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Cross-Layer based Energy Efficient Wireless Sensor Network for Large Farms

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Abstract: In recent years, researchers have focused their efforts on improving agricultural production by automating farming applications using wireless sensor networks (WSNs). The agricultural information must be accurate and updated in order to take the necessary actions. Sensor nodes (SNs) deployed in agricultural fields are power-constrained and require lot of energy to transmit data on regular basis. As a result, robust approaches are required to manage energy-related concerns for long-distance communication in large farms. To address long-distance agricultural needs, a cross-layer-based energy-efficient wireless sensor network model called CL-EEWSN that employs the wild horse optimizer (WHO) has been proposed. The primary goal of this research is to select the optimal cross-layer based cluster heads (CH) in terms of energy efficiency, communication delay, and latency. The physical layer, medium access control layer and network layer properties of each SN are used to evaluate and select the best CH. Further, a deep learning-based approach is used to determine the best data transmission path. The CL-EEWSN reduces energy consumption, end-to-end delay, and improves packet delivery ratio when compared to existing state-of-the-art protocols. The average energy consumption of CL-EEWSN for 100 nodes and 400 nodes is 0.16 nJ and 0.31 nJ respectively and is lowest in comparison to existing techniques.

Keywords: Wireless sensor networks, Sensor nodes, Cluster head, Energy efficiency, Cross layer.

1. Introduction

WSNs have recently emerged as a new field for communication between small, wireless, battery-powered devices namely sensor nodes (SNs). SNs collect data from remote sites, compute and send to the base station (BS). WSN communication is based on the fusion of several SN, ranging from simple (moisture, temperature, and pressure) to complicated (such as localization, position tracking and micro-radars), allowing WSNs to monitor a wide variety of environments and collect precise information from the field. WSN is becoming a popular research topic due to its uses in remote, inaccessible, and hazardous environments such as battlefields, healthcare, industry, environment, agriculture and so on. Agriculture is more visible than other sectors that are projected to be heavily touched by WSNs. As the global population grows at an exponential rate, agrarian practices must be modernized to meet the need for food [1].

Precision agriculture is a very promising notion for contributing to increased food production in a sustainable way [2]. Precision agriculture (PA) employ WSNs to monitor yield conditions and automate agriculture precision by utilizing a variety of SNs. WSNs increase crop yield by providing more detailed farming judgments about current conditions, such as early warnings of potential risks and improved automated control signals in their cultivation area [3]. Internet of things (IoT) and the various technologies associated with WSNs have enormous potential to improve the agricultural sector's overall performance [4]. Furthermore, the main aim of these technologies is to provide the end user with regular and timely updates on their current status [5].

IoT, which is a boon in today's world, is used in farming to monitor plants even from remote locations and to improve plant yield. In IoT, any object that can utilize connection will be connected. The SNs on the other hand, have limited processing, energy, and transmitting capacities, which might have a negative impact on agricultural production. Although the use of WSNs has steadily increased over time, battery manufacture has not kept same pace [6]. As a result, WSNs are primarily constrained by their batteries [7].

Various clustering-based methods have been presented to save energy in WSNs, which promotes energy-efficiency in farming applications. Traditional clustering approaches such as LEACH [8], EEHC [9], TEEN [10], and others were used in recent simulation-based methodologies, which may not be the best long-term solution for scaled agricultural areas. Therefor taking into consideration an energy efficient cross layer WSN (CL-EEWSN) model for long distance farming has been introduced in this paper. In CL-EEWSN, parameters from multiple layers are combined, and a deep learning-based solution is provided for efficient route selection. For long-distance farming applications, the CL-EEWSN proposal aims to deliver energy-efficient data transmission.

The literature of relevant studies is briefly summarized in section 2. The CL-EEWSN design is presented in section 3. Section 4 shows the outcomes of the proposed model when compared to existing state-of-the-art methodologies. Finally, section 5 concludes the work.

2. Related work

This section presents a brief overview of various existing energy-efficient techniques in WSNs. In WSNs, scalability and reliability are considered to be major problems in long range farming networks. Various real-time, simulation-based and clustering works for farming has been reviewed in the literature.

LEACH [8] is the first WSN-specific hierarchical routing protocol. In LEACH, CHs are chosen randomly without taking into account the SNs residual energy or distance parameters. As a result, the CHs are unevenly distributed, increasing node energy consumption. Because the CHs chosen are not in close proximity, LEACH cannot be used in large networks. Many extended versions of LEACH have been proposed, including M-LEACH [11], V-LEACH [12], W-LEACH [13], and TL-LEACH [14]. EEHC [9] is an acronym for energy efficient hierarchical clustering. CHs send data in a single hop. HEED [10] a hybrid energy efficient distributed scheme selects CH on the basis of residual energy of SNs and intra-cluster communication cost. Because of these factors SNs are equally distributed in the network. However, in the HEED, CH selection process involves a number of iterations, which increases energy consumption. By regulating SN energy consumption, the cluster-based routing protocol [15] extends network lifetime. Despite the fact that the CH is distributed uniformly among the SNs, the energy hole problem remains unresolved. In [16], a weighted energy efficient clustering protocol considers residual energy, distance, and the construction of a routing tree during data transmission in a WSN. However, in a homogeneous network, optimized CH selection and energy consumption remain ineffective. Aggregator based on location node election protocol (PANEL) [17] divides the network into geographical clusters using a grid cluster-based routing mechanism. The position of SNs is utilized in PANEL to locate SN aggregators. The SN that is closest to the reference point is chosen as CH. However, the infrastructure cost of PANEL is high due to requirement of special hardware and software for implementation based on geographical knowledge of SNs. Power-efficient gathering in sensor information systems (PEGASIS) [18] is a hierarchical chain protocol for data transfer and aggregation that organizes SNs into chains. The chain is formed by starting with the SN that is farthest from the sink and selecting its closest neighbour as the next SN in the chain, and so on. The larger the network, the longer the transmission latency, resulting in a scalability issue for PEGASIS. Concentric grid clustering routing protocol (GROUP), which is a hybridization of clustering and location-based routing proposed in [19]. In GROUP, CH receives queries from all SNs in its cluster and uses the location information to route them to the appropriate destination SN.

In [20] cuckoo's search algorithm based smart irrigation system has been developed. ThingSpeak an IoT enabled WSN is used to collect various parameters such as temperature, humidity, pH. The data received in IoT has been processed in cuckoo's search algorithm to find appropriate crops according to soil. IoT-enabled deep learning neural network based intelligent irrigation system for precision agriculture is presented in [21]. It emphasizes on period of irrigation by controlling the functionality of the irrigation scheduler. In [22] IoT and WSN enabled architecture has been designed to monitor humidity, moisture and temperature to conserve water efficiently in small fields. An IoT-based greenhouse management system has been proposed in [23] to encapsulate various applications, communication protocols, and SNs. The main aim of proposed technique in [24] is energy efficiency and real time data transmission using greedy algorithm for an IoT enabled monitoring system. In [25] an energy efficient IoT enabled WSN has been designed to monitor agriculture field accurately. The system mainly focuses to provide information of humidity, salinity, and temperature to farmers. The equalized cluster head election routing protocol (ECHERP), a novel automated irrigation system has been presented in [26]. The designed system's primary goal is to efficiently conserve water in cultivated fields. In [27], a WSN-based precision agriculture application for potato fields was designed. To form clusters in a grid fashion, the HEED (hybrid energy efficient distributed) is used. through the PotatoSense simulator, the precision agriculture application collects humidity, pH of soil, and temperature data. The game-theory-based energy-efficient clustering (GEEC) for WSN discussed in [28]. To achieve symmetric energy consumption and increase network lifetime, the GEEC employs a game theory-based clustering routing protocol. Energy efficient clustering protocol improves the energy performance of heterogeneous networks (EECPEP-HWSN) and thus network stability, throughput, and lifetime [29]. A nature-inspired algorithm-based cross-layer clustering protocol has been described in [33] to improve the network lifetime of SNs deployed to regularly monitor farm conditions. Bacterial foraging optimization (BFO) algorithm has been employed for clustering and data transmission. The parameters considered for CH selection in EECPEP-HWSN are residual energy, initial energy, and hop count. In [30], to create energy-efficient clusters in WSNs, a particle swarm optimization (PSO)-based multi-objective energy efficient scheme (MOEES) has been proposed. MOEES chooses the most energy-efficient cluster heads (CHs) based on intra-cluster distance, inter-cluster distance, and node degree. A new model namely memetic optimized expectation maximization clustering (MOEMC) is proposed in []. Initially the MOEMC computes residual energy for SNs in the network. Further, dice similarity based expectation maximization (DS-EM) clustering algorithm designed to efficiently construct different number of clusters by means of residual energy level. Biogeography-based energy-saving routing architecture (BERA) in [34]. BERA selects CH by considering the intra-cluster distance, residual energy, and CH-sink distance for the optimal cluster. Moreover, for optimal routing three parameters residual energy, node degree, and intra-cluster distance are considered for the fitness function [34]. To increase network performance, a novel energy-efficient centroid based routing protocol (EECRP) for WSN-assisted IoT has been presented in [31]. The proposed EECRP a new distributed cluster formation technique to self-organize the SNs, a new set of algorithms for adapting clusters and centroid position-based CH rotation. EECRP distributes the energy load evenly across all SNs that reduces the energy consumption for long-distance communication.

Various real-time methodologies, simulation-based systems, and clustering algorithms have been discussed in the literature. Real-time approaches have a limited collection of SNs, simulation-based systems rely on traditional clustering techniques that are inadequate for long-distance transmission, and clustering methods in WSNs are primarily focused on achieving energy efficiency. As the SNs consume more energy for long distance communication, the works addressed in the literature for farming applications demonstrate a lack of scalability, energy efficiency, and latency. Comparison of various real-time, simulation based and clustering algorithms depicted in Table 1.

Using existing techniques, resolving trade-offs in long-distance farming applications is a difficult issue. As a result, a cross-layer-based cluster head (CH) selection employing nature-inspired optimization and deep learning-based data transmission has been proposed to overcome the long-distance communication challenges in farming. In cross layer design the requirements of different layers are considered while the selection of CHs. The main contributions of the paper are:

- The nature-inspired wild horse optimization (WHO) algorithm has been employed for cross-layer-based CH selection.
- Deep learning-based optimal inter-cluster and intra-cluster data transmission route has been obtained that leads to energy efficiency and computational efficiency.
- Exhaustive simulations have been conducted to evaluate the effectiveness of CL-EEWSN in comparison to LEACH, BERA, EECRP and MOEES.

3. Cross-layer based energy-efficient technique for wireless sensor networks

The proposed model has been detailed in this section in order to achieve energy efficiency, reduce communication delay, and latency for farming applications by efficient CH selection. The WHO

Table 1. Comparison of real-time, simulation and clustering-based algorithms

Citation/year	Algorithm/Technique	Parameters	Comparison algorithm	Benefits
[10] 2004	HEED	Residual energy, intra-cluster distance		Optimize network usage, Enhance network lifetime
[17] 2010	PANEL	Grid clustering, uses position information	HEED	Ensures load balancing
[18] 2002	PEGASIS	SN chains	LEACH	
[19] 2006	GROUP	BS builds a cluster structure	LEACH	Better energy consumption distribution
[20] 2019	Cuckoo's search based smart irrigation	ThingSpeak IoT enabled WSN collect humidity, temperature information		Crop search according to soil,Prevent water wastage
[21] 2021	Deep learning-based irrigation system	Long short-term memory network (LSMN)	FFANN, T-based	Predict water requirement
[22] 2018	IoT enabled field parameter monitoring system	Monitor moisture, temperature		Farmers can schedule upcoming activities e.g. cultivation, harvesting, irrigation, fertilization
[23] 2017	IoT enabled greenhouse management system	Light, temperature, humidity sensors deployed		Monitoring management, weather forecasting
[24] 2017	Data driven greedy algorithm-based data transmission	SNs collect data upon environmental change	SPIN, ESPIN	Energy efficient monitoring
[25] 2018	IoT enabled monitoring	SNs learn and adapt		SNs reduce transmit power consumption
[26] 2015	ECHERP	Consider threshold value	LEACH, ELCH	Lifetime improved
[27] 2014	WSN based system for potato fields, HEED	Grid manner deployment based on SN range		Reduce environmental fluctuating effect
[28] 2016	GEEC	Game theory mechanism to achieve energy exhaust equilibrium	LEACH, LEACH-C	Enhance energy efficiency, Network performance
[29] 2018	EECPEP-HWSN	Initial energy, hop count, residual energy	LEACH, SEP, DEEC	enhance stability period, energy efficiency
[31] 2017	EECRP	Residual energy for centroid position	LEACH, LEACH-C, GEEC	Evenly distribute the energy load among SNs.

[35] is used to find the optimal CH by taking into account the needs of different layers. The probability value for each SN has been determined using MAC layer (ML), physical layer (PL), and network layer (NL) parameters. Furthermore, a deep learning approach used to select the best data transmission route. Fig. 1 shows the CL-EEWSN system model.

The main aim of this paper is to address the issues formulated as follows:

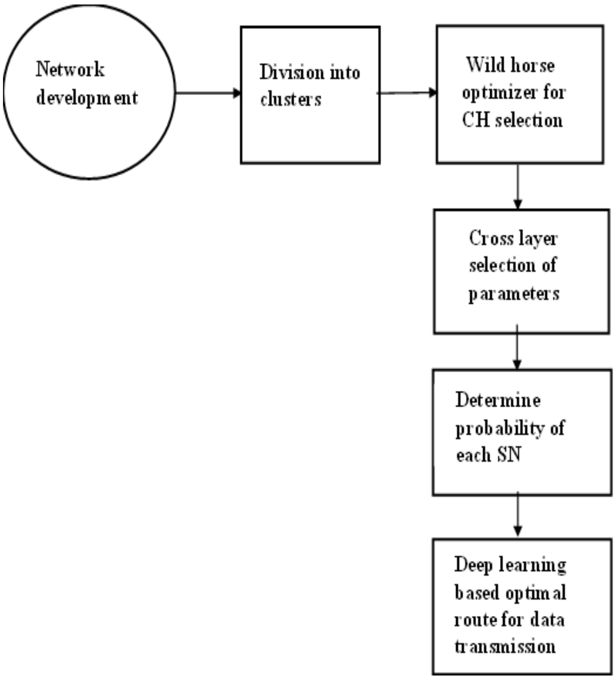

Figure. 1 CL-EEWSN system model

- Energy consumption for communication in large farms is extremely high, necessitating the selection of energy-efficient CH.
- Selection of the optimal data transmission route to reduce transmission delay, latency, and energy usage.

3.1 System model

The SNs accumulated together by employing a bi-concentric hexagonal structure to form clusters. The CL-EEWSN performs WHO algorithm-based CH selection to transmit the information to BS. Each cluster comprises of S number of SNs, i.e., $G^c = \{G^1, G^2, G^3, \ldots\ldots G^S\}$, where G^C indicates the SNs belonging to c^{th} cluster. Fig. 2 illustrates the optimal CH selection for each cluster performed periodically by cross layer SN probability value. The parameter node degree (N_{degree}) is taken from ML (L_i^1), residual energy R_{energy} is from PL (L_i^2) and inter-cluster distance ($I_{distance}$) and intra-cluster distance $Ia_{distance}$ from NL (L_i^3) to calculate the probability value (L_i) for i^{th} SN in c^{th} cluster. Notations are described in Table 2.

Some assumptions of proposed model are as follows:

- The homogeneous SNs are deployed randomly across the field area.
- The SNs used are humidity, temperature, light to monitor farm parameters and are static.
- The BS is situated outside the field area without energy constraints.
- Multi-hop and symmetric communications are used among the SNs in the network.
- We assume that each SN periodically collects the data and transmit towards CH node.

3.2 Layer-wise probability computation of SNs

N_{degree} is defined as the number of linkages formed by a SN in the radio range of any other SN. Energy consumption is minimal for neighbor SNs joining adjacent CH. In general, fitness function nominates CH having higher node degree to save communication energy. The probability value of i^{th} node in the ML can be determined as:

$$L_i^1 = N_{degree} \tag{1}$$

The parameter R_{energy} has been chosen from PL used to compute the energy of SNs. The SNs having higher R_{energy} are given more priority to select as CH. Residual energy for i^{th} SN is computed as:

$$R_{energy} = Ini_{energy}^{i} - cons_{energy}^{i} \tag{2}$$

where, $Init_{energy}^i$ indicates the initial energy of i^{th} node and $Cons_{energy}^i$ indicates consumed energy of the i^{th} SN. Then, the probability value of i^{th} SN in the PL can be determined as follows:

Table 2. Notation table

Notation	Significance
N_{degree}	Node degree
R_{energy}	Residual energy
Ini_{energy}	Initial energy
E_{Total}	Total energy
E_a	Average energy
PDR	Packet delivery ratio
$I_{distance}$	Inter-cluster distance
$Ia_{distance}$	Intra-cluster distance
$P_{received}$	Packets received
$P_{generated}$	Packets generated
L_i^1	i^{th} sensor node probability of Mac layer
L_i^2	i^{th} sensor node probability of Physical layer
L_i^3	i^{th} sensor node probability of Network layer

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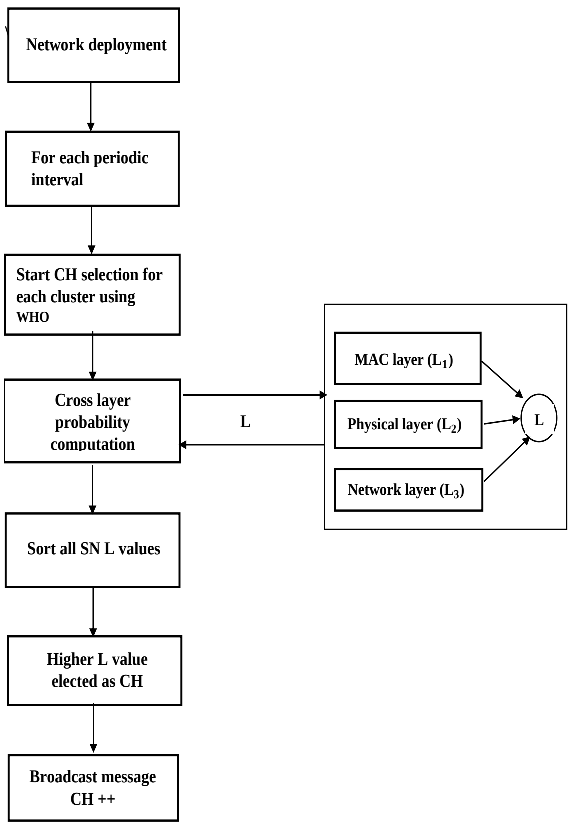

Figure. 2 Cross-layer-based CH selection

$$L_i^2 = R_{energy} \tag{3}$$

The $I_{distance}$ is the represented as the distance between CH and BS. The minimum $I_{distance}$ leads to optimal consumption of energy, network latency, and overall transmission delay. $Ia_{distance}$ is the distance between each SN and the cluster's CH. Because energy is consumed when SNs communicate with each other, the intra-cluster distance should be minimized to reduce energy consumption. The probability value of i^{th} node in the NL can be determined as:

$$I_{distance}=1-\frac{\text{distance (ch,bs)}}{f_{max}}$$
$$Ia_{distance}=1-\frac{\text{distance }(s^i,\text{ch})}{f_{max}}$$
$$L_i^3 = I_{distance} + Ia_{distance} \tag{4}$$

Where distance (ch, bs) is the distance between CH and BS and (s^i, ch) is the distance between SN and CH. f_{max} determines the maximum positive value. SNs having higher probability value L are selected as CH. The summarized layer probability value of i^{th} SN is calculated as:

$$L_i=L_i^1\times w_1+L_i^2\times w_2+L_i^3\times w_3 \tag{5}$$

w_1, w_2, and w_3 represents weighing factors of ML, PL and NL respectively. These factors play an important role for calculation of probability value. The probability value for each SN can be computed in the range of [0,1].

3.3 Wild horse optimizer (WHO) for CH selection

In CL-EEWSN cross-layer based CH is selected by employing WHO [35] to manage energy related concerns. The WHO is a new algorithm inspired by the life behavior of horses. Usually, horses live in groups and exhibit many behaviors. The main inspiration of WHO is the decency behavior of horses. Horse decency is such that to prevent the father from mating the foals leave before reaching Puberty. Steps of WHO for CH selection are as follows:

- WHO randomly initiates the population $\vec{c} = \{\vec{c_1}, \vec{c_2}, \vec{c_3}, \ldots \vec{c_p}\}$ in each cluster. CH for each cluster selected on the basis of maximum probability value (L) among the cluster members.
- SNs search around the center considering CH to be at the center of their cluster and expressed as:

$$\vec{Y}^{s}_{q,I}=2M\cos(2\pi TM)\times(ch^{S}-Y^{s}_{q,I})+ch^{s} \tag{6}$$

where, $Y^s_{q,I}$ denotes the SNs current position, ch^s indicates CH's current position, M denotes an adaptive mechanism. T indicates the uniform random number in the range of $[-2,2]$, which causes the searching of SNs at different angles of CH. The cos function establish the movement in several radius. $\vec{Y}^{s}_{q,I}$ represents the new position of SN after searching.

In mating behavior, the SNs having less probability leave the cluster before selecting as CH and joins other cluster to elect as CH. The crossover operation defined to determine the movement of SNs is as follows:

$$Y^b_{I,t}=\text{Cross}_{over}\left(Y^a_{I,q}, y^c_{I,s}\right)\ q\neq s\neq t,\ a=b=end \tag{7}$$

$$\text{Cross}_{over}=\text{Mean} \tag{8}$$

where, $Y^b_{I,t}$ defines the position of SN b from cluster t and leave the cluster and provide its position to a SN whose parents are SNs who have to leave cluster q and s, and attained as member for election. Then, they elect and determine better probability value.

- In group leadership, CH led the cluster for specific position. Update the CH position relative to best position as follows:

$$\overline{Ch_{I_q}}=\begin{cases}2M\cos(2\pi TM)\times(XE\text{-}ch_{I_q})+XEi\ fT_3>0.5\\ 2M\cos(2\pi TM)\times(XE\text{-}ch_{I_q})\text{-}XE\ ifT_3\leq 0.5\end{cases} \quad (9)$$

Where, $\overline{ch_{I_q}}$ indicates the next position of the CH in the q^{th} cluster, XE represents the waterhole position, ch_{I_q} resembles the current position of the CH in the q^{th} cluster, M describes the adaptive mechanism, T highlights the uniform random number in the range [-2, 2], and π indicates the value 3.14.

- CHs are selected based on the cross-layer probability value L if one of the member SNs having better fitness than the CH, then the position exchanged are described as:

$$Ch_{I_q}=\begin{cases}X_{I,q}\ \text{if cost}\left(X_{I,q}\right)<\text{cost}\left(Ch_{I,q}\right)\\ Ch_{I,q}\ \text{if cost}\left(X_{I,q}\right)>\text{cost}\left(Ch_{I,q}\right)\end{cases} \quad (10)$$

WHO employs PL, ML and NL parameters for the optimal CH selection. Finally respective SN with better fitness values exchange the position with CH according to Eq. (10).

3.4 Data transmission

After the selection of CH, the main objective is to optimize the intra-cluster and inter-cluster data transmission. Routing problems are multi objective and can be well optimized by deep learning-based nature inspired techniques. Golden eagle optimizer (GEO) is a nature-inspired swarm-based metaheuristic algorithm that mimics the intelligence of golden eagles [36]. CL-EEWSN utilizes deep learning model-based GEO to find most appropriate data transmission route from the accessible path. The input layer comprised of input neurons, and the candidate routes $\gamma=\{RT_1,RT_2,RT_3,\ldots..RT_n\}$ have initiated. Cross-layer based characteristics are considered to select the optimal paths. $\{HL_1,HL_2,HL_3,\ldots\ldots.HL_p\}$ are hidden neurons in a deep neural network model. Based on the cross-layer parameters, all accessible routes discovered in hidden layer are expressed as $RT_\alpha=\{RT_1,RT_2,RT_3,\ldots..RT_N\}$. Further, every route has discovered with a weighted value in the hidden layers. The weighted value has determined in terms of fitness value $F(R)$. In the proposed method, minimum distance is considered as fitness function for routing using GEO-based deep learning model. The fitness function is considered as the objective function for the presented algorithm. The SN distance is computed as:

$$node\ distance_{i,j}=\sqrt{\left(m_i-m_j\right)^2+(n_i-n_j)^2} \quad (11)$$

$$F(R)=minimum\ (node\ distance_{i,j}) \quad (12)$$

where, (m_i,n_i) and (m_j,n_j) specifies the coordinates of nodes i and j.

Every CH choose a route in each iteration to ensure efficient data transmission. The optimal route is referred to as the best solution in this context, and each CH has the ability to memorise the best solution. Algorithm 1 describes the optimal route selection.

Algorithm 1

1. Input: $\gamma=\{RT_1,RT_2,RT_3,\ldots..RT_n\}$
2. Output: RT_α // accessible routes
3. Initialize $RT_n\ \epsilon\ \gamma$
4. for $RT_n\ \epsilon\ \gamma$ do
5. Generate $RT_\alpha=\{RT_1,RT_2,RT_3,\ldots..RT_N\}$
6. end for
7. for $RT_n\ \epsilon\ RT_\alpha$ do
8. Determine F(R_n) using eqn (12) // weighted value
9. Assign F (R_n) → weight function
10. for every CH
11. select a random route
12. Determine fitness function for new position
13. Restore the best position
14. end for
15. end for

The suggested deep learning approach enables for optimal route selection and delivery of optimized results in terms of energy-efficiency, computational-efficiency, and QoS-efficiency. Further the analysis of simulation results has been detailed exhaustively.

4. Performance evaluation

The implementation and assessment of CL-EEWSN for farming applications was accomplished using Matlab 2021b. The ease of mathematical operations and appropriate data analysis are the primary reasons for using Matlab. The networks for simulation are created with different number of SNs (100-400) deployed in farm field of 1000m × 1000m. Table 3 presents a list of simulation parameters considered for experimentation. The symbols represent the units, such as m for meters, nJ for nanojoule. The goal of this research is to find the most energy-efficient CH and the optimal data

Table 3. Simulation parameters

Parameter	Value
Network area	1000m × 1000 m
SNs	100-400
Packet size	512 bits
SN deployment	Random
Initial energy	5e + 8 nJ
Transmitter energy consumption	1.67e -8 nJ
Receiver energy consumption	3.61e- 8 nJ

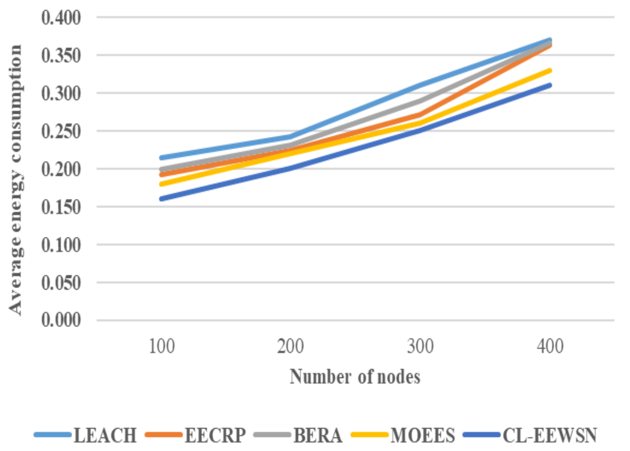

Figure. 3 Average energy consumption

transmission path. As a result, the cross-layer based energy efficient wireless sensor network (CL-EEWSN) has been designed by utilizing the parameters of different layers. Further the CL-EEWSN is compared with LEACH [8], BERA [34], EECRP [31] and MOEES [30]. The corresponding results are presented in next sub-sections.

4.1 Average energy consumption

Average energy consumption is evaluated as the energy consumed by SN in each round. The average energy (E_a) consumed is computed as:

$$E_a = \frac{E_{Total}}{N} \tag{13}$$

E_{Total} and N represents the total energy consumed by network and total number of SNs respectively. Energy efficiency of CL-EEWSN in terms of E_a as compare to LEACH, BERA, EECRP and MOEES is depicted in Fig. 3.

In comparison to existing techniques the CL-EEWSN shows energy efficiency in terms of average energy usage for 100, 200, 300, and 400 SNs. CL-EEWSN makes use of cross-layer based parameters for cluster head selection, which reduces clustering overhead. In EECRP, only residual energy and centroid location characteristics are used to select the CH node, which is insufficient to reduce energy usage. For long-distance communication applications, the LEACH protocol selects CH nodes based on the threshold energy, which is not scalable or energy-efficient.

4.2 Packet delivery ratio (PDR)

PDR is QoS performance metric evaluated as the ratio of packets received ($P_{received}$) to packet generated ($P_{generated}$) at all SNs during the complete simulation time.

$$PDR = \frac{P_{received}}{P_{generated}} \tag{14}$$

The PDR evaluation of proposed model is compared with state-of-art protocols for varying SNs as demonstrated in Fig. 4. The performance achieved by proposed model is higher due to cross layer-based approach used for CH selection and optimal data transmission route. Fig. 4 depicts the PDR performance measurement and evaluation for varying SNs. Normally, PDR performance dropped due to increased SN density and network congestions, whereas CL-EEWSN achieved higher PDR for all network conditions. In CL-EEWSN, deep learning-inspired solution selects accurate data forwarding nodes, resulting in the dependability of data packets transferred between the intended source and destination pairs in the network.

4.3 End-to-end delay

The average communication delay evaluates the average time of the packet generation at every source node to the packets received at every destination SN.

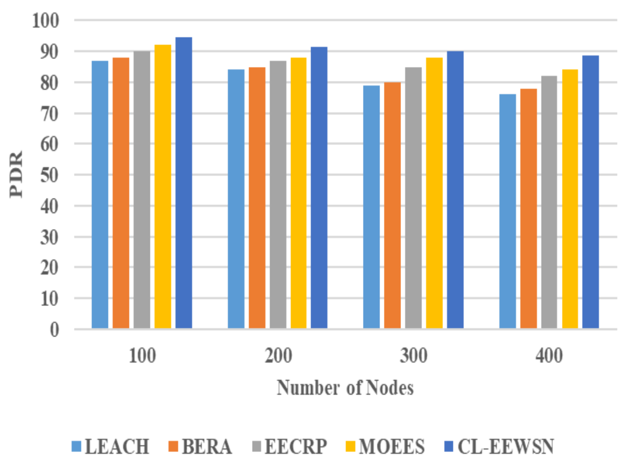

Figure. 4 Packet delivery ratio

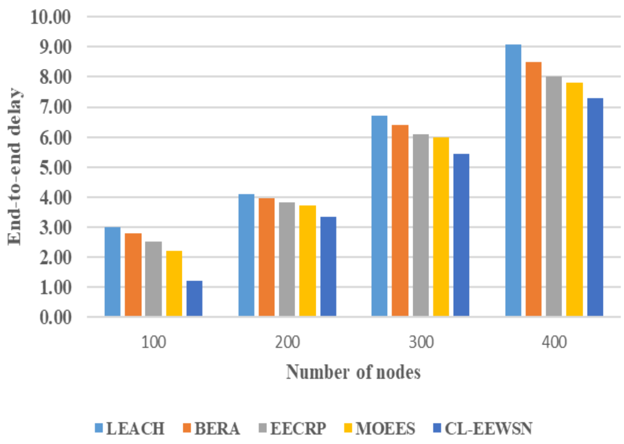

Figure. 5 End-to-end delay

Table 4. Average performance

Protocols	Average energy consumption (nJ)	Packet delivery ratio (%)	End-to-end delay (ms)
LEACH	0.284	81.5	5.73
BERA	0.271	83	5.41
EECRP	0.263	86	5.10
MOEES	0.248	88	4.93
CL-EEWSN	**0.230**	**91.24**	**4.24**

Fig. 5 clearly shows, CL-EEWSN has a shorter end-to-end delay in comparison to existing techniques. Delay is a significant requirement for large farms, as reducing the delay enhanced farm monitoring and output. The average delay value increased as the population density, data volume and congestion increased. The CL-EEWSN has a lower end-to-end delay due to the implementation of a deep learning-inspired data transmission mechanism. The SNs determined in this way are the best for transmitting data from source to destination. However, in EECRP the routes are selected without considering the link quality.

Moreover, Table 4 clearly represents the outperformance of CL-EEWSN in comparison to LEACH, BERA, EECRP and MOEES. It is observed in Table 4, the average energy consumption of CL-EEWSN protocol improved by 0.02 nJ. Similarly, average end-to-end delay has been reduced by 0.69 ms and PDR improved by 3.24 %. The performance enhancement of CL-EEWSN is significant enough to consider for scalable farming applications.

5. Conclusion

In this paper, the CL-EEWSN for large farm fields has been proposed and evaluated against the conventional LEACH, BERA, EECRP and MOEES protocol. The main aim of study is to show the effectiveness of CL-EEWSN concerning energy consumption, quality of service and computational efficiency for large farms. The CL-EEWSN mainly focused to select optimal CH and identifying the most effective route for data transmissions by exploiting the cross-layer parameters. The existing methods employing distance and energy related parameters for cluster head selection and transmission of data which is ineffective to solve the long-distance communication problems in farming applications. In CL-EEWSN, the SNs evaluated by considering network, physical, and MAC layer parameters to achieve more stable and precise clustering as well as data transmissions. In CL-EEWSN, CHs are selected by utilizing the nature inspired algorithm namely WHO and consider parameters of different layers. To learn the network, deep learning-based GEO is employed to find the most efficient path for data transmission. The performance of proposed technique has been compared with LEACH, BERA, EECRP and MOEES under varying SN densities. The experimental results shows that CL-EEWSN solve the shortcomings of existing solutions by reducing average end-to-end delay by 0.69 ms and improved average packet delivery ratio by 3.24 %. At last, it is inferred from results that CL-EEWSN is capable to deploy in large farms.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Data collection, concept, analysis, methodology, original draft preparation and writing—have been done by 1st author. The supervision, analysis, editing, and investigation have been done by 2nd author. The supervision, concept validation, review, investigation and finalization have been done by 3rd author.

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