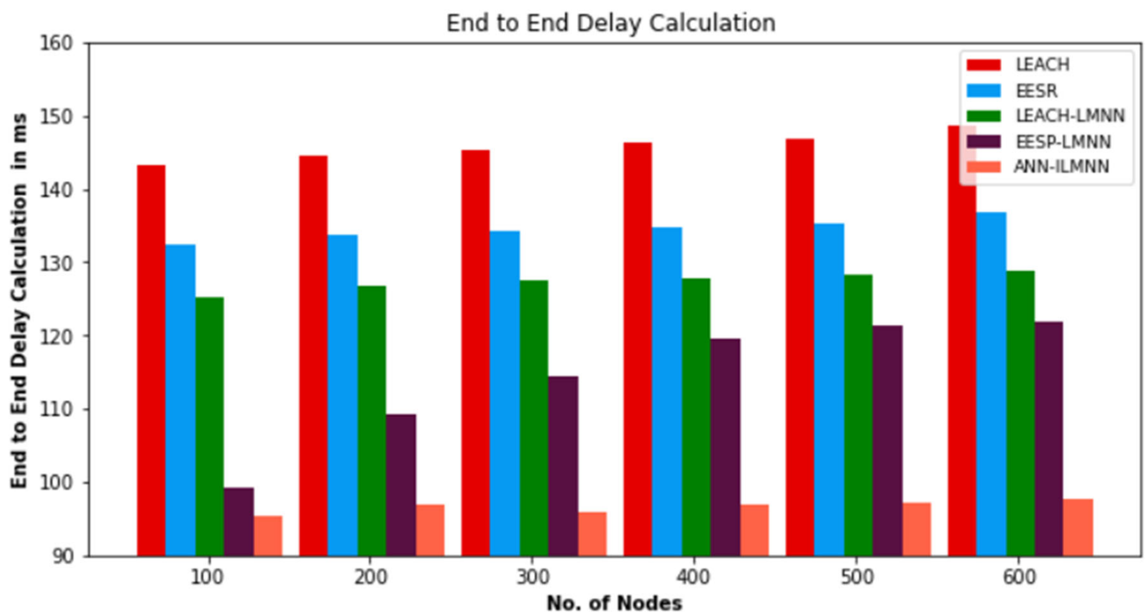

Fig. 6 End-to-End Delay Calculation for ANN-ILMNN method with existing system

Table 2 End-to-End Delay Calculation for ANN-ILMNN method with existing system

No of Nodes	LEACH	EESR	LEACH-LMNN	EESP-LMNN	ANN-ILMNN
100	143.38	132.34	125.32	99.23	95.23
200	144.48	133.68	126.74	109.35	96.79
300	145.28	134.27	127.56	114.46	95.78
400	146.38	134.84	127.89	119.57	96.93
500	146.94	135.27	128.27	121.44	97.14
600	148.66	136.89	128.95	121.78	97.56

EESR, LEACH-LMNN, and EESP-LMNN models have obtained accuracy of 84.89%, 87.94%, 90.69%, and 94.59%, respectively [25].

4.4 Energy consumption

Energy consumption analysis of the ANN_ILMNN method with other existing methods is shown in Table 4 and Fig. 8.

Table 3 Accuracy Analysis for ANN-ILMNN method with existing systems

No of data from dataset	LEACH	EESR	LEACH-LMNN	EESP-LMNN	ANN-ILMNN
100	82.33	85.39	88.24	91.19	95.21
200	82.75	85.89	89.31	91.73	96.35
300	83.18	86.41	89.81	92.26	96.78
400	83.69	87.69	88.59	93.63	95.69
500	84.52	86.91	90.11	92.82	97.44
600	84.89	87.94	90.69	94.59	97.85

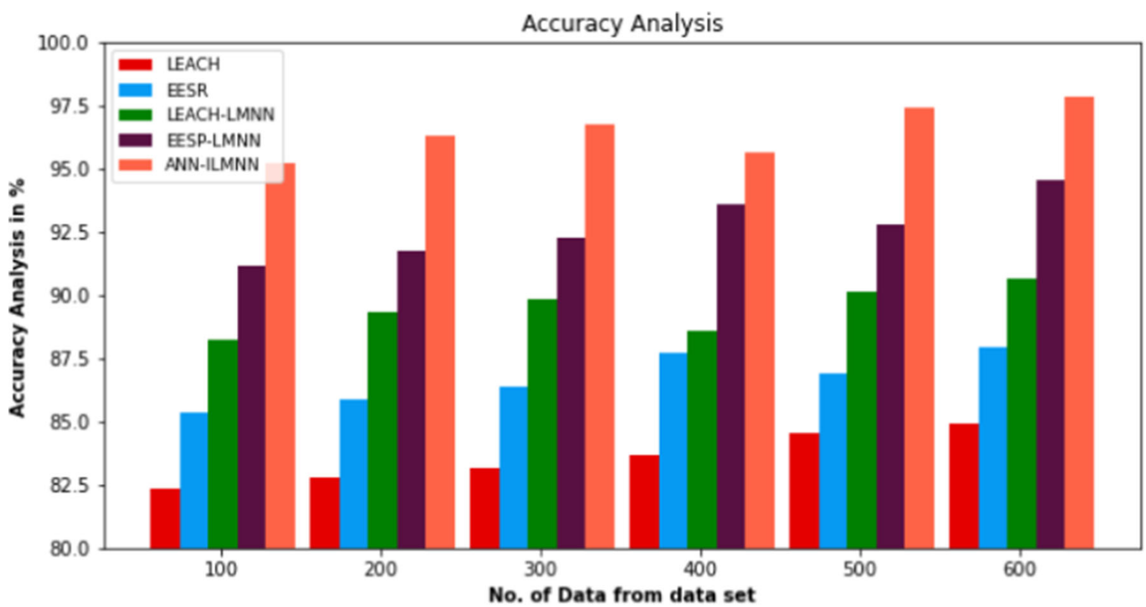

Fig. 7 Accuracy Analysis for ANN-ILMNN method with existing systems

Depending on how well a node performs in the network, it will have a varying trust value. In order to distinguish between legitimate and malicious nodes, each node's trust value is compared to a predetermined threshold. A malicious node is one that intends to deny service to other nodes in the network. Malicious node is a term used to describe a node that modifies data before, during, or after transmission, but the legitimate user or node may have several connections to other legitimate nodes as well as to the attacker, infected neighbors, and/or other legitimate nodes. Any link with an assault or affected neighbors sets this individual at risk for infection. ANN-ILMNN's energy consumption is compared to that of the LEACH, EESR, LEACH-LMNN, and EESP-LMNN methods. The ANN-ILMNN uses 29.12 J for 20 nodes, while the other methods, LEACH, EESR, LEACH-LMNN, and EESP-LMNN, consume 41.24 J, 38.36 J, 35.14 J, and 32.18 J respectively. As the network expands in size, the overall quantity of energy it consumes increases. Existing systems like LEACH, EESR, LEACH-LMNN, and EESP-LMNN for 120 nodes consume 43.69 J, 40.85 J, 37.85 J, and 34.91 J respectively, while the ANN-ILMNN method uses only 30.83 J. This proves that the proposed method has improved performance with less energy consumption.

4.5 Throughput

Table 5 and Fig. 9 show the throughput examination of the ANN_ILMNN method with other current methods. For 10 nodes, the throughput of the ANN-ILMNN protocol has been found to be 91.18 Kbps. This is a significant achievement. For LEACH, EESR, LEACH-LMNN, and EESP-LMNN methods, the network throughputs are 77.26 Kbps, 80.32 Kbps, 83.53 Kbps, and 87.35 Kbps. Similarly, for 60 nodes, the throughput of ANN-ILMNN is 93.59 kbps while it is 79.66 Kbps, 81.91 Kbps, 86.96 Kbps, and 88.86 Kbps for LEACH, EESR, LEACH-LMNN, and EESP-LMNN methods, respectively. Based on the findings, the ANN-ILMNN technique outperforms the others in terms of effectiveness.

Table 4 Energy consumption for ANN-ILMNN method with existing systems

No of Nodes	LEACH	EESR	LEACH-LMNN	EESP-LMNN	ANN-ILMNN
20	41.24	38.36	35.14	32.18	29.12
40	42.35	38.77	36.33	33.25	29.66
60	41.68	39.18	35.69	33.69	30.16
80	42.79	39.76	36.72	32.74	31.27
100	43.16	40.15	37.22	34.45	31.78
120	43.69	40.85	37.85	34.91	30.83

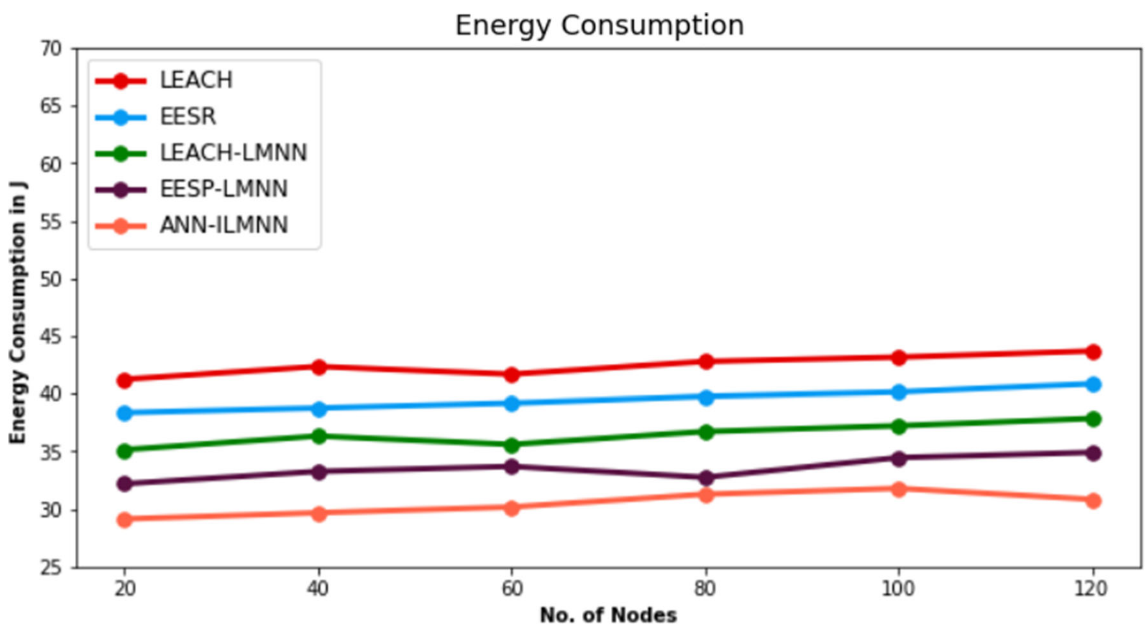

Fig. 8 Energy Consumption for ANN-ILMNN method with existing system

Table 5 Throughput for ANN-ILMNN method with existing systems

No of Nodes	LEACH	EESR	LEACH-LMNN	EESP-LMNN	ANN-ILMNN
10	77.26	80.32	83.53	87.35	91.18
20	78.17	80.71	84.37	87.84	91.69
30	77.83	81.21	84.79	88.55	92.34
40	78.72	82.34	85.89	89.42	92.95
50	79.13	82.89	86.46	89.87	93.17
60	79.66	81.91	86.96	88.86	93.59

4.6 Packet loss ratio

A packet loss rate analysis is shown in Table 6 and Fig. 10. When transport information from a device bulge to a base station, the packet loss ratio measures the proportion of packets that are lost in the process. Packet loss is frequently caused by network congestion. LEACH, EESR, LEACH-LMNN, and EESP-LMNN drops to 40.18%, 36.18%, 32.41%, and 29.18%, respectively, whereas ANN-ILMNN only loses 25.14% of packets with 20 nodes. With 100 nodes, the ANN-ILMNN approach has a packet loss ratio of 26.79%, while the LEACH, EESR, LEACH-LMNN, and EESP-LMNN protocols have higher packet losses of 42.33%, 37.69%, 34.93%, and 30.95%, respectively.

4.7 Packet delivery ratio

A packet distribution ratio (PDR) is a measure of how many packages are being sent from one node to another and how many packages are being received at their respective destinations. Table 7 and Fig. 11 shows ANN-ILMNN packet delivery ratio analysis with existing

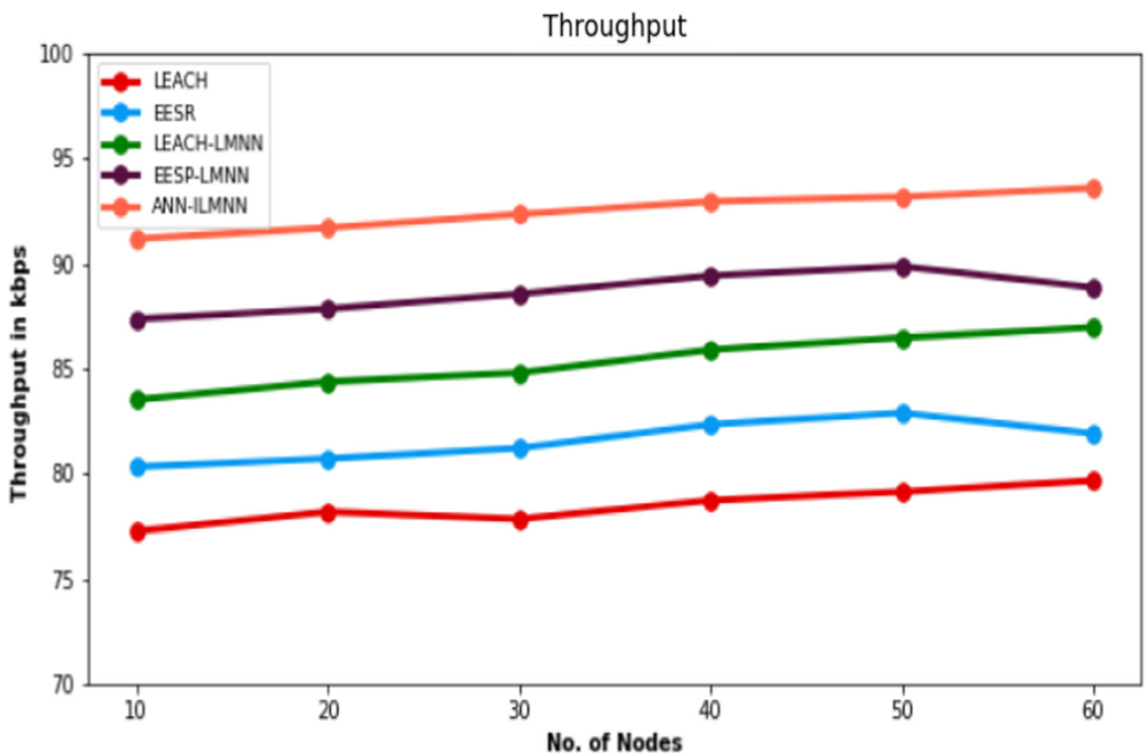

Fig. 9 Throughput for ANN-ILMNN method with existing system

Table 6 Packet Loss Ratio for ANN-ILMNN method with existing systems

No of Nodes	LEACH	EESR	LEACH-LMNN	EESP-LMNN	ANN-ILMNN
20	40.18	36.18	32.41	29.18	25.14
40	40.77	37.69	32.76	29.79	25.79
60	41.56	36.95	33.26	30.53	26.34
80	41.82	38.24	33.82	31.46	27.39
100	42.33	37.92	34.14	31.79	26.79
120	43.78	38.69	34.93	30.95	27.83

techniques like LEACH, EESR, LEACH-LMNN, and EESP-LMNN. It's estimated that for 10 nodes, the ANN-ILMNN approach has a package distribution ratio of 76.35%, while the other methods like LEACH, EESR, LEACH-LMNN, and EESP-LMNN have a PDR of 62.24% to 65.33%, 68.32%, and 72.33%, respectively. Similarly, for 60 nodes, the PDR for ANN-ILMNN is 80.46% while it is 64.86%, 66.29%, 70.93%, and 75.89% for LEACH, EESR, LEACH-LMNN, and EESP-LMNN respectively.

5 Conclusion

WSNs are typically widely spread-out fields to monitor necessary parametric variables. Any wireless sensor network's primary goal is to maximize the network lifetime overall. As a result, any effective management must place high importance on energy efficiency as a characteristic for any sensor network. In this work, the proposed protocols were evaluated using two qualities of service-based characteristics, including vigor competence and end-to-end postponement. In relation to the authors' earlier work, the main contribution of the work can be summed up as follows: The Levenberg–Marquardt neural network was integrated with well-known energy-efficient techniques to lengthen the lifespan of the network: The ILMNN technique was used in the EESR, Sub-LEACH, and LEACH. According to the simulation results, Sub-LEACH-LMNN performs better than the rival procedures in rapports of together vigor and endwise metrics. As part of its second addition to the field of anomaly detection, this paper made use of ANN-ILMNN to identify normal and anomaly

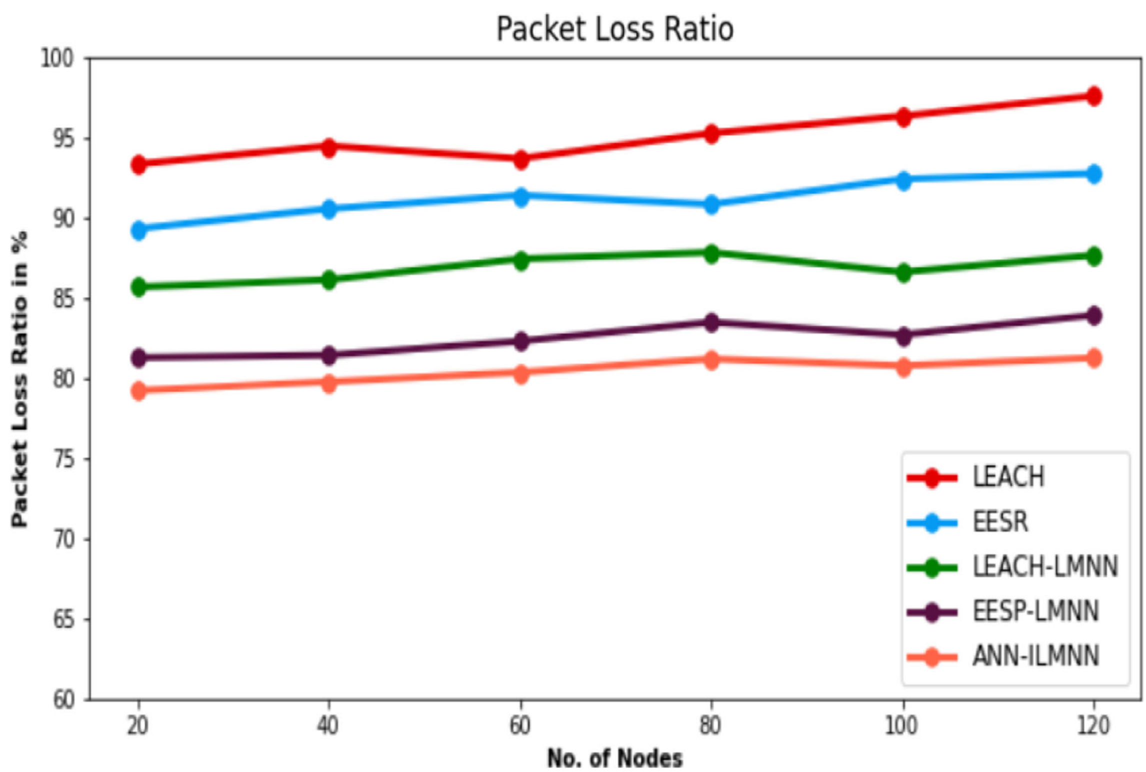

Fig. 10 Packet Loss Ratio for ANN-ILMNN method with existing system

Table 7 Packet delivery ratio for ANN-ILMNN method with existing system

No of nodes	LEACH	EESR	LEACH-LMNN	EESP-LMNN	ANN-ILMNN
10	62.24	65.33	68.32	72.33	76.35
20	63.45	65.78	69.46	72.75	77.54
30	63.87	66.32	69.69	73.37	78.38
40	62.69	67.25	68.78	73.87	77.94
50	64.22	67.83	70.33	74.44	78.83
60	64.86	66.29	70.93	75.89	80.46

classes. This method, which also demonstrates superior accuracy in comparison to other models already in existence, was done as part of this paper. The primary purpose of any wireless sensor network is to maximize the amount of time that the network as a whole can remain operational for. Therefore, energy efficiency is a high priority characteristic for any sensor network, and as a result, any management that is intended to be efficient needs to concentrate on it. The proposed protocols were judged according to their energy efficiency as well as their end-to-end delay times. Both of these factors are quality-of-service based features. The Levenberg–Marquardt neural network was combined with well-known energy-saving strategies in order to increase the lifespan of the network. In subsequent work, more complex algorithms that are derived from machine learning methods will be used in order to create a protocol that is both more cost-effective and uses less energy.

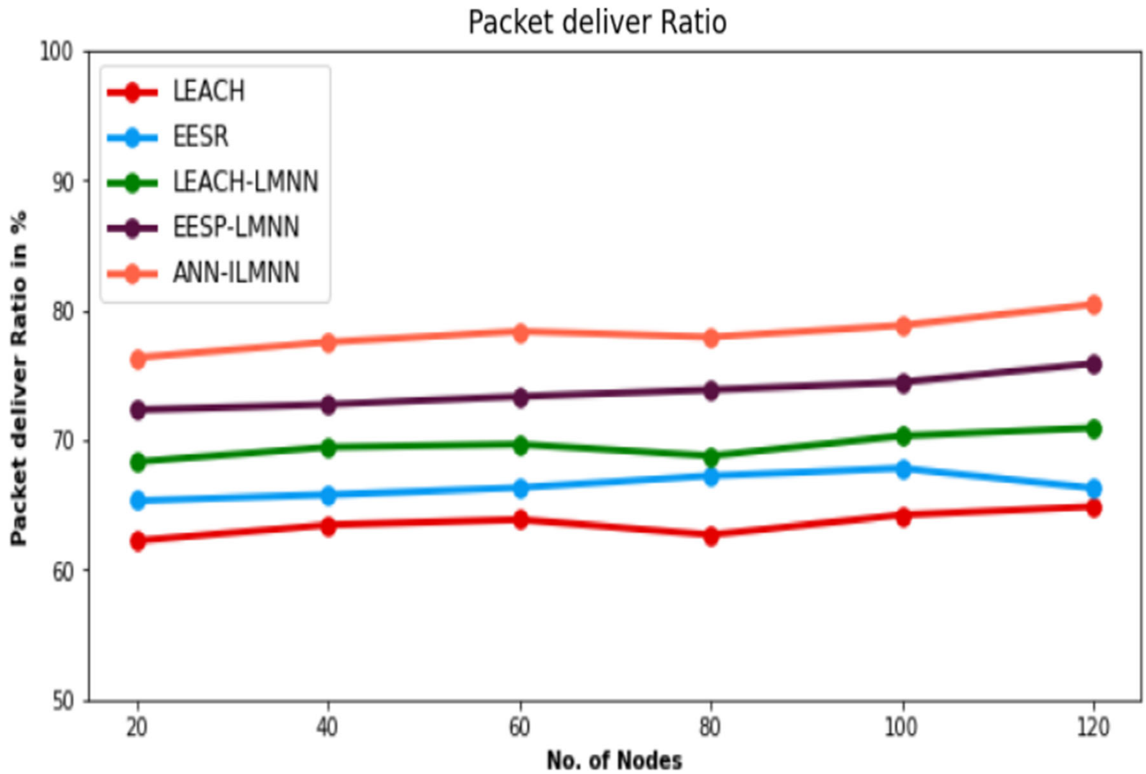

Fig. 11 Packet deliver ratio for ANN-ILMNN methodwith existing system

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Declarations

Conflict of interest Authors do not have any conflicts.

References

1. Liu, J. L., & Ravishankar, C. V. (2011). LEACH-GA: Genetic Algorithm-based energy efficient adaptive clustering protocol for Wireless Sensor Networks. *International Journal of Machine Learning and Computing, 1*, 79–85.
2. Xu, J., Jin, N., Lou, X., Peng, T., Zhou, Q., & Chen, Y. (2012). Improvement of Leach protocol for WSN. In *Proceedings of the 9th international conference on fuzzy systems and knowledge discovery, Chongqing, China*, 29–31 May 2012; (pp. 2174–2177).
3. Salim, A., Osamy, W., & Khedr, A. M. (2014). IBLEACH: Intra-balanced Leach protocol for Wireless Sensor Networks. *Wireless Networks, 20*, 1515–1525.
4. Heinzelman, W. B., Chandrakasan, A., & Balakrishnan, H. (2002). Application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications, 4*, 660–670.
5. Khan, F. A., Ahmad, A., & Imran, M. (2018). Energy optimization of PR-LEACH routing scheme using distance awareness in internet of things networks. *International Journal of Parallel Programming, 48*(2), 244–263.
6. Alotaibi, Y., Alghamdi, S., & Khalaf, O. I. (2022). An efficient metaheuristic-based clustering with routing protocol for underwater wireless sensor networks. *Sensors, 22*(2), 415. https://doi.org/10.3390/s22020415
7. Alotaibi, Y., Alghamdi, S., Khalaf, O. I., & Ulaganathan, S. (2022). Improved metaheuristics-based clustering with multihop routing protocol for underwater wireless sensor networks. *Sensors, 22*, 1618. https://doi.org/10.3390/s22041618
8. Al-Baz, A., & El-Sayed, A. (2017). A new algorithm for cluster head selection in leach protocol for wireless sensor networks. *International Journal of Communication Systems, 31*(1), e3407.
9. Rajakumar, R., Dinesh, K., & Vengattaraman, T. (2021). An energyefficient cluster formation in wireless sensor network using Grey Wolf Optimisation. *International Journal of Applied Management Science, 13*(2), 124.
10. Jain, D. K., Tyagi, S. K. S., & Natrayan, L. (2022). Metaheuristic optimization-based resource allocation technique for Cybertwin-driven 6G on IoE environment. *IEEE Transactions on Industrial Informatics, 18*(7), 4884–4892. https://doi.org/10.1109/TII.2021.3138915
11. Feng, Y. F., Pan, S. G., Huang, Z. Y., & Lin, H. C. (2019). Improvement of energy efficiency in wireless sensor networks using low-energy adaptive clustering hierarchy (LEACH)-based energy betweenness model. *Sensors and Materials, 31*, 2691–2702.

12. Anand, G., & Balakrishnan, R. (2013) Leach-Ex protocol—A comparative performance study and analysis with Leach variants of Wireless Sensor Networks. In *Proceedings of the national conference on frontiers and advances in information science and technology* (pp. 192–196).
13. Jain, D. K., Veeramani, T., Bhatia, S., & Memon, F. H. (2022). Design of fuzzy logic-based energy management and traffic predictive model for cyber physical systems. *Computers and Electrical Engineering, 102*, 108135. https://doi.org/10.1016/j.compeleceng.2022.108135
14. Singh, H., Ramya, D., Saravanakumar, R., Sateesh, N., Anand, R., & Singh, S. (2022). Artificial intelligence based quality of transmission predictive model for cognitive optical networks. *Optik*. https://doi.org/10.1016/j.ijleo.2022.168789
15. Chen, H., Shi, Q., Tan, R., Poor, H. V., & Sezaki, K. (2010). Mobile element assisted cooperative localization for wireless sensor networks with obstacles. *IEEE Transactions on Wireless Communications, 9*, 956–963.
16. Venu, D., Mayuri, A. V. R., & Murthy, G. L. N. (2022). An efficient low complexity compression based optimal homomorphic encryption for secure fiber optic communication. *Optik, 252*, 168545. https://doi.org/10.1016/j.ijleo.2021.168545
17. Sreekala, K., Cyril, C. P. D., Neelakandan, S., Chandrasekaran, S., Walia, R., & Martinson, E. O. (2022). Capsule network-based deep transfer learning model for face recognition. *Wireless Communications and Mobile Computing*. https://doi.org/10.1155/2022/2086613
18. Feng, Q., He, D., Zeadally, S., Khan, M. K., & Kumar, N. (2019). A survey on privacy protection in blockchain system. *Journal of Network and Computer Applications, 126*, 45–58.
19. He, D., Kumar, N., & Lee, J. H. (2016). Privacy-preserving data aggregation scheme against internal attackers in smart grids. *Wireless Networks, 22*, 491–502.
20. Perumal, S. K., Kallimani, J. S., Ulaganathan, S., Bhargava, S., & Meckanizi, S. (2022). Controlling energy aware clustering and multihop routing protocol for IoT assisted wireless sensor networks. *Concurrency and Computation Practice and Experience*. https://doi.org/10.1002/cpe.710
21. Yick, J., Mukherjee, B., & Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks, 52*, 2292–2330.
22. Anuradha, D., Khalaf, O. I., Alotaibi, Y., Alghamdi, S., & Rajagopal, M. (2022). Chaotic search-and-rescue-optimization-based multi-hop data transmission protocol for underwater wireless sensor networks. *Sensors, 22*, 2867. https://doi.org/10.3390/s22082867
23. Elsisi, M., Mahmoud, K., Lehtonen, M., & Darwish, M. M. F. (2021). Effective nonlinear model predictive control scheme tuned by improved NN for robotic manipulators. *IEEE Access, 9*, 64278–64290.
24. Subramani, N., Alotaibi, Y., Alghamdi, S., & Nanda, A. K. (2022). Improved metaheuristic-driven energy-aware cluster-based routing scheme for IoT-assisted wireless sensor networks. *Sustainability, 14*, 7712. https://doi.org/10.3390/su14137712
25. Awad, A., German, R., & Dressler, F. (2011). Exploiting virtual coordinates for improved routing performance in sensor networks. *IEEE Transactions on Mobile Computing, 10*, 1214–1226.

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