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A Hybrid Approach for Network Lifetime Enhancement in Wsns with Graph Neural Networks and Probabilistic Regression

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ABSTRACT

Routing protocols energy consumption can heavily influence the network lifetime of a Wireless Sensor Network (WSN). Specifically, to reduce energy, data aggregation is utilized to discard data redundancy at each sensor and minimize the amount of data packet transmitted in a WSN. Moreover, energy-efficient routing is extensively utilized in deciding the optimal route between source and destination, to minimize energy for relaying the sensed data packets. Owing to the energy restrictions of the sensor nodes in WSN, employing an optimal model for routing and controlling WSNs can be efficient in improving energy efficiency and overall network lifetime. To overcome these issues, proposed Deep Correlated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR) method introduced for network lifetime optimization in WSN. Initially, Deep Dominant Correlated and Rescorla Wagner Graph Neural Network are performed where determine the back propagation model lesser dominant and better correlated regions were considered. After that, Gaussian Probabilistic Regression models for network lifetime optimization is performed to obtain the minimum dominant highly correlated regions (i.e., highly correlated sensors) as input and improve the overall network lifetime by tradeoff sensor nodes of minimal dominant highly correlated regions. Finally, simulations were performed to evaluate the performance of the proposed network lifetime optimization method and compared it with that of the conventional methods for improving and optimizing network lifetime and discusses the trade-offs that exist between them. Lifespan of wireless sensor network based on the proposed method is greatly increased whereas the energy consumption, network life time and training time is greatly decreased by the techniques we have proposed.

Keywords: *Wireless Sensor Network, Network Lifetime, Deep Neural Network, Rescorla Wagner, Gaussian Probabilistic Regression*

1. INTRODUCTION

Wireless Sensor Network (WSN) comprises of spatially-distributed autonomous devices communicating in a wireless manner and employing sensors with the intent of acquiring information. It consist of small, low-cost sensors easy to deploy, cost-effective solution for different applications These sensor devices are prospective of sensing, processing and communicating between devices in a simultaneous manner with the intent of performing certain applications like, surveillance, logistic management, health monitoring and so on. The WSN is utilized for processing, analysis, storage, and mining of the data. It eradicates the need for wired connections, which are costly. Wireless communication also enables flexible deployment and reconfiguration of the network.

For example, certain channel features, like, resource constraints, bit error ratio and other quality of service (QoS) requirements play a paramount part in influencing the time span of network's requisite operation, that is referred to as the Network Lifetime (NL). The WSN NL denotes the total amount of time over which the network remains operational and as a result aids the application taken into consideration. Hence, the network's lifetime is considered as one of the most significant influencing factors as far as WSNs is concerned.

A Trust Index Optimized Cluster Head Routing (TIOCHR) method was proposed in [1] that was proved to be energy efficient. Here, cluster head selection was done based on energy backup, data packet consistency and data packet delivery rate. Moreover, with the intent of ensuring, both, integrity and reliability, the most reliable and dependable path out of all of the prospective paths were selected. With this resulted in the overall improvement of energy efficiency and network lifetime.

Energy efficient network was created in [2] employing intelligent clustering that performed clustering in an arbitrary manner in the presence of uncertain parameter and used multi-criterion decision making mechanisms with the objective of selecting energy efficient cluster head. Alsointelligent clustering using Silhouette Index (SI) score was applied that in turn improved number of nodes alive or the overall network lifetime considerably with improved residual energy and computational complexity.

Deep Belief Networks based Routing Protocol (DBN-RP) was proposed in [3] where initially cluster formation was performed using reinforcement learning. Followed by which Mantaray Foraging Optimization (MRFO) algorithm was applied with the intent of selecting cluster head optimally and finally deep learning technique was designed for efficient routing with maximum number of alive nodes (i.e., maximum network lifetime) and energy efficiency.

ELPSO (Ensemble learning particle swarm optimization) and PSO-BPNN (Back-propagation neural network optimized by particle swarm optimization)] ELPSO-PSO-BPNN was proposed in [4] for localization of sensor node based on range. Here, localization was ensured employing ELPSO and PSO-BPNN therefore reducing the localization error significantly.

WSN can be applied to several consumer electronics, to name a few being, environmental monitoring, and smart homes and so on. The structural features of the sensors themselves decide that their performance is very constrained in all facets. As a result the optimizationobjective is specifically to improve the overall network lifetime while constructing a definite coverage quality on the basis of arbitrary organization.

Broad transfer learning network was applied in [5] with the objective of designing batter lifetime prediction in an extensive manner. However the energy consumption involved in the process was not analyzed. To address on this gap, stacked auto encoder and probabilistic neural network was presented in [6] with the intent of predicting distance between unknown and known nodes. This in turn reduced the overall energy consumption. Nevertheless the mean square error involved in prediction was not focused. To address on this gap, transfer learning technique was applied in [7]. Here, by using this technique by fusing Bayesian Model and Weighted Orthogonal Matching Pursuit aided in minimizing the root mean square error in an extensive manner.

In aWSN, when a large amount of sensors are organized in an arbitrary manner into a detection area, an effective sleep/active scheduling for sensors to improve the network lifetime of detection area is referred to as the coverage problem, contemplated as a paramount issue. To focus on the error involved in network lifetime optimization, a cell based transfer learning method was applied in [8]. Here by employing the cell based transfer learning a new method for localization that was found to be strong enough to the differences of nodes density was designed that in turn not only ensured accuracy but also improved robustness. Yet another method to ensure optimal quality of sensing coverage in WSN employing deep reinforcement learning was presented in [9].

By using the Deep Q Network in turn resulted in the convergence stage stability. A feasible scheduling mechanism employing Maximum Coverage Sets Scheduling was proposed in [10]. Here by identifying a feasible scheduling for coverage set collection in turn resulted in optimal network lifetime. However the network coverage efficiency was not focused. To address on this gap, a learning automata approach was proposed in [11] that in turn selected the best logical partition at each interval therefore improve the network coverage in an extensive manner. Deep learning technique with long short term memory was applied in [12] for ensuring energy efficient transmission in WSN.

Numerous courses of actions are utilized to demonstrate the network performance, to name a few being, average number of hops packets to reach destinations and its corresponding network lifetime, depending on the energy and power consumption at that node. Therefore, load balancing over the sensors in WSN can notable improve the overall network lifetime. Lagrangean heuristic strategy was applied in [13] for lifetime maximization in WSN. Deep reinforcement learning was applied in [14] for extending network lifetime by initially balancing the loads and then employing alternative routes to dispatch the packets in an extensive manner. Yet another method to ensure quality routing in WSN was designed in [15] employing blockchain architecture. Though quality routing was ensured but at the cost of energy consumption.

1.1 The novel Contributions of the proposed work

To inscribe the above mentioned issues, the subsequent contributions are put together in the proposed work. The contributions of the proposed method, proposed DeepCorrelated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR) is listed below.

- A proposed DCGNN-GPR method is designed to optimize the network lifetime in wireless sensor network with mean square error based on two major processes such as minimal dominant highly correlated region and network lifetime optimization.
- A novelty of three-dimensional correlations model and based on the convergence highly correlated nodes with minimal dominant set were selected for further processing on the basis of feed forward neural network.
- A novelty of Gaussian Probabilistic Regression method uses proposed DCGNN-GPR method utilized to tradeoffs based on lowest residual energy of each dominating set by improve the overall sensor nodes being address for data aggregation process, therefore boosting the overall network lifetime
- RescorlaWagner rule to fine-tune the weight for validating the sensors and arrive at the objective function to improve the scheduling time and minimum mean absolute error via proposed DCGNN-GPR method is designed.
- Finally, comprehensive experimental assessment is carried out with four different types of parameters namely; energy consumption, network lifetime, and scheduling time and mean absolute error to illustrate the proposed DCGNN-GPR method over traditional methods.

1.2 Organization of the work

The structuring of the remaining manuscript is carried out in thefollowing manner. Section 1 presents introduction pertaining to network lifetime optimization in WSN using machine learning, deep learning and optimization techniques while thesubject matter of Section 2 is the related work. Section 3 provides the elaborate description of the proposed DeepCorrelated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR) method while the experimental setup is given in Section 3.Moving ahead, the model's extensive evaluation by means of graphical representation and tabulation format is providedin Section 5. Finally, the paper is concluded in Section 6.

2. RELATED WORKS

WSN is a fusion of numerous sensors positioned on physical devices that dispersed geographically to acquire data on the basis of different application. The dispersed nodes can be split into groups with the intent of delivering information to base station (BS). In most WSN applications, it is not probable to recharge sensor node batteries. The major issues in WSNs are selection of optimal number of CHs, coverage of network in an optimal fashion, stability and network lifetime to name a few.

An energy management strategy employing deep transfer learning was proposed in [16] for prediction-based schemes to improve network lifetime in an extensive manner. To ensure effective transfer preprocessing and feature mapping were applied for both source and target data. Yet another method to maintain connectivity employing Delaunay triangulation and enhanced virtual force algorithm was presented in [17] to not only circumvent the presence of environmental hurdles but also prolonging network connectivity. A method combining Extreme Learning Machine and Bat algorithm for heterogeneous wireless network to prolong network lifetime was designed in [18]. However premature convergence was not focused. To address on this issue, an improved grey wolf optimization algorithm was presented in [19]. Here by employing this optimization algorithm not only the premature convergence was avoided but also enhanced the WSN's lifetime.

Network lifetime (NL) optimization methods have received a lot of research awareness among industry and research persons due to their significance for improving duration of operations in battery-constrained WSNs. An algorithm based on reinforcement learning for efficient management of energy was proposed in [20]. Here three different approaches to navigate correctly, design sleep scheduling and restrict data transmission separately were presented with which based on the received data change rate improved overall network lifespan. A two-stage NL maximization technique was proposed in [21] using exhaustive search algorithm that in turn prolonged network lifetime. A hybrid routing protocol was designed in [22] to improve network lifetime by combining particle swarm optimization and genetic algorithm. Yet another enhanced energy optimization model was designed in [23] to ensure higher efficiency and longer network lifetime.

In [24] a Q-learning based data aggregation model was designed with the intent of extending the lifetime of WSN via sensor-type-dependent aggregation rewards. Location information were used in [25] by utilizing hybrid positioning algorithm to make full utilization of sensor node energy with the objective of prolonging network lifetime. A summary of existing methods, technology employed, advantages, drawbacks and the dataset in used are provided in Table 1.

Table 1 Existing methods summary

Reference	Work	Methodology	Advantages	Drawbacks
[1]	Lifetime improvement of	Trust Index Optimized Cluster Head Routing	Energy efficiency and	Scheduling time

	wireless sensor network	(TIOCHR)	network lifetime	
[2]	Improvement of WSN lifetime	Intelligent Clustering Under Uncertainty	Residual energy and computational complexity	Mean absolute error
[3]	Efficient data transmission in WSN	Deep Belief Networks based Routing Protocol (DBN-RP)	Maximum network lifetime and energy efficiency	Mean absolute error
[4]	Sensor node localization	ELPSO-PSO-BPNN	Localization error	Energy consumption
[10]	Maximizing network lifetime	Maximum Coverage Sets Scheduling	Network lifetime	Energy consumption
[11]	Lifetime expansion in WSN	Learning automata	Network lifetime and energy efficiency	Mean absolute error
[14]	Extending wireless sensor network's lifetime	Deep reinforcement learning	Energy consumption and network lifetime	Scheduling time
[19]	Network lifetime enhancement	Improved grey wolf optimization	Network lifetime	Energy consumption
[22]	Network lifetime improvement	Hybrid routing protocol	Network lifetime	Energy consumption
[25]	Lifetime optimization algorithm	Hybrid positioning algorithm	Network lifetime	Scheduling time and energy consumption

Most of traditional network lifetime maximization algorithms are generally employing machine learning to aggregate data packet and to identify optimum route to sink. However, they havenot considered correlation between sensor nodes, in which they depend on. To capture correlation between sensor nodes, deep learning-based evaluation mechanism is required. In this article,we propose a Deep Wagner Graph Neural Network and Gaussian Probabilistic Regression (DWGNN-GPR) for network lifetime optimization in WSN. The elaborate description of the DWGNN-GPR method is provided in the following sections.

3. METHODOLOGY

As our economic and energy systems become progressively connected, there uneven energy depletion phenomenon of sensor nodes gets more eminent and hence becomes the requirement for energy efficient methods. These sensor nodes diffuse or spread rapidly and eventually die down. Network lifetime (NL) maximization techniques in WSN have received a great deal of research awareness due to the significance for increasing the duration of the operations in the battery-constrained WSNs. In this work a two-stage network lifetime optimization method for a fully connected WSN called, DeepCorrelated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR) is proposed. During the first stage minimal dominated highly correlated region is formulated using Deep Dominant Correlated and Rescorla Wagner Graph Neural Network. The second stage involves the design of Gaussian Probabilistic Regression models for network lifetime optimization. The DCGNN-GPR for network lifetime optimization in WSN structure is illustrated in figure 1.

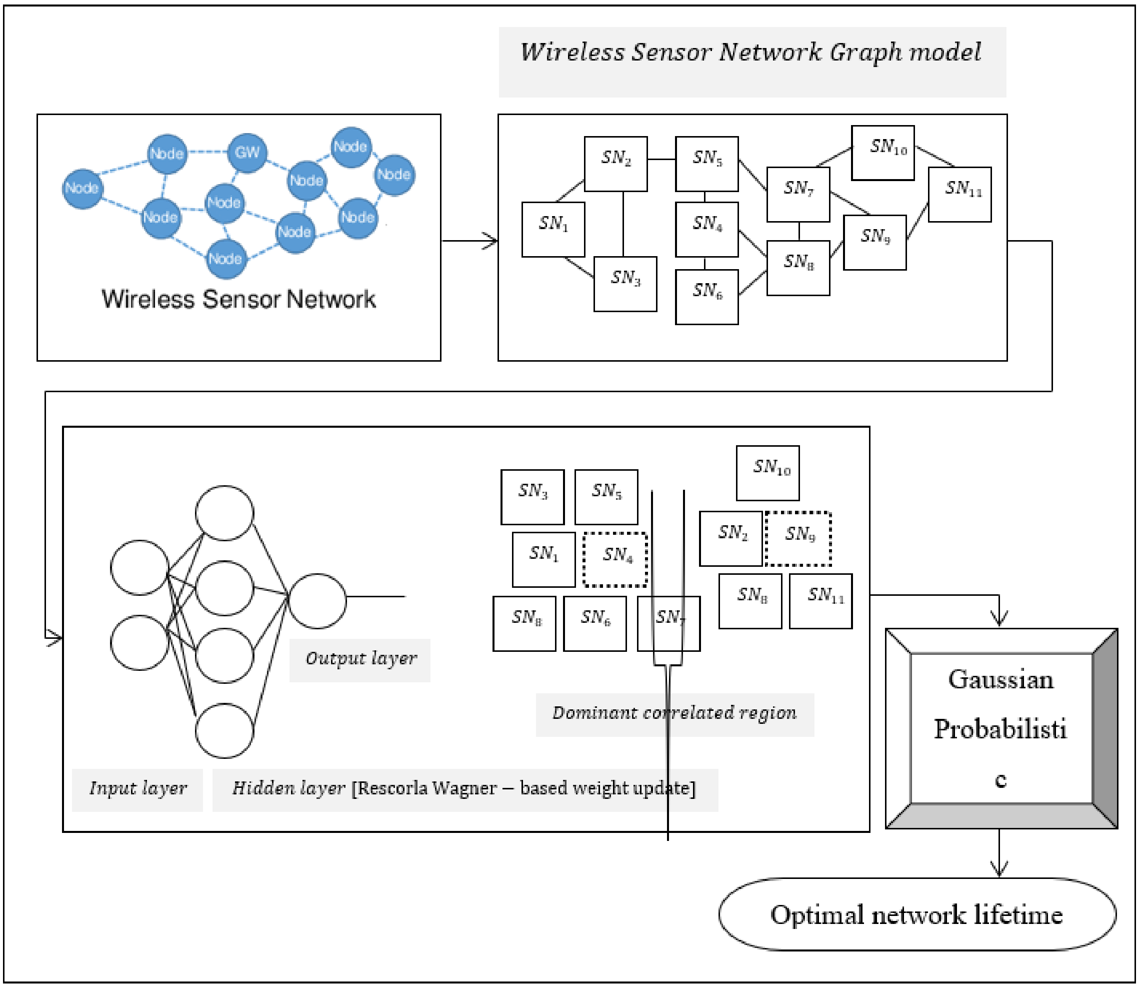

Figure 1 Structure of DeepCorrelated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR)

As illustrated in the above figure initially, Deep Dominant Correlated and Rescorla Wagner Graph Neural Network is designed with the objective of identifying minimal dominant with highly correlated region. Here sensor nodes with highly correlated region is identified then from them minimal dominant sensor node with least amount of residual energy is obtained for further processing. From the above figure initially two correlated regions are formulated followed by which minimal dominant sensor nodes in the two correlated regions are identified to be 'SN_4' and 'SN_9' respectively. These are performed in the hidden layer. Next in the output layer, Gaussian Probabilistic Regression models for network lifetime optimization are performed.

3.1 Network model

Let us consider Wireless Sensor Network (WSN) graph '$G = (V, E)$', where '$V \in SN$' denotes the set of vertices referred to as sensor nodes and '$E \in e_i$' denotes the set of edges that connects sensor nodes of the WSN for efficient and optimal communication. Moreover, we will consider that all sensor nodes in WSN possess the same range of communication. In a graph 'G' any subset 'S' is referred to as the dominating set such that '$S \subseteq V$' and each vertex '$v \in V$' is said to be proximity to at least one vertex in graph '$G = (V, E)$' by splitting the network into correlated regions.

In this work the issue of network lifetime improvement in WSN is addressed using minimal dominant highly correlated region where numerous sensors take control of homogeneous copy of data owing to close spatial proximity and called as minimal dominant correlated region. Once this is accomplished, the overall network lifetime is evaluated by summing up the life spans of each of separated dominant correlated regions. Here, the least amount of energy in a specific correlated region is referred to as minimal dominant correlated region.

3.2 Deep Dominant Correlated and Rescorla WagnerGraph Neural Network

To start with the state vector '$SV \in R^D$' is formulated by taking into consideration the features involved in process (i.e., degree of sensor node, proximity sensor node, label of sensor node) that is associated with each sensor node. To evaluate state vector with 'D' dimension of each sensor node, the idea behind feed forward neural network (FFNN) is employed by designing a fine-tuned adaptation network. In conventionaladaptation network based on the state vector 'SV', sensor node 'n' generate output 'Out_n'.

In our work by taking into consideration the conventional adaptation network and minimal dominant highly correlated region is employed. This is performed by evaluating its neighboring sensor node difference between spherical caps 'SC' and output function that generates output denoted by local output function 'Out_{SC}' respectively. Then, the mathematical representation of state vector 'SV' as a function of spherical caps 'SC' is represented as given below. Let us suppose that two sensor nodes 'SN_i' and 'SN_j' are positioned at '$(0,0,0)$' and '$p_{ij}, 0,0$'. Then sensing region for two sensor nodes 'SN_i' and 'SN_j' are represented as given below.

$$SV_i = p^2 + q^2 + r^2 = R_i^2 \quad (1)$$

$$SV_j = \left(p - p_{ij}\right)^2 + q^2 + r^2 = R_j^2 \quad (2)$$

From the above equations (1) and (2), 'p_{ij}' denotes the distance between two sensor nodes 'SN_i' and 'SN_j' with sensing ranges represented as 'R_i' and 'R_j' respectively for two different state vectors 'SV_i', 'SV_j'. Each sensor node 'SN_n' has its own label, 'SN_i' and it's proximity node 'SN_j'. Then, there represents a feed forward neural network associated with each sensor node. Based on the number of proximity sensor nodes frequency of input patterns also differ.

In this work a three-dimensional correlation model performs linearly and is defined based on the convergence. Let us consider that two sensors 'SN_i' and 'SN_j' are positioned at '$(0,0,0)$' and '$\left(p_{ij}, 0,0\right)$' as illustrated in figure 2.

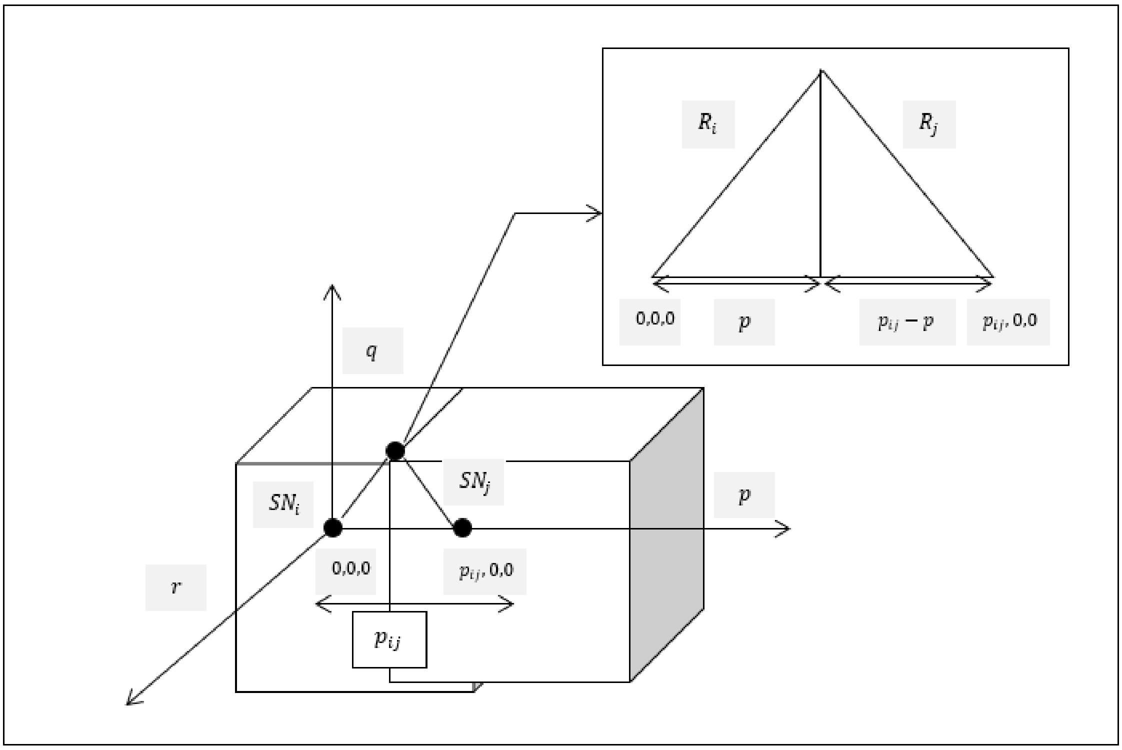

Figure 2 Structure of three-dimensional correlations model

The convergence of two sensor nodes 'SN_i' and 'SN_j' characterizes a three-dimensional correlations model and the volume of two spherical caps 'SC' is determined based on the height as given below.

$$H_i = \frac{(R_i - R_j + p_{ij})(R_i + R_j - p_{ij})}{(2p_{ij})} \quad (3)$$

$$H_j = \frac{(R_j - R_i + p_{ij})(R_i + R_j - p_{ij})}{(2p_{ij})} \quad (4)$$

With the obtained height 'H_i' and 'H_j' from the above equations (3) and (4) for two spherical caps 'SC' i.e., two sensor nodes

'SN_i' and 'SN_j' the aggregated volume between two sensor nodes 'SN_i' and 'SN_j' is then mathematically obtained as given below.

$$Vol_{agg} = Vol\,(R_i, H_i) + Vol(R_j, H_j) \tag{5}$$

$$Vol\,(R_i, H_i) = \frac{\pi}{3} H_i^2 (3R_i - H_i) \tag{6}$$

$$Vol\,(R_j, H_j) = \frac{\pi}{3} H_j^2 (3R_j - H_j) \tag{7}$$

With the above aggregated volume results as given in equations (5), (6) and (7), this computing is designed as a recurrent network consisting of units and fine-tuned adaptation networks that measure the correlation coefficient between two sensor nodes 'SN_i' and 'SN_j' the units or nodes associated from the point of view of graph topology.

Each sensor node in a graph in turn has an output network on the basis of feed forward neural network that obtains or acquires as input the balanced node state acquired from recurrent network and its subsequent node label. The output 'Out' is then measured for each sensor node 'SN' is mathematically formulated using the local output function '$\rho(i,j)$' as given below.

$$\rho(i,j) = \frac{Vol_i^j + Vol_j^i}{Vol} \tag{8}$$

From the above equation (8), the correlation coefficient '$\rho(i,j)$' between two sensor nodes 'SN_i' and 'SN_j' is expressed to measure highly correlated sensor nodes in proximity

$$DS = \rho(i,j) = \begin{cases} 1, if\ 0 \leq p_{ij} < CORR,\ Where\ CORR = 2R \\ 0, if\ p_{ij} \geq CORR,\ Where\ CORR = 2R \end{cases} \tag{9}$$

From the above equation result (9) the resultant value of correlation coefficient between two sensor nodes 'SN_i' and 'SN_j' '$\rho(i,j)$' is zero when sensing regions do not converge with each other. On the other hand, the resultant value of correlation coefficient between two sensor nodes 'SN_i' and 'SN_j' '$\rho(i,j)$' is non-zero when sensing regions have common sensing region. In this manner highly correlated region is initially formed and then the minimal of highly correlated region node is selected as the dominating set.

3.3 Rescorla Wagner-based Weight Update

As mentioned in the above section graph neural network deep learning based feed forward network consists of adaptation and output network. Here, the weight has to be fine-tuned in both adaptation and output networks. So, to perform fine-tuning of weight updates, we employ RescorlaWagnerrule. As far as conventional back propagation function is concerned, weight updates are performed by means of gradient descent function as given below.

$$\Delta\omega(t) = -\eta \frac{1}{n} \sum_{i=1}^{n} (\alpha_i - \beta_i)^2 \tag{10}$$

From the above equation (10), 'η' denotes the learning rate to formulate the weight updates based on the proposed output 'β_i' and network output 'α_i' respectively.

With the intent of boosting learning rate and network lifetime, stability, we consider classical conditioning using the RescorlaWagner rule for obtaining the updated weight and hence fine-tuned updated weight rule is mathematically stated as given below.

$$\Delta\omega(t)[SN] = \alpha SN \beta(\lambda) - \eta \frac{1}{n} \sum_{i=1}^{n} (\alpha_i - \beta_i)^2 \tag{11}$$

The RescorlaWagner rule being a classical conditioning operates on the principle of terms of association between two sensor nodes 'SN_i' and 'SN_j'. From the above equation (11) results the updated weight rule is obtained by considering the salience of sensor node 'α' (lying between '0' and '1'), 'β' the rate parameter for receiving sensor node 'SN_j' (lying between '0' and '1'), 'λ' the maximum associative strength (i.e., maximum possible data packet reception) for receiving sensor node 'SN_j', '$\Delta\omega(t)[SN]$', the current associative strength of sensor node respectively.

3.4 Gaussian Probabilistic Regression models for network lifetime optimization

Once the highly correlated region with minimal dominant sensor node possessing least amount of residual energy is identified by Deep Dominant Correlated and Rescorla Wagner Graph Neural Network, after that highly correlated minimal dominating set to measure network lifetime of WSN using the proposed Gaussian Probabilistic Regression models is presented in this section. The Gaussian Probabilistic Regression model generates an index of all the tradeoffs based on lowest residual energy of each sensor nodes present in the dominating set. In the generated tradeoff index, few tradeoffs in this index may have the probability to reduce the network lifetime.

Nevertheless, it conducts only on that tradeoff that will result in the greatest optimization in network lifetime and includes this tradeoff index to keep track of it. This process is said to be carried on with as long as there are feasible tradeoffs accessible. Moreover, if two sensor nodes 'SN_i' and 'SN_j' are tradeoff in any of the stages, next steps will not have a tradeoff necessitating the same two nodes. Figure 3 shows the structure of Gaussian Probabilistic Regression models for network lifetime optimization.

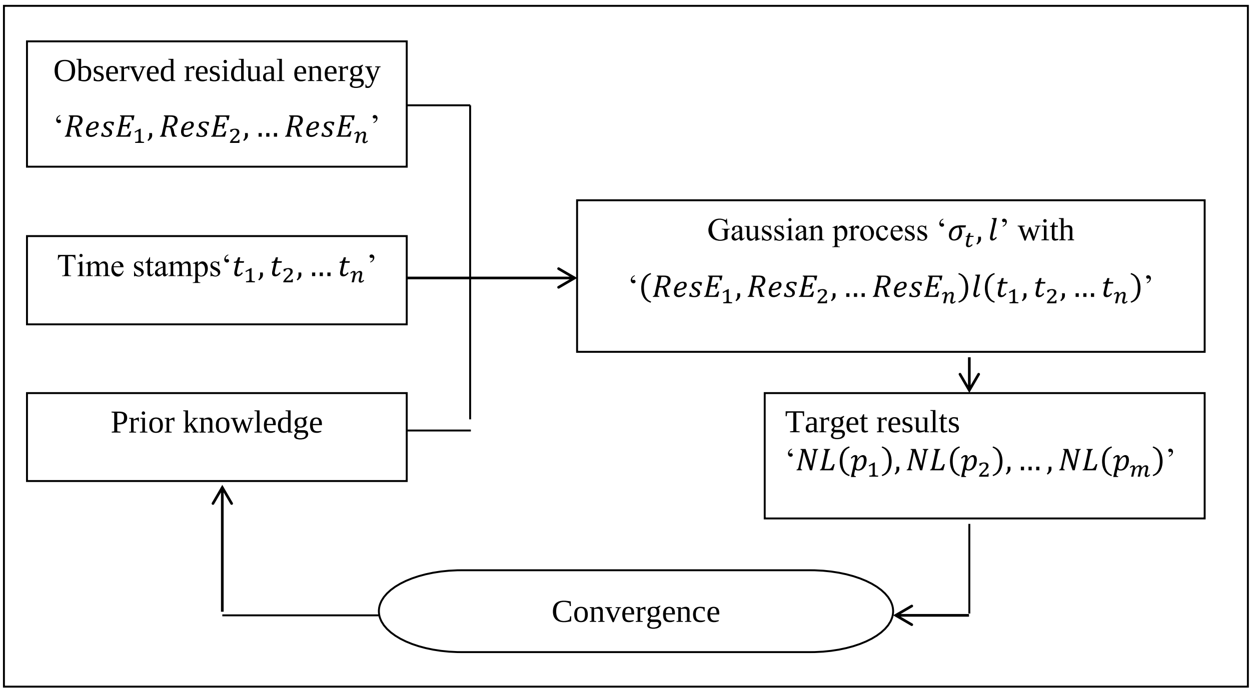

Figure 3 Structure of Gaussian Probabilistic Regression models for network lifetime optimization

As illustrated in the above figure residual energy of 'n' sensor nodes are observed at different time stamps '$t_1, t_2, \dots, t_n$'. With Gaussian Probabilistic Regression being fine-tune updates of two different parameters, variance 'σ_t' and length 'l', regression is performed in an extensive manner by identifying a prior and then fine-tuning in an iterative manner to generate posterior with optimal network lifetime.

To start with initially, the network lifetime of a sensor node in dominating set 'DS' having lowest residual energy is obtained using the following equation as given below.

$$LResE = \sum_{i=1}^{n} \frac{ResE(SN_i)}{IE(SN_i)} \quad (12)$$

From the above equation (12) the sensor node with lowest residual energy '$LResE$', is obtained using the residual energy of each sensor node '$ResE(SN_i)$' in dominating set 'DS' and the initial energy of each sensor node '$IE(SN_i)$' respectively. Following which the network lifetime is measured using Gaussian Probabilistic Regression function. For a training set '(p_i, q_i)' the Gaussian Probabilistic Regression function is formulated as given below.

$$NL = Prob(q|f, p) \sim n(q|HB + f\sigma^2) \quad (13)$$

$$B = PNL - ANL \quad (14)$$

From the above equations (13) and (14) the network lifetime 'NL' is measured by taking into consideration the Gaussian process 'f' with zero mean for each sample sensor node 'p', 'H' projecting the sample sensor node into feature space, 'B' bias referring to the error that is introduced by the model's network lifetime prediction 'PNL', actual network lifetime 'ANL' and error variance 'σ^2' respectively.

With the objective of the work being to maximize the network lifetime, total network lifetime is measured repeatedly for each tradeoff node till optimized and maximized network lifetime is arrived at. By employing this Gaussian Probabilistic Regression function to obtain the optimized and maximized network lifetime in turn minimizes the mean squared errors. The pseudo code representation of DeepCorrelated Graph Neural Network Gaussian Probabilistic Regression for network lifetime optimization in WSN is given below.

Input: Sensor Node '$SN = \{SN_1, SN_2, \dots, SN_n\}$'

Output: Error-minimized optimal network life time
Step 1: **Initialize** 'n', sensing radius of 'SN_i' as 'R_i', sensing radius of 'SN_j' as 'R_j'
Step 2: **Initialize** 'α' (lying between '0' and '1'), 'β'(lying between '0' and '1')
Step 3: **For** two sensor nodes 'SN_i' and 'SN_j'
//Input layer
Step 4: Obtain sensing region as given in equations (1) and (2)
Step 5: Evaluate height for three-dimensional correlation model as given in equations (3) and (4)
Step 6: Measure aggregated volume between two sensor nodes 'SN_i' and 'SN_j' as given in equations (5), (6) and (7)
Step 7: Measure correlation coefficient '$\rho(i,j)$' between two sensor nodes 'SN_i' and 'SN_j' as given in equation (8)
//Hidden layer
Step 8: **If** '$\rho(i,j) = 0$'
Step 9: **Then** sensing regions do not converge with each other
Step 10: **End if**
Step 11: **If** '$\rho(i,j) \neq 0$'
Step 12: **Then** sensing regions have common sensing region
Step 13: **End if**
Step 14: Fine-tune weight in both adaptation and output network using RescorlaWagner rule as given in equations (10) and (11)
Step 15: **Return** dominating set 'DS'
//Output layer
Step 16: Measure lowest residual energy in dominating set 'DS' as given in equation (12)
Step 17: Measure sensor network lifetime in dominating set 'DS' as given in equations (13) and (14)
Step 18: **End for**
Step 19: **End**

Algorithm 1 DeepCorrelated Graph Neural Network Gaussian Probabilistic Regression

As given in the above algorithm with the objective of imparting optimal network lifetime a two-stage processing model comprising of DeepCorrelated Graph Neural Network and Gaussian Probabilistic Regression is designed via three different layers, input layer, hidden layer and finally output layer. Here, the initialized sensor nodes are subjected to three-dimensional correlation models where aggregated volume between sensor nodes is evaluated. This in turn reduces the overall training time involved in determining network lifetime. Second in the hidden layer, minimal dominating set with maximal or highly correlated region is observed by means of RescorlaWagner rule or function. By applying this RescorlaWagner rule or function that by working on the operation of the principle of terms of association between two sensor nodes in turn assists in reducing energy consumption significantly. Finally, in the output layer, Gaussian Probabilistic Regression for network lifetime optimization is applied that by means of optimal bias, mean absolute error is also reduced in an extensive manner.

4. EXPERIMENTAL SETUP

In this section, simulation of the proposed DeepCorrelated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR) for network lifetime optimization in WSN and existing four methods, Trust Index Optimized Cluster Head Routing (TIOCHR) [1], Intelligent Clustering Under Uncertainty [2], Deep Belief Networks based Routing Protocol (DBN-RP) [3] and ELPSO (Ensemble learning particle swarm optimization) PSO-BPNN (Back-propagation neural network optimized by particle swarm optimization)] ELPSO-PSO-BPNN [4] are implemented in Python by means of graphical user interfaces using health monitoring system employing dataset obtained from =

https://www.kaggle.com/datasets/nraobommela/health-monitoring-system. The dataset comprises of 4286 patient data or sample instances with an overall of 20 features. Moreover, different sensors are positioned in patient body and acquire the information's to name a few being, temperature, heart rate, pulse, blood pressure, respiratory rate, oxygen saturation, PH and so on. Based on the collection of the sensor data, the network lifetime of WSN is evaluated. For experimental purpose different numbers of sensor nodes ranging between 50 and 500, in addition to different data packet in the range of 100 to 1000 is taken into consideration.

5. RESULTS AND DISCUSSION

The proposed Deep Correlated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR) for network lifetime optimization in WSN and different existing methods [1], [2], [3] and [4] are conducted on different performance metrics listed below,

- Energy consumption
- Network lifetime
- Scheduling time
- Mean absolute error

The detail explanation of different parameters described in below section.

5.1 Performance analysis of energy consumption

In this section the energy consumption involved in the process of data aggregation or obtaining aggregated volume resultsfor measuring correlation coefficient between two sensor nodes is performed. This is mathematically stated as given below.

$$EC = n * Con_E\ (sensing\ single\ sensor\ node) \quad (15)$$

From the above equation (15) energy consumption 'EC' is measured based on the sensor nodes involved in the simulation process 'n' and the actual energy consumption of single sensor node to measure how correlated it is with respect to the other sensor nodes in vicinity '$Con_E\ (sensing\ single\ sensor\ node)$'. It is measured in terms of joules. Table 2 shows the energy consumption analysis of the proposedDCGNN-GPR method compared with four other methods, TIOCHR [1], Intelligent Clustering Under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4] respectively.

Table 2 Comparison of Energy consumption analysis using DCGNN-GPR, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4]

Sensor nodes	Energy consumption (Joules)				
	DCGNN-GPR	TIOCHR [1]	Intelligent Clustering Under Uncertainty [2]	DBN-RP [3]	ELPSO-PSO-BPNN [4]
50	0.001	0.002	0.003	0.004	0.04
100	0.003	0.005	0.007	0.008	0.065
150	0.009	0.0010	0.0012	0.015	0.07
200	0.012	0.015	0.019	0.024	0.092
250	0.017	0.019	0.024	0.027	0.068
300	0.025	0.027	0.029	0.03	0.15
350	0.028	0.031	0.035	0.04	0.135
400	0.035	0.043	0.047	0.052	0.155
450	0.041	0.048	0.055	0.067	0.18
500	0.050	0.060	0.069	0.075	0.2

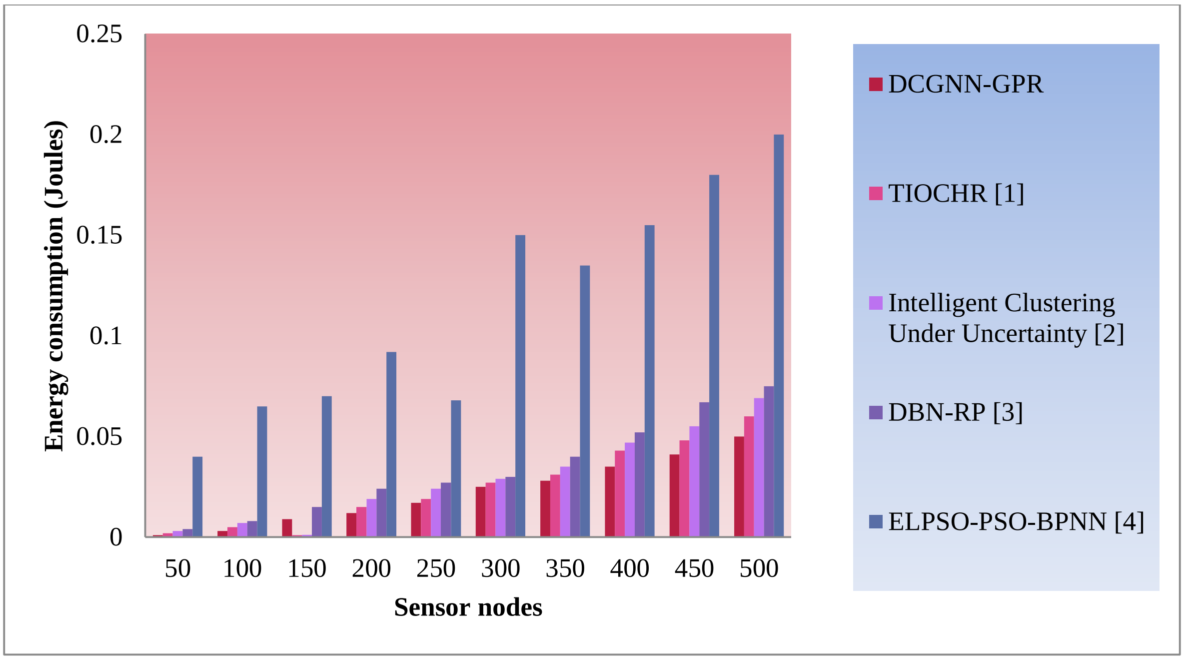

Figure 4 Comparisons of energy consumption using DCGNN-GPR, existing [1], [2], [3] and [4]

Figure 4 given above shows the graphical representation of energy consumption using the proposed DCGNN-GPR method and four existing methods, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3], ELPSO-PSO-BPNN [4] respectively. From the above figure x axis represents 500 different sensor nodes ranging between 50 and 500 and y axis represents the energy consumption of it correspondingly. Increasing the number of sensor nodes subsequently causes an increase in the energy consumption though simulations performed with respect to 50 sensor nodes consumed energy of 0.001 using proposed DCGNN-GPR method, 0.002Joules using [1], 0.003Joules using [2], 0.004 Joules using [3] and 0.04Joules using [4] respectively. With this analysis the energy consumption for 50 different sensor nodes using proposed DCGNN-GPR method was observed to be better than [1], [2], [3] and [4]. The reason was due to the application of fine-tuned adaptation network with respect to minimal dominant highly correlated region. Also to evaluate state vector with 'D' dimension of each sensor node, feed forward neural network (FFNN) was employed associated with each sensor node. Also based on the number of proximity sensor nodes frequency of input patterns also differ. Finally with the application of three-dimensional correlations model and based on the convergence highly correlated nodes with minimal dominant set was performed. This in turn reduced the energy consumption using proposed DCGNN-GPR method by 61%, 35% and 42% compared to [1], [2], [3] and [4] respectively.

6. PERFORMANCE ANALYSIS OF NETWORK LIFETIME

The network lifetime is defined as the time span from the deployment of wireless sensor network formation to the time when the overall network becomes nonfunctional. Network lifetime in our work is mathematically stated as given below.

$$NL = \left(\frac{SN_{addressed}}{n}\right) * 100 \qquad (16)$$

From the above equation (16), network lifetime 'NL' is expressed based on the number of sensor nodes involved in simulation process 'n' and the sensor nodes addressed in the aggregation process for obtaining highly correlated dominating region '$SN_{addressed}$'. The network lifetime is measured in terms of percentage (%). Table 3 given below shows the network lifetime analysis of the proposed DCGNN-GPR method and existing four other methods, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4] respectively.

Table 3 Comparison of Network lifetime analysis using DCGNN-GPR, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4]

Sensor nodes	Network lifetime (%)				
	DCGNN-GPR	TIOCHR [1]	Intelligent Clustering Under Uncertainty [2]	DBN-RP [3]	ELPSO-PSO-BPNN [4]

50	98.35	96.35	95.35	94	92
100	98	96.25	94.35	92	91.15
150	97.45	95.15	93.25	91.33	90
200	96.35	94	92	91	89.15
250	97.85	95.25	93	92	90
300	98	96	94	92.33	91.15
350	98.55	96.55	94.35	93.14	92
400	97.45	95.25	93	92.5	90
450	95.25	93.85	91.55	90.22	88.25
500	94	92	90	88.6	85

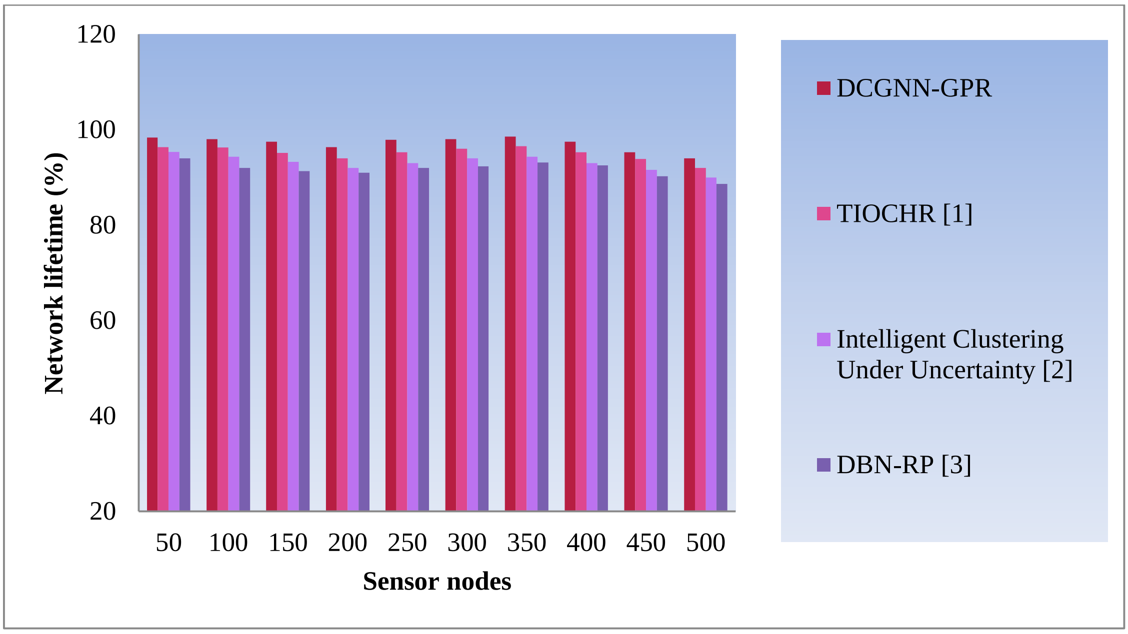

Figure 5 Comparisons of network lifetime using DCGNN-GPR, existing [1], [2], [3] and [4]

Figure 5 given above illustrates the graphical representation of network lifetime using the four methods, DCGNN-GPR, TIOCHR [1], intelligent clustering under uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4] respectively. With 500 sensor nodes represented in the horizontal direction, the equation results of 16 was applied to arrive at the network lifetime results in the vertical direction for an average of 10 simulation runs. From the above graphical representation, it is evident that the network lifetime is said to be neither inversely proportional nor directly proportional to each other (i.e., between sensor nodes and network lifetime). Nevertheless, simulations performed for 50 sensor nodes the network lifetime was found to be 98.35% for DCGNN-GPR method, 96.35% for [1], 95.35% for [2], 94% for [3] and 92% for [4] respectively. With this inference the energy consumption was found to be comparatively better using DCGNN-GPR method upon comparison to [1], [2], [3] and [4]. The reason was due to the application of Gaussian Probabilistic Regression model. By applying this model an index of all the tradeoffs based on lowest residual energy of each dominating set was initially measured. Then in the generated tradeoff index, tradeoff that results in the greatest optimization in network lifetime was retained and also mechanism was included to keep track. Also, the procedure was carried out as long there resulted in feasible tradeoffs. Also, if two sensor nodes were found to be tradeoff in any of the stages, the consecutive steps need not had a tradeoff necessitating for the same two nodes. This in turn aided in the improvement of network lifetime using DCWGNN-GPR method by 2%, 4%, 6% and 8% respectively.

6.1 Performance analysis of scheduling time

Third in this section the scheduling time refers to the process of scheduling the sensor node appropriately. The scheduling time is mathematically stated as given below.

$$ST = n * Time\ [S] \quad (17)$$

From the above equation (17) scheduling time 'ST' is measured by taking into considerationsthe number of sensor nodes involved in simulation process '$n * Time\ [S]$' and the time consumed in scheduling the appropriate node in the dominating set via measuring highly correlated region. Table 4 given below shows the scheduling time analysis of the proposedDCGNN-GPR method, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4] respectively.

Table 4 Comparison Scheduling time analysis using DCGNN-GPR, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4]

Sensor nodes	Scheduling time (ms)				
	DCGNN-GPR	TIOCHR [1]	Intelligent Clustering Under Uncertainty [2]	DBN-RP [3]	ELPSO-PSO-BPNN [4]
50	5.55	6.25	7.55	8.25	9.5
100	6.35	6.85	8.35	10.5	11.15
150	7	7.35	9.25	12.75	14
200	7.25	7.85	11.15	13.6	14.85
250	7.55	8.15	12	14.75	15.35
300	8.15	9.35	12.85	15	15.85
350	9.35	10.25	13.55	16.1	17
400	10.55	11	14.15	17.2	17.35
450	10.75	11.35	15.55	17.55	17.85
500	11	13	16.35	18	19

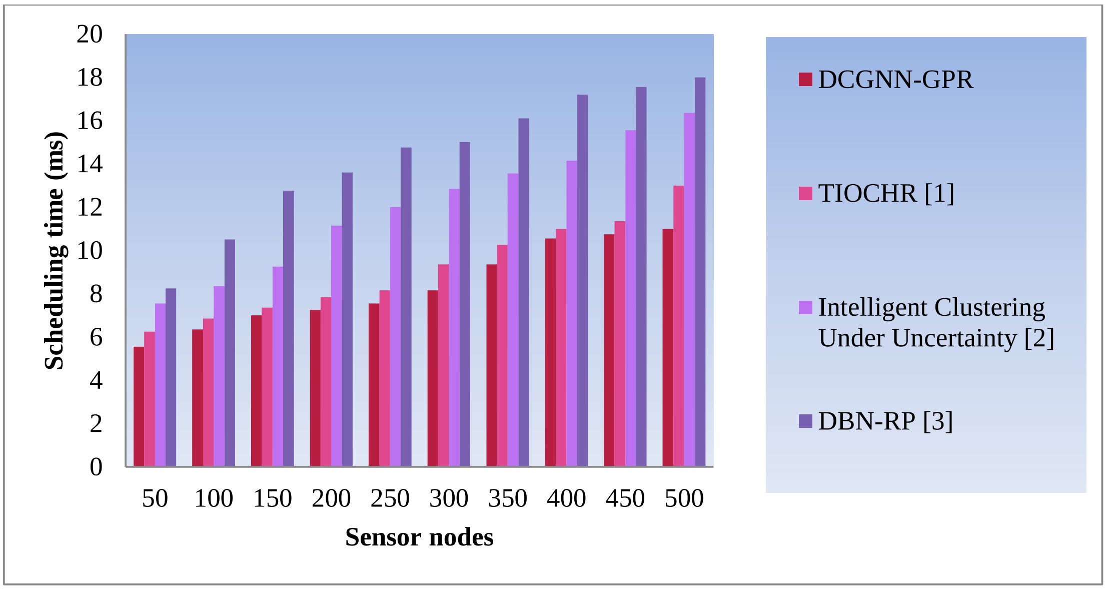

Figure 6 Comparison of scheduling times using DCGNN-GPR, existing [1], [2], [3] and [4]

Figure 6 given above shows the graphical representation of scheduling times using five methods, DCGNN-GPR, TIOCHR

[1], intelligent clustering under uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4]. From the above figure the scheduling time using all the five methods were found to be directly proportionate with the increasing number of sensor nodes. Also, from the simulation results by substituting the values in equation (17), the scheduling time using the five methods were observed to be 5.55ms, 6.25ms, 7.55ms, 8.25ms and 9.5ms respectively. From this result the scheduling time for sensor node in appropriate minimal dominating highly correlated region using DCGNN-GPR method was found to be comparatively better than [1], [2], [3] and [4]. The improvement in scheduling time using DCGNN-GPR method was due to the application of fine-tuning of weight updates employing the RescorlaWagner function. Also the classical conditioning was fine-tuned using the Rescorla Wagner rule for obtaining updated weight and hence fine-tuned updated weight rule. The fine-tuned updated weight rule using RescorlaWagner function in turn increases the learning pace while maintaining the network stability. This in turn reduces the scheduling time using DCGNN-GPR method by 8% [1], 30% [2], 42% [3] and 45% [4] respectively.

6.2 Performance analysis of mean absolute error

Finally in this section the mean absolute error involved in mapping entire input data withoutput data correctly, with very little or no error. The mean absolute error is mathematically formulated as given below.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(Pred_i - Act_i) \qquad (18)$$

From the above equation (18) the mean absolute error 'MAE' is measured based on the predicted output '$Pred_i$' and actual output 'Act_i'. It is measured in terms of percentage (%). Table 5 given below provides the mean absolute error analysis of the proposed DCGNN-GPR method, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4] respectively.

Table 5 Comparison of Mean Absolute Error analysis using DCGNN-GPR, TIOCHR [1], Intelligent Clustering under Uncertainty [2], DBN-RP [3] and ELPSO-PSO-BPNN [4]

Sensor nodes	Mean absolute error (%)				
	DCGNN-GPR	TIOCHR [1]	Intelligent Clustering Under Uncertainty [2]	DBN-RP [3]	ELPSO-PSO-BPNN [4]
50	1.35	1.85	2.25	2.45	3
100	1.65	2.15	3	3.85	4.25
150	1.95	2.55	3.45	4.15	4.85
200	2.25	3	3.75	4.55	5
250	2.85	3.45	4.25	5	5.35
300	3	4	4.85	5.35	5.95
350	3.15	4.55	5	6	6.85
400	3.35	4.85	5.35	6.25	7.25
450	4	5.35	5.85	6.85	8.55
500	4.25	5.85	6.25	7	9.35

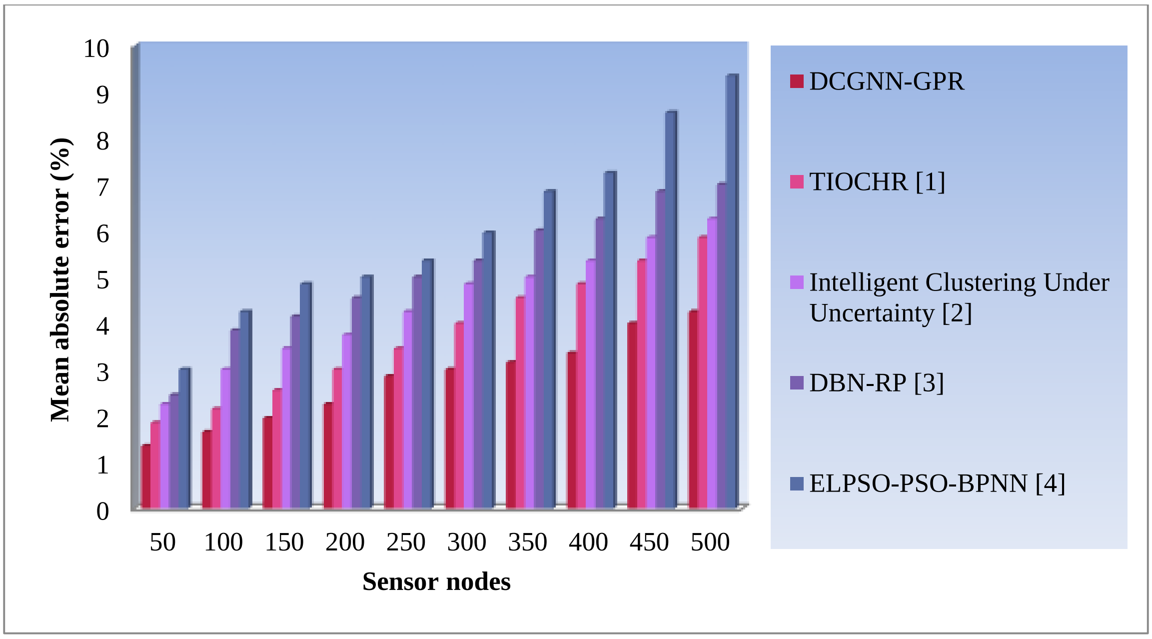

Figure 7 Comparison of mean absolute errors using DCGNN-GPR, existing [1], [2], [3] and [4]

Finally, figure 7 given above shows the mean absolute error analysis using the five different methods. From the above graphical representation an increasing trend is observed using all the five distinct methods. However simulation results for 50 sensor nodes observed an improvement using DCGNN-GPR method where the mean absolute error was recorded to be 1.35%, 1.85% using [1], 2.25% using [2] 2.45% using [3] and 3% using [4] respectively. With this the overall mean absolute error for 50 sensor nodes was found to be comparatively lesser than [1], [2], [3] and [4]. The reason behind the improvement was due to the application of Deep Wagner Graph Neural Network Gaussian Probabilistic Regression algorithm. By applying this algorithm, first minimal dominant highly correlated sensor nodes in a specific region wasidentified using Deep Wagner Graph Neural Network. Here, in the input layer with the aid of three dimensional correlation models aggregated volume with highly correlated sensors were first evaluated. Followed by which in the hidden layer RescorlaWagner rule was applied to fine-tune the weight. Finally, in the output layer, Gaussian Probabilistic Regression function was applied for network lifetime optimization that in turn reduced the mean absolute errorof the DCGNN-GPR method by 26% compared to [1], 38% compared to [2], 47% compared to [3] and 54% compared to [4].

7. CONCLUSION

WSNs are valuable systems that enable efficient monitoring and data collection across various applications. They play a crucial role in industries like environmental monitoring, healthcare, and agriculture by providing real-time data insights. In this article, we proposed a DeepCorrelated Graph Neural Network and Gaussian Probabilistic Regression (DCGNN-GPR) for network lifetime optimization in. To calculate the highly correlated sensor node with minimal dominant set with the objective of optimizing the network lifetimeand minimize energy consumption of the network, we defined a three-dimensional dominant correlations model that considered the aggregated volume between two sensor nodesand volume of two spherical caps based on the height of data aggregation at each node. For efficient data aggregation at each node with different sensor types, we presented a data aggregation by fine-tuning of weight updates employing RescorlaWagner function. This function defined in this study classical conditioning was fine-tuned according to the rate parameter for receiving sensor node and maximum associative strength for receiving sensor node. Finally, Gaussian Probabilistic Regression model was applied for network life time optimization. To demonstratethe applicability of the proposed algorithm to various data aggregation scenarios, we defined three different dataaggregation models. We compared the performance of the proposed DCGNN-GPR with that of the conventional network life time maximization method in terms of its energy consumption, network lifetime, and scheduling time and mean absolute error of data aggregation. Theresults indicate that the proposed DCGNN-GPR method can obtain node’s residual energy to improve energy and data aggregation effectiveness upon comparison to the traditional method.We demonstrated that the proposed DCGNN-GPR method can minimize the overall data transmission load and optimize the lifetime of the WSN. In future, although challenges namely energy efficiency and security, WSNs continue to develop with advancements in technology, promising even more effective and reliable performance.

8. DECLARATION

We hereby declare that this manuscript, titled *"A Hybrid Approach for Network Lifetime Enhancement in WSNs with Graph Neural Networks and Probabilistic Regression,"* represents original research conducted by the authors. This work has not been submitted or published elsewhere.

Author Contributions:

- **Neethu Krishna**: Led the study's conceptualization and design, developed the methodology, conducted data collection and analysis, and drafted the initial manuscript.
- **Dr. G. Naveen Sundar**: Provided critical oversight, extensive review, and guidance, refining both the methodology and analytical framework.
- **Dr. D. Narmadha**: Contributed to detailed data analysis, validated results, and assisted in revising the manuscript to enhance scientific clarity and rigor.

Conflict of Interest

The authors declare that there are no conflicts of interest associated with this work. All authors have reviewed and approved the manuscript for submission.

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