Kriging Regressive Deep Belief WSN-Assisted IoT for Stable Routing and Energy Conserved Data Transmission

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Abstract
With the evolution of wireless sensor network (WSN) technology, the routing policy has foremost importance in the Internet of Things (IoT). A systematic routing policy is one of the primary mechanics to make certain the precise and robust transmission of wireless sensor networks in an energy-efficient manner. In an IoT environment, WSN is utilized for controlling services concerning data like, data gathering, sensing and transmission. With the advantages of IoT potentialities, the traditional routing in a WSN are augmented with decision-making in an energy efficient manner to concur finer optimization. In this paper, we study how to combine IoT-based deep learning classifier with routing called, Kriging Regressive Deep Belief Neural Learning (KR-DBNL) to propose an efficient data packet routing to cope with scalability issues and therefore ensure robust data packet transmission. The KR-DBNL method includes four layers, namely input layer, two hidden layers and one output layer for performing data transmission between source and destination sensor node. Initially, the KR-DBNL method acquires the patient data from different location. Followed by which, the input layer transmits sensor nodes to first hidden layer where analysis of energy consumption, bandwidth consumption and light intensity are made using kriging regression function to perform classification. According to classified results, sensor nodes are classified into higher performance and lower performance sensor nodes. The higher performance sensor nodes are then transmitted to second hidden layer. Here high performance sensor nodes neighbouring sensor with higher signal strength and frequency are selected and sent to the output layer where the actual data packet transmission is performed. Experimental evaluation is carried out on factors such as energy consumption, packet delivery ratio, packet loss rate and end-to-end delay with respect to number of patient data packets and sensor nodes.

Keywords:
Wireless Sensor Network, Internet of Things, Kriging Regressive, Deep Belief Neural Learning, Routing, Data Transmission

1. Introduction

Wireless sensor network (WSN) plays a significant character in numerous WSN-assisted Internet of Things (IoT) applications. WSN-assisted IoT has a comprehensive extent of applications that involves a smart parking system, industrial wireless network, healthcare monitoring system, border surveillance monitoring, and space monitoring system. The efficiency of WSN in IoT-based large scale application is highly influenced on the method being utilized together with the routing mechanism. Owing to the fact that the sensor nodes are a paramount constituent of WSN-assisted IoT network streaming on constrained energy resource, the WSN-assisted IoT performance is dwindled when network is disposed at large area. So, designing robust and energy-efficient routing is a demanding piece of work to improve network lifetime.

To put down the issues in WSN communication arising out of energy consumption and data transmission, Application Centric Information Aware Routing (ACIAR) method was proposed in [1]. This routing mechanism concentrated on route discovery and information handling with the assistance of decision making process in an iterative manner. Also, neighbour selection based on weight to accord absolute reinforces for IoT data requirements.

The neighbour selection based on weight was designed in an adaptable manner being influenced by the requirement and application run-time establishing unanimous data support from the sensor network. As a result, high throughput with minimum delay and data loss was ensured. Despite improvement observed in throughput and data loss, the packet delivery ratio involved during routing was not focused.

A multi-tier hierarchical framework called, Scalable and energy-efficient routing protocol (SEEP) was proposed in [2] on the basis of sub division technique therefore ensuring load balancing and scalability. Every zone was split into definite number of clusters with the number of clusters increased

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towards the base station and on the other hand the zone width was decreased.

Also, optimal nodes in the cluster were promoted as a Relay Node (RN) and Cluster Head (CH) wherein the ordinary nodes send their sensed data to base station via RN and CH in a multi-hop fashion. With this, a trade-off between distance and energy was ensured therefore increasing network lifetime. Though trade-off between distance and energy was attained with improved network lifetime, the delay involved was not addressed.

The solution proposed in this work treats routing and data packet transmission as a unified problem. A node classifier method employing Deep Belief Neural Learning has been proposed in this work where two hidden layers are utilized based on the Kriging Regressive function. By employing this Kriging Regressive function, in the first layer, nodes are classified with the provision of energy and bandwidth consumption. This method reduces the energy consumption and end-to-end delay imposed during routing. Next, with the Kuhn Tucker equality constraints, neighbouring sensor node with improved signal strength and frequency are selected for further processing. The main contributions of this work are as follows:

- To increase the packet delivery ratio and reduce packet loss rate, a novel Kriging Regressive Deep Belief Neural Learning (KR-DBNL) is introduced.
- An energy-efficient data packet routing with better stability for WSN-assisted IoT is proposed. This solution is based on the Kriging Regressive function of wireless sensor nodes and employs a simplified residual function that classifies sensor nodes based on the performance.
- A Kriging Regressive function is applied in the KR-DBNL method with the energy and bandwidth consumption as constraint for obtaining high performance sensor node.
- To reduce the energy consumption and end-to-end delay equality constraints is taken into account using Kuhn Tucker.
- Finally, experimental evaluation is performed to estimate the quantitative analysis of the proposed KR-DBNL method with the existing methods and numerous performance metrics.

This paper is organized as follows: Related works are discussed in section 2. In section 3, the preliminaries covered with the introduction of principles are presented. Also, the detailed design of the proposed method is provided. Section 4 presents simulation experiments results along with the detailed discussion in section 5. Section 6 concludes the study.

2. Related Works

With the ceaseless evolution of wireless communication technology, the IoT is being utilized in an extensive scope of areas. The IoT gathers and interchanges vast amount of data with objects, like sensors, connected to the Internet. WSNs being the elements of IoT systems are employed in numerous IoT systems, like, surveillance, object tracking and detection, to acquire pertinent information and disseminate it to the intended users.

Energy efficient IPv6 packet delivery scheme was used by IIoT based WSN in [3]. Here, G.9959 protocol was introduced improve the IPv6 packet delivery rate with respect to energy and latency. An analysis was also carried out to minimize the energy consumption. Though the energy consumption was reduced, but the delay was not said to be reduced. A new routing protocol termed balanced energy adaptive routing (BEAR) was introduced in [4] to increase the lifetime of Underwater Wireless Sensor Network. The BEAR protocol was split into initialization phase, tree construction phase and data transmission phase. Here, all nodes shared the information on the basis of the residual energy level and location. But, packet delivery ratio was not improved by BEAR protocol.
An efficient CH election scheme was introduced in [5] to rotate cluster head position between nodes with higher energy level. The designed algorithm considered the residual energy and optimum value of cluster head to choose the next group network in IoT applications like environmental monitoring and smart cities.

Though the energy consumption was minimized by cluster head election scheme, the computational cost was not reduced. A centralized routing algorithm termed interference-aware energy efficient routing algorithm (IA-EERA) was introduced in [6] to enhance the network lifetime. However, scalability was not addressed by IA-EERA.

Distance and time are no longer blockades, as people and objects now convey with each other everywhere and at one's convenience unambiguously with the push of a gesture control. Also, both living and non-living beings attached with small and minute electronic devices called sensor communicate in a wireless fashion by relaying sensed data to remote locations where the data is required for further processing. This new prototype is called as Internet of Things (IoT) and Wireless Sensor Networks (WSN) embodies the fabrication block of IoT.

In [7] a mechanism that provides media packetization relying on IoT-based transport protocols was proposed. To be more specific, sensors that hitherto contain the protocol reiterate it to bestow media transport in an energy efficient manner. In [8], the hypothesis of class of service (CS) was applied for heterogeneous data prioritization. With this, a backoff MAC scheme that was prioritize in an optimal manner, called Class of Service Traffic Priority-based Medium Access Control (CSTP-MAC) was proposed. This method in turn classified the data into High Priority Data (HPD) and Low Priority Data (LPD). This type of classification was performed by measuring backoff times with certain types of expressions distinctive to the data priority class.

A recent survey has indicated that sensor deployments over the past few years have enhanced in a significant manner and has therefore predicted an elevated growth in the future growth rate. For example, in health-care services, sensors are utilized as a paramount factor to enable IoT oriented health-care monitoring systems.

In [9], a two-stage elementary model to ease the implementation for healthcare services was proposed. As far as first stage was concerned, sensors predominantly acquired particle measurements of an android application. Followed by which in the second stage, the data that were collected were sent over a Femto-LTE network by employing a novel scheduling mechanism, therefore improving the scheduling mechanism.

Wireless sensor network (WSN)-based Internet of Things (IoT) applications endures from issues like, constrained battery capacity, persistent breakups owing to multi-hop communication and a minuscule range of transmission. An improved clustering and routing protocol was proposed in [10] employing area-based clustering that in turn demonstrated enhanced network lifetime.

The objective of IoT is to streamline pieces of work and validate it to carry out in a smart manner by acquiring a high magnitude of intelligence in applications and services with the minimum human interference utilizing numerous sensors.

In [11], the role of offloading to meet the requirements of IoT enabled services utilizing edge computing, therefore ensuring optimality was proposed. Yet another method utilizing improved ant colony optimization for constructing optimal path towards efficient data transmission was proposed in [12]. With this energy consumption and data packet loss rate was found to be reduced in a significant manner. A state-of-the-art method for designing sustainable development of society using Internet of Things was investigated in [13].

IoT has been applied in several fields and to be more specific has found its profound interests in healthcare monitoring applications. In [14], two levels of security algorithms employing hash and AES 128 bit was proposed to minimize the interference involving clustering with low data delivery loses. A review article to provide a comprehensive discussion concerning and technological and social perspective were proposed in [15].

Moreover, almost all of data transmission methods do not attain session-specific temporary information security. To address this issue, a data transmission method for WSNs in heterogeneous IoT environment by employing heterogeneous ring signcryption was presented in [16].

The data transmission method employed permitted WSN node under certificate less cryptography (CLC) that in turn transmitted the data being collected by employing public key infrastructure (PKI) with numerous cryptographic system parameters. An architectural perspective concerning from technology centric to user centric employing cross layer architecture was proposed in [17]. An energy-efficient reliable data transmission in cloud-based IoT employing mixed integer linear programming was investigated in [18]. Yet another analysis of IoT-based wireless sensor for environment monitoring was proposed in [19].

Motivated by the above facts in this work, IoT-based learning classifier with routing called, Kriging Regressive Belief Neural Learning (KR-DBNL) is proposed for efficient data packet routing to cope with scalability issues and fore ensure robust data packet transmission.

3. Methodology

The sensor nodes participating in WSN-assisted IoT model the physical object aware about the numerous real attributes in the deployed network. Some of them include, sensing, monitoring, feeling, and trigger an event with the cooperation of other devices. Sensed data generated in the network are transmitted to the Base station (BS) by routing mechanism. Most of the sensor nodes participating in WSN-assisted IoT networks are operated on constrained energy. Hence, efficient energy management is a critical topic in WSN-assisted IoT. In this section IoT-based deep learning classifier with routing called, Kriging Regressive Deep Belief Neural Learning (KR-DBNL) for efficient data packet transmission in WSN is proposed. Figure 1 shows the block diagram of KR-DBNL method.

As illustrated in the below figure 1, the KR-DBNL method includes four layers. They are, input layer, two hidden layers and one output layer for significant data transmission between source and destination sensor node. In the input layer, with the IoT devices equipped in sensor nodes, patient data are acquired from different location. Next in the two hidden layers, using kriging regression function sensor node classification are performed. In the first hidden layer, energy and bandwidth consumption is utilized as the constraint and in the second hidden layer, signal strength and frequency is employed as constraint. Finally, in the output layer, actual data transmission process in WSN is done.

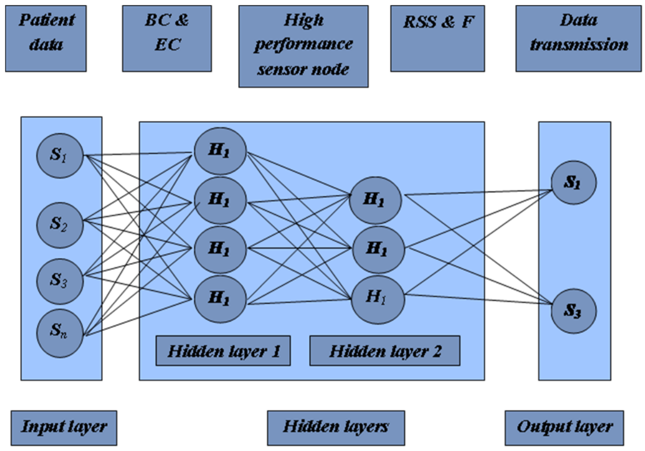

Figure 1 Block diagram of KR-DBNL

3.1 WSN-assisted IoT network model

In the proposed KR-DBNL method, the WSN-assisted IoT network has been modelled as weighted randomly distributed graph '$G(V, E)$'. Here in WSN-assisted IoT network, 'V' denotes the set of sensor nodes and 'E' denotes the set of edges. For each edge '(i, j)', a function in WSN-assisted IoT network is defined to map the distance between nodes to its respective weight '$w(i, j)$'. This weight formulation is as given below.

$$W(i,j) = \begin{cases} 0, if\ Dis_{i,j} > S_{Max[Rad]} \\ S_{Max[Rad]} - Dis_{i,j} \Big/ S_{Max[Rad]} - S_{Min[Dis_{i,j}]}, if S_{Min[Dis_{i,j}]} \leq S_{Max[Rad]} \\ 1, if\ Dis_{i,j} \leq S_{Min[Dis_{i,j}]} \end{cases} \quad (1)$$

From the above equation (1), '$Dis_{i,j}$' denotes the actual distance between sensor node 'i' and sensor node 'j', '$S_{Max[Rad]}$' representing maximum radius of communication between sensor node 'i' and sensor node 'j', '$S_{Min[Dis_{i,j}]}$' denoting the minimum distance between sensor node 'i' and sensor node 'j' in WSN-assisted IoT network respectively. From the above equation it is inferred that if '$W(i, j) = 0$' represents '$E(i, j) \notin G$' and on the other hand if '$W(i, j) = 1$' represents the '$E(i, j) \in G$'.

3.2 WSN-assisted IoT using Kriging Regressive Deep Belief Neural Learning (KR-DBNL)

Deep Belief Neural Learning is a generative graphical model comprising of stacked Restricted Boltzmann Machines (RBMs). On the basis of its deep structure DBNL acquire hierarchical representation of input data (i.e., patient data from different location) that trains one layer at a time. Given visible unit 'S' (i.e., WSN-assisted IoT sensor nodes '$S = S_1, S_2, S_3, \ldots S_n$') and '$l$' hidden layers (i.e., two hidden layers) the joint distribution is mathematically formulated as given below.

$$Prob\ (S, H^1, H^2, H^3, \ldots, H^n) = Prob\ (H^{n-1}, H^n)\left(\prod_{k=1}^{l} Prob\ (H^k |\ H^{k+1})\right) Prob\ (S|H^1) \quad (2)$$

With the above DBNL training, to start with the IoT devices in sensor nodes are employed to obtain the patient data from different location. Let us consider the WSN-assisted IoT sensor nodes '$S = S_1, S_2, S_3, \dots S_n$' utilized to acquire the patient data '$D = D_1, D_2, D_3, \dots, D_n$' stored in the vector matrix as given below.

$$VM = \begin{bmatrix} S_1D_1 & S_1D_2 & S_1D_3 & \dots & S_1D_n \\ S_2D_1 & S_2D_2 & S_2D_3 & \dots & S_2D_n \\ \dots & \dots & \dots & \dots & \dots \\ S_mD_1 & S_mD_2 & S_mD_3 & \dots & S_mD_n \end{bmatrix} \quad (3)$$

From the above equation (3), 'S_1D_1' refers to the first WSN-assisted IoT sensor first patient data, 'S_1D_2' refers to the first WSN-assisted IoT sensor second patient data, 'S_2D_1'refers to the second WSN-assisted IoT sensor first patient data and so on. The patient data is acquired from https://www.kaggle.com/eiodelami/disease-outbreaks-in-nigeria-datasets [20] includes 40 columns or 40 features '$F = F_1, F_2, F_3, \dots, F_n$'. Then, the feature representation for each WSN-assisted IoT sensor is mathematically expressed as given below.

$$S_1D_1 \rightarrow S_1D_1[F_1, F_2, F_3, \dots, F_n];\ S_1D_2 \rightarrow S_1D_2[F_1, F_2, F_3, \dots, F_n];\ S_2D_1 \rightarrow S_2D_1[F_1, F_2, F_3, \dots, F_n];\ S_2D_2 \rightarrow S_2D_2[F_1, F_2, F_3, \dots, F_n] \quad (4)$$

As formulated above (4), the remaining '2,80,000 $rows$' and '39 $columns$' are modelled in the input layer. After that, input layer transmits the sensor nodes to the first hidden layer. In that layer, the energy consumption and bandwidth consumption of each sensor node is analyzed using kriging regression function.

The Kriging being an interpolation method provide linear unbiased predictions to collect the patient data from different location. The purpose of employing the kriging regression function with residuals is to minimize the uncertainties of estimation, therefore reducing classification errors. With this, kriging regression function with residuals perform classification between high performance and low performance sensor nodes with energy and bandwidth as the constraints. Figure 2 shows the structure of regression kriging classifier model.

As shown in the below figure, the Kriging linear unbiased estimator for each sensor location to validate

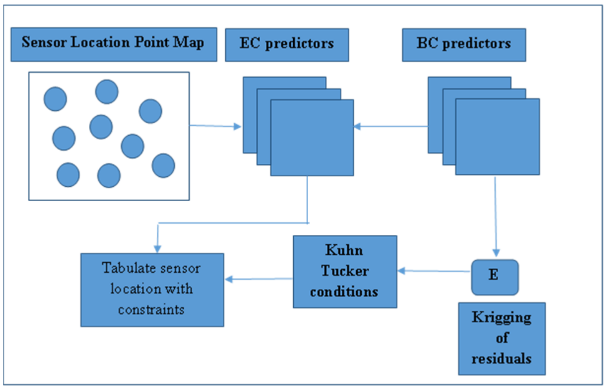

Figure 2 Structure of regression krigging classifier

'$S(Loc_i)$' based on the energy consumption 'EC' (i.e., EC predictors) and bandwidth consumption 'BC' (i.e., BC predictors) is mathematically expressed as given below.

$$S'(Loc_i) = \sum_{i=1}^{n} W_i S_{EC}(Loc_i) + W_i S_{BC}(Loc_i) \quad (5)$$

From the above equation (5), 'S'' represents the estimated value of the sensor at location 'Loc_i' with 'n' representing the number of the neighbouring sensor nodes utilized for interpolation, with 'W_i' denoting the Kriging weight assigned to each observation. Then, optimal estimation necessitates the minimum variance of errors and this is mathematically estimated as given below.

$$\sigma_k^2 = Var\,[S(Loc_0) - S'(Loc_0)] \quad (6)$$

$$= Min\,(E\,\{[S(Loc_0) - \sum_{i=1}^{n} W_i S_{EC}(Loc_i) + W_i S_{BC}(Loc_i)]^2\}) \quad (7)$$

From the above equation (6) and (7), minimum variance of errors 'σ_k^2'is estimated based on the krigging of residuals '$E()$' formulated based on the constraints, energy and bandwidth consumption of each sensor node location. To solve the constrained optimization, the Karush Kuhn Tucker is adopted. With equation (5) as the objective function and minimum energy and bandwidth consumption as the constraint, the Karush Kuhn Tucker minimizes the following cost function. This is mathematically formulated as given below.

$$f S_{EC} S_{BC}(W_1, W_2, W_3, \ldots., W_n, \mu) = \frac{1}{2} E\ \{[S(Loc_0) - \sum_{i=1}^{n} W_i S_{EC}(Loc_i) + W_i S_{BC}(Loc_i)]^2\} + \mu\ (1 - \sum_{i=1}^{n} W_i) \quad (8)$$

From the above equation (8), 'μ' represents the Kuhn Tucker that takes into account equality constraints. At the minimum point of the cost function, the differentiation of 'f' with the optimization problem break downs into one of solving the following set as either high performance sensor nodes or low performance sensor nodes. After that, the higher performance sensor nodes are transmitted to the hidden layer 2 or the second hidden layer. In that layer, every sensor node chooses the neighbouring sensor node with higher signal strength and frequency for reducing the delay and packet loss rate during the data transmission process in WSN. This is formulated as given below.

$$f S_{RSS} S_F(W_1, W_2, W_3, \ldots., W_n, \mu) = \frac{1}{2} E\ \{[S(Loc_0) - \sum_{i=1}^{n} W_i S_{RSS}(Loc_i) + W_i S_F(Loc_i)]^2\} + \mu\ (1 - \sum_{i=1}^{n} W_i) \quad (9)$$

From the above equation (9), 'μ' represents the Kuhn Tucker, the differentiation of 'f' with the optimization problem break downs into one of solving the following set as either sensor to be selected for transmission or proceed with other set of sensors until process completed. Finally, the fine tune optimal data packet transmission is carried out in the output layer with minimum loss function as given below.

$$\min\left\{\frac{1}{|D|}\sum_{i=1}^{|D|}\left[\mathcal{L}\left(\varphi; y^{(i)}, H\left(S^{(i)}\right)\right)\right]\right\} \quad (10)$$

From the above equation (10), '$\mathcal{L}$' denotes the loss function with 'H' representing the final hidden sensors ready for data packet transmission and 'φ' denoting the parameters (i.e., the data packets) of the classifier. The pseudo code representation of Kriging Regressive Deep Belief Neural Learning Classifier is given below.

Input: WSN-assisted IoT sensor nodes '$S=S_1,S_2,S_3,\ldots S_n$', Patient data '$D= D_1,D_2,D_3,\ldots,D_m$'

Output: Scalable data packet transmission
1: **Initialize** features '$F=F_1,F_2,F_3,\ldots,F_n$'
2: **Begin**
3: **For** each WSN-assisted IoT sensor nodes 'S' with Patient data 'D'
//input layer
4: **Formulate** vector matrix as in equation (3)
5: **Obtain** the feature representation for each WSN-assisted IoT sensor as in equation (4)
6: **Return**Patient data '$S_i D_i = S_1D_1, S_2D_2, S_1D_3, \ldots, S_2D_1, S_2D_2, S_2D_3$' collected from vector matrix
// first hidden layer (hidden layer 1)
7: **For** each sensor 'S' with location 'Loc i'
8: **Formulate** Kriging linear unbiasedestimator for each sensor location as in equation (5)
9: **Estimate** minimum variance of errors as in equation (6) and equation (7)
10**:** **Estimate** Karush Kuhn Tucker along with krigging of residual
11: **If** 'df/(dW_i)>1,df/dμ>1'
12: **Then** '$S(Loc_i)$' are high performance sensor nodes
13: **End if**
14: **If** 'df/(dW_i)<1,df/dμ<1'
15: **Then** '$S(Loc_i)$' are low performance sensor nodes
16: **End if**
17: **If** 'df/(dWi)=0,df/dμ=0'
18: **Then** '$S(Loc_i)$' are out of communication sensor nodes
19: **End if**
20: **End for**
//second hidden layer (hidden layer 2)
21: **If** '$df/(dW_i)>1, df/d\mu>1$'(where signal strength and frequency is higher)
22: **Then** '$S(Loc_i)$' selected
23: **Proceed** with data transmission
24: **End if**
25: **If** '$df/(dW_i)<1, df/d\mu<1$'(where signal strength and frequency is lower)
26: **Then** '$S(Loc_i)$' are not selected
27: Process with other set of sensor nodes
28: **End if**
29: **If** '$df/(dW_i)=0, df/d\mu=0$'
30: **Then** '$S(Loc_i)$' are out of communication sensor nodes
31: **End if**
32: **End for**
33: **End**

Algorithm Kriging Regressive Deep Belief Neural Learning Classifier

As given in the above Kriging Regressive Deep Belief Neural Learning Classifier, the objective remains in designing an efficient data packet transmission in a scalable manner. To attain this objective a Deep Belief Neural Learning with two hidden layers with the aid of Kriging Regressive function with residuals is employed for significant classification of high performance and low performance sensor. Next, with the high performance sensor, with high signal strength a frequency as constraint, scalable and robust patient data packet transmission is ensured.

4. Simulation Setup

The simulation of the proposed Kriging Regressive Deep Belief Neural Learning (KR-DBNL) and existing methods namely Application-Centric Information-Aware Routing (ACIAR)[1] and Scalable and energy-efficient routing protocol (SEEP)[2] are implemented using the NS2.34 simulator. To ensure fair comparison, 500 sensor nodes deployed over a squared area of A^2 (1100 m * 1100 m) is selected with the sensor node's speed of 0-20m/s. Moreover, a Random Waypoint node mobility model is employed for performing the simulation. In addition, DSR protocol is utilized for significant patient data transmission between source and destination. The IoT devices are affixed into the patient and the data is acquired from the dataset Disease Outbreaks in Nigeria Datasets in India [https://www.kaggle.com/eiodelami/disease-outbreaks-in-nigeria-datasets]. The dataset includes information pertaining to patient information such as ID, name, gender, and patient health information, and so on. This information is collected and sent from source to sink node with the simulation time being set to 300 secs, simulations conducted 40 10 simulation runs. Table 1 given below lists the simulation parameters.

Table 1 Simulation Parameters

Simulation parameter	Value
Simulator	NS2 .34
Network size	1100m * 1100m
Node density (Number of nodes)	50,100,150,200,250,300,350,400,450,500
Data packets	100,200,300,400,500,600,700,800,900,1000
Radio transmission range	20m
Transmission data rate	10 – 50 Mbps
Data size	1 – 5 MB
Initial energy	2J
Protocol	DSR
Simulation time	300sec
Mobility model	Random Way Point model
Nodes speed	0-20m/s
Simulation runs	10

An in-depth analysis is performed by measuring metrics like, energy consumption, packet delivery ratio, packet loss rate and end-to-end delay with respect to number of patient data packets and sensor nodes.

5. Discussion

In this section, the effectiveness of our proposed Kriging Regressive Deep Belief Neural Learning (KR-DBNL) method is analyzed via results obtained and compared the performance with existing methods in literature as Application-Centric Information-Aware Routing (ACIAR) [1] and Scalable and energy-efficient routing protocol (SEEP) [2].

5.1 Performance analysis of energy consumption

In this section, the impact of energy consumption is analyzed on the performance of the proposed KR-DBNL method with increased node size. A proportion of energy is said to be consumed during the process of routing and data transmission for WSN-assisted IoT. This is owing to the reason that while obtaining routing for efficient data transmission, several routes are said to exist and only the optimal stable route has to be identified for further processing. Due to this a small portion of energy is said to be consumed. This is mathematically formulated as given below.

$$Con_E = n * Con_E\ (single\ sensor\ node) \tag{11}$$

From the above equation (11), the energy consumption 'Con_E' is measured based on the number of nodes involved in the process of routing and transmission 'n' and the actual energy consumed for single sensor node to perform the overall process '$Con_E\ (single\ sensor\ node)$'. It is measured in terms of joules (Joule). Table 2 given below provides the energy consumption analysis using KR-DBNL, existing ACIAR [1] and SEEP [2] respectively.

Table 2 Tabulation for energy consumption

Sensor nodes	Energy consumption (J)		
	KR-DBNL	ACIAR	SEEP
50	10	12	14
100	12	14	15
150	14	16	18
200	14	16	18
250	16	18	21
300	17	19	22
350	18	22	24
400	18	23	25
450	18	23	26
500	22	25	28

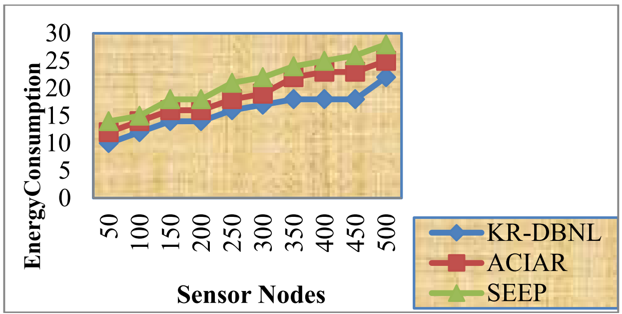

Figure 3 Energy Consumption using KR-DBNL, existing ACIAR [1] and SEEP [2]

Figure 3 given above shows the graphical representation of energy consumption for three different methods, KR-DBNL, existing ACIAR [1] and SEEP [2]. It can be observed from figure 3 that the node density starts at 50 and ends to 500. The sensor node in our work stays at every step for certain amount of time between 5second and 8 second as pause interval. This can be observed from figure 3 that some energy consumptions are represented by two numbers for different number of sensor nodes. The reason is that the WSN-assisted IoT sensor node stays at these positions for some amount of time depending on the pause interval. Also an increase in the number of sensor nodes results in the improvement in the energy consumption. The improvement in the energy consumption is due to the utilization of kriging regression function to classify the sensor node into high performance and low performance based on the energy and bandwidth consumption. The application of this function and to utilize the high performance sensor node for further processing results in the improvement of energy consumption using KR-DBNL by 15% compared to [1] and 24% compared to [2] respectively.

5.2 Performance analysis of packet delivery ratio

In this section, the impact of number of patient data on packet delivery ratio is analyzed. The second metric of significance is the packet delivery ratio. During the process of data transmission for WSN-assisted IoT, the efficiency of the method can be analyzed based on the packet delivery ratio. The packet delivery ratio refers to the percentage ratio of number of patient data (i.e. data packets) received at the intended recipient to the total number of data packets being transmitted by the source sender node. The packet delivery ratio is mathematically formulated as given below,

$$R_{PD} = \left[\frac{NPR}{NPS}\right] * 100 \tag{12}$$

From (12), the packet delivery ratio 'R_{PD}' is measured on the basis of the number of patient data packets received by the intended recipient 'NPR' to the number of patient data packets sent 'NPS'.It is measured in terms of percentage (%). Table 3 given below provides the packet delivery ratio analysis using KR-DBNL, existing ACIAR [1] and SEEP [2] respectively.

Table 3 Tabulation for packet delivery ratio

Number of patient data	Packet delivery ratio (%)		
	KR-DBNL	ACIAR	SEEP
100	95	93	92
200	93	91	89
300	92	90	88
400	91	88	86
500	92	89	87
600	93	90	88
700	91	89	87
800	93	90	88
900	95	91	89

1000	94	90	88

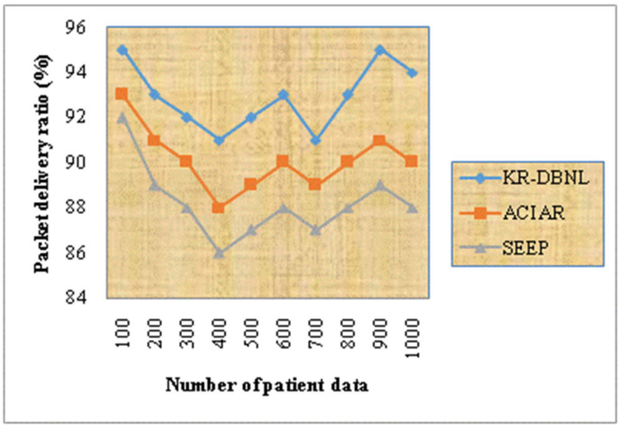

Figure 4 Packet delivery ratio using KR-DBNL, existing ACIAR [1] and SEEP [2]

Figure 4 shows packet delivery ratio under different number of patient data. From the above figure, x axis represents the number of patient data whereas y axis represents the packet delivery ratio. As the number of patient data increases, node density increases and this in turn depending upon the topology variance results in either increase or decrease in the packet delivery ratio. However, simulation results for 100 number of patient data using all the three methods observed 95 number of patient data packets received by the intended recipient using KR-DBNL, 93 number of patient data packets received by the intended recipient using [1] and 92 number of patient data packets received by the intended recipient using [2]. From this analysis, the packet delivery ratio using the three methods was observed to be 95%, 93% and 92% respectively. The reason behind the improvement using the proposed KR-DBNL was due to the application of kriging regression function that in turn selects the neighbouring sensor node with higher signal strength and frequency. This in turn causes improvement in the packet delivery ratio using proposed KR-DBNL method by 3% compared to [1] and 5% compared to [2] respectively.

5.3 Performance analysis of packet loss rate

The packet loss rate is a paramount performance measure for WSN-assisted IoT data transmission. This is owing to the reason that these patient data flows are secured certain data rates for smooth and seamless patient data packet transmission, the number of patient data packets lost during transmission must be kept low. The packet loss rate is defined as the percentage ratio of number of patient data (i.e. data packets) lost to the total number of data packets sent from the source node. The packet loss rate is mathematically formulated as given below,

$$R_{PL} = \left[\frac{NPL}{NPS}\right] * 100 \tag{13}$$

From the above equation (13), the packet loss rate 'R_{PL}' is measured based on the number of patient data packets lost 'NPL' and the number of patient data sent 'NPS'. It is measured in terms of percentage (%).Table 4 given below provides the packet loss rate analysis using KR-DBNL, existing ACIAR [1] and SEEP [2] respectively.

Table 4 Tabulation for packet loss rate

Number of patient data	Packet loss rate (%)		
	KR-DBNL	ACIAR	SEEP
100	6	8	10
200	7	10	12
300	9	11	13
400	10	12	14
500	9	11	13
600	10	12	14
700	11	13	15
800	10	12	14
900	9	11	13
1000	8	10	12

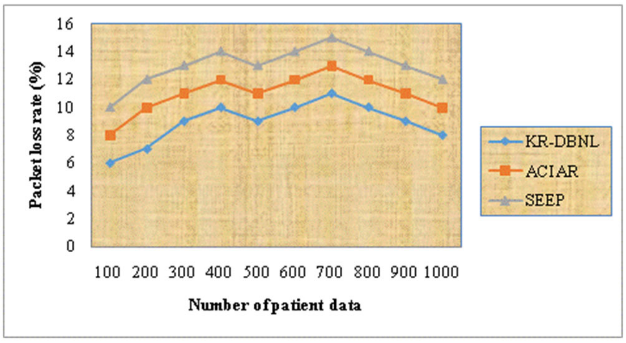

Figure 5 Packet loss rate using KR-DBNL, existing ACIAR [1] and SEEP [2]

Figure 5 given above shows the graphical representation of packet loss rate for 1000 different patient data acquired at different time intervals. Figure 5 illustrates the packet loss rates of both the KR-DBNL, existing ACIAR [1] and SEEP [2] methods for patient data. In Figure 5, all the three methods exhibit an incremental trend from 100 to 400 patient data. This is due to the reason that the interference generated becomes more intense as the number of patient data to be sent increases, resulting in more traffic flows and leads to increased packet losses. Moreover, the neighbouring sensor node might have assigned more signal strengths to the flows that suffer from poor channel conditions. As a result, increased number of patient data packets dropped from the transmission queue. The KR-DBNL method has a better packet loss rate performance compared to the existing ACIAR [1] and SEEP [2] as shown in the above figure. This is because the KR-DBNL method provides better sensor node selection for further WSN-assisted IoT data transmission. By applying the Kriging Regressive Deep Belief Neural Learning Classifier algorithm, it optimizes a subjective measure, i.e., the number of data packet received at the destination as opposed to an objective quality measure of packet loss at the destination. Next, it incorporates the constraints of signal strength and frequency adjustment schemes. With this the packet loss rate using KR-DBNL method was said to be reduced by 19% compared to [1] and 32% compared to [2] respectively.

5.4 Performance analysis of end-to-end delay

Finally, end-to-end delay is measured in this section to estimate the performance of the proposed method. It is defined as the expected arrival time of the patient data and the actual arrival time of the data packets at the destination end. The overall end-to-end delay is mathematically formulated as given below.

$$Delay_{EE} = [t_{act}] - [t_{ex}] \qquad (14)$$

From the above equation (14), the end to end delay '$Delay_{EE}$' is measured on the basis of the actual arrival time '$[t_{act}]$' and the expected arrival time '$[t_{ex}]$' respectively. It is measured in terms of milliseconds (ms). Finally, table 5 given below provides the end-to-end delay analysis using KR-DBNL, existing ACIAR [1] and SEEP [2] respectively.

Table 5 Tabulation for end-to-end delay

Number of patient data	End-to-end delay (ms)		
	KR-DBNL	ACIAR	SEEP
100	11	13	15
200	12	14	16
300	13	16	18
400	14	18	20
500	16	20	22
600	18	22	24
700	20	24	25
800	22	25	27
900	23	28	30
1000	25	29	32

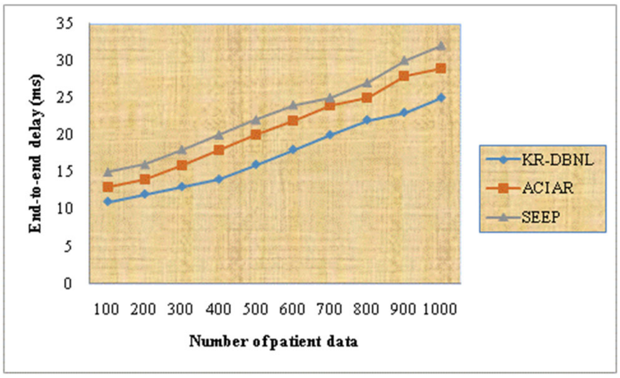

Figure 6 End-to-end delay using KR-DBNL, existing ACIAR [1] and SEEP [2]

Figure 6 given above shows the graphical representation of end-to-end delay using the three methods, KR-DBNL, existing ACIAR [1] and SEEP [2]. The end-to-end delay here refers to the overall average time consumed in sending patient data packet between the source sensor and destination sensor node respectively. The end-to-end delay includes both the times consumed in identifying the stable nodes and the time for routing to send patient data packets successfully between source sensor and destination sensor node. From the above figure, though with the increase in the number of patient data causes a swift rise in the end-to-end delay, however, the delay using KR-DBNL was significantly reduced upon comparison with the [1] and [2]. The reason behind the improvement was due to the incorporation of Deep Belief Neural Learning for efficient routing and data transmission for WSN-assisted IoT employing the Kriging Regressive function. With this function and energy consumption, bandwidth consumption, signal strength and frequency as the constraint neighbouring sensor node were selected for efficient routing and transmission. Therefore, as only with the high performance node processing was done, therefore reducing the end-to-end delay using KR-DBNL by 17% compared to [1] and 25% compared to [2] respectively.

6. Conclusion

In this paper, a proposed efficient node stable routing and data transmission method for WSN-assisted IoT called, Kriging Regressive Deep Belief Neural Learning (KR-DBNL) is proposed to guarantee the stability of patient data transmission between source and destination nodes. The stable node is explored by introducing the Kriging Regressive function with which only the resource efficient, energy and bandwidth consumed WSN-assisted IoT sensor with higher performance is selected for further processing in the first hidden layer. Next, with the signal strength and frequency as the constraint in the second hidden layer, neighbouring sensor node is further selected for significant data transmission between the source and the destination nodes. The Kuhn Tucker equality constraints for packet retransmission is taken into account, where the accurate calculated packet retransmission minimizes the extra overhead of the network, therefore contributing to better packet delivery ratio and packet loss rate. Simulation analysis is provided to advocate the efficiency and stability of KR-DBNL and it is proved that KR-DBNL can choose almost optimal stable routes. Moreover, the results of the simulation show that the proposed method reduces end-to-end delay and energy consumption and behaves better than the existing data transmission methods in terms of network efficiency and network stability.

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