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A Data Prediction in Wireless Sensor Networks using Deep Learning-based RSA Algorithm

Anand Dohare, Tulika, Sweta Sachan, B.Mallikarjuna

Abstract. In wireless sensor networks (WSN) data collection and gathering data from surroundings and removing the redundancy, process the appropriate data is a challenging task, in spite of low battery, less memory space, low computational speed, reduce the energy consumption are major research areas in WSN. Temperature sensor, humidity sensors are majorly used to climate monitoring, agricultural, humidity observation, due to energy consumption of sensors, low battery power, computational speed of sensors are used to maintain a long time is a crucial issue. To overcome such type of problems data prediction techniques are required, several data prediction, aggregation techniques are proposed in this issue and several research has been done, but not solved all challenging issues. In this paper proposed deep learning-based RSA algorithm to provide security and efficiently handle the data by using a feed-forward filter to remove the aggregated data, Least Mean Square (LMS) variable step-size method to remove error rate that will improve the energy consumption and size of the memory space for data collection, the experimental results proved that 98% predicted data and minimum error rate on cluster network as per considered (Intel Lab) data set.

Keywords: wireless sensor networks, prediction, aggregation, redundant, LMS

I. INTRODUCTION

In the present-day scenario, sensors are used in traffic monitoring, healthcare, burglar alarm and various domestic appliances for safety purposes [1]. Sensor is the most wanted device for accessing the data and process to the corresponding application, the most common device used in the military for border security enforcement, in irrigation for crop purpose to rectify an attack monitoring, in health care applications, to check heart pulse and heart beep reading. The temperature and humidity sensors are most useful sensors in many applications, earthquake, to check the vibrations and measure the sound and estimate the pollution in the air, air pressure and vibrations in the air, etc... The following Table 1 provides the challenging isssues and major areas of research used in WSN [2].

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* Correspondence Author
Anand Dohare*, Research scholar, SHAUTS, University, Allahabad, India.
Dr. (Mrs) Tulika, Assistant Professor, Department of Computer Science and Information technology, Allahabad, India.
Dr. Basetty Mallikarjuna, Department of Computer Science and Information technology, Allahabad, India.
Mrs. Sweta Sachan, Department of Computer Science and Information technology, Allahabad, India.

Table 1: Challenging issues and major areas used in WSN [1-3].

Wireless Sensor Networks (WSN)	
Challenging Issues on WSN	**Major Area used WSN**
Energy consumption	Health care Applications
Energy conservation	Military Applications
Hardware and Software related design issues	Transportations system
Synchronization	Agricultural Applications
Quality of Service (QoS)	Irrigations and crop
Data Computation	Environmental monitoring
Security	Animal habitats
Data collection	Forest fires
Minimum communication	Natural disasters
High sensing	Inventory Management
Flexibility	Smart home

Combination of two or more trees it becomes the cluster tree network architecture, it combinations of several sink nodes, the rook node can act as head node[1], all remaining nodes can gather the data from the respective head node and transmit the data to the base station, it is responsible for preserving the data for a long time. Energy consumption, improve the performance of battery life time was a challenging task for researchers, sometimes huge amount of data stored in the WSN database and occupy huge memory space and increase transmission rate [2]. Data prediction can be done three stages i) time series forecasting ii) Algorithm approaches iii)Stochastic approaches. In the time series forecasting used filters and calculates the error and adjusts the weights and it provides acceptable accurate and it is easy to implement. Algorithmic approach works with the as per the algorithm defined. In stochastic approach works with the probability density function, it provides the large computational speed. Aggregate prediction techniques are used to transfer the data based probabilistic values, aggressive prediction techniques are easy to implement. The data compression technique used to reduce the data, in this technique the data can be moved to the sink node by applying code strategy and semantic information. Network aggregation strategy, in this process data transfer between the source nodes to sink node this approach is depend upon the minimum and maximum average result of data [3]. Deep learning-based models [23-25] can be implemented in mobile ad hoc networks [18], sentimental analysis for recommender system on the cloud [21-22], deep learning models consist of the feed forward network [19-20] model and it consist of the recursive approach as shown in the Figure 1, feed ford network consists of the one input layer, one output layer many hidden layers. Deep learning-based models can be implemented in Facebook and obtain the effective results of the performance of data prediction 97% while transferring the pictures, messages, etc. [21]. Google used deep learning models on its data centers and minimize energy consumption upto 40% [22].

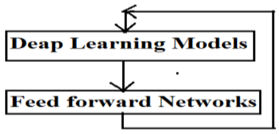


Figure 1: Deep Learning Models with Feed Forward Network [23]

In this paper, we proposed a deep learning-based RSA algorithm [18-25] with feed-forward filter computes the error rate (it named as feed forward filter it works with the same principal of Kalman filter [15]), LMS based variable step-size [13] method can compute the data rate in wireless sensor networks, which helps to reduce the energy consumption and increase battery performance as well as memory size by decreasing the transmission rate. Feed -orward [19] filter find the error rate and deep learning-based RSA method is used for reducing the redundant data and provide the security at source as well as a sink node. The proposed approach contains two techniques used in data prediction first one is feed -orward filter and the second one is LMS(Least mean square) based variable step size technique, in feed forward filter based prediction algorithm, adjust coefficient of predicted value and compared with threshold value if the prediction error is greater than the threshold error then predicted data will be removed if prediction error is less then threshold error than data will be considerable. While LMS used initial prediction at the actual value and based on the current time data error for reduced the mean square error. It compared step sized parameter with previous values by using a recurrence relation. The best things regarding LMS algorithms require previous knowledge of collected data. In this paper we used LMS algorithms for data reduction with variable step size and apply at three different network topology [4] like star, tree, and cluster-based on real-time Intel data set [17] as shown in the Figure 2, it shows the three different architectures.

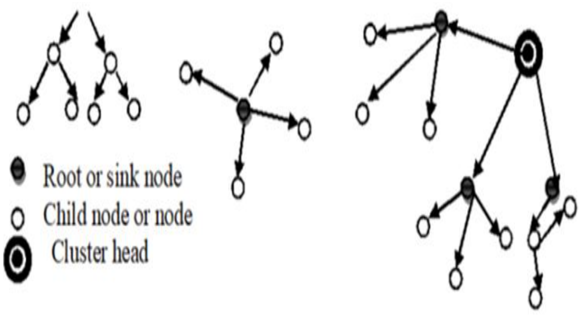


Figure 2: Tree, Star and Cluster topologies [4]

The aforementioned three topologies are most popular for data collection and time series forecasting as per the literature, the child node send data to the parent and parent node become a child node, it again send to the its parent node (super parent of its child node and so on) while data transfer it contains many sink nodes, the root can act as head node of the network [4]. Cluster based network topology is efficient network architecture for collecting and transfer the data with head and sink nodes [4].

The rest of the paper followed by section 2 related work, section 3 consist of deep learning-based RSA algorithm with LMS approach, section 4 contains the experimental evaluation and section 5 ends with the conclusion.

II. RELATED WORK

Temperature and humidity sensors best devices from collecting the data and monitoring the pollution, temperature, levels of humidity, sensors are used in most sensitive places like health care and military enforcement, border security [5]. Energy consumption [5], battery life is the most challenging issue for researchers in WSN [5]. Data prediction means to reduce the redundancy data and remove the useless data [6-13], huge amount of research has been done on data prediction but no literature available on a deep learning-based RSA algorithm. The following Table 2 shows the major research gaps are identified by the prediction methods are used by the WSN.

Table 2: The major research gaps identified in data prediction in WSN

Author	Research Gaps
Ramsey Faragher (2012) [6]	In this study provides the basic principle of working 'Kalman filter' , error occurrence has been done after adjustment of waits, energy consumption is not discussed.
Guiyi Wei (2011) [7]	Combining Gray model based data aggregation (GMDA) in Kalman filter but it improves the communication only.
Olston (2005) [8]	Proposed TRAPP (Tradeoff in replication precision and performance) query based optimization approach but it is not suitable for all challenges in WSN.
Rajagopalan (2006) [9]	This study gives a survey on various data prediction techniques on wireless sensor networks
Anastasi (2008) [10]	The study techniques receive data redundancy technique, but not solve Energy consumption, memory space, etc..
Deshpande (2004) [11]	This study gives classifies the data aggregation approach in three ways stochastic approaches, algorithmic and time series forecasting approaches, it solves energy consumption only.
Chu (2006) [12]	Data collection in sensor networks solved by using probabilistic models, but it reduces the anomalous data, it not solved by the energy consumption, memory space etc..
Stojkoska (2012) [13]	Data prediction in wireless sensor networks solved by using variable step size LMS algorithm, but not used updated descriptions.

As per Table 2, data prediction is a technique to remove the useless data and reduce the redundant data, the various research has been done on data prediction, data compression in WSN, Kalman Filters [6] was proposed prediction based data models are used in wireless networks, Guiyi Wei[7] proposed a novel approach for data prediction by the combination of (GMDA)with Kalman-Filter named as Kalman filter data aggregation (KFDA), it improves accuracy, but suffering from energy consumption. Olston [8] proposed TRAPP based data reduction used query-based optimization and deliberated different models of the sensor node, it performs data transmission between synchronous intervals, it is mainly focused on energy savings but not solve the major challenging issues. Rajagopalan [9] survey on various data normal operational techniques and stochastic models to reduce the communication overhead, remove data redundancy and increase the battery lifetime the data need not be reported on every sink node where the sink node does not give the information to the root node, this model fails on aggregated data in this model lack communication and also cannot improve memory space.

Deshpande [11] the probabilistic models only used to solve this approach, this is model not suitable for improvement of energy, and lifetime of the battery. Chu [12] this prediction model useful to reduce the. anomalies of the data, this model used sensor nodes to send the information base stations and anomalous data. Biljana Risteska Stojkoska [13] explain the LMS based data prediction method, in this process used previous knowledge of data, it implemented on variable step-size method and proved 95% aggregated data has improved on the cluster network. Carmalatta [14] provide a taxonomy of various data prediction models, LMS prediction and optimal step size algorithm compared with a threshold value, this model applicable for environmental monitoring and it is most effect on temperature and humidity sensors, In this paper the same approach has been implemented with updated technology, Kalman [15] made for cluster-based wireless sensor network and it is most applicable feed-forward approach, hence this model is most suitable for the proposed approach, El-Telbany [16] suggest to increase the battery life and improve energy consumption, while transmission if any node failure source and destination provides the same prediction values, in this paper also used the same prediction approach and improves the proposed model as shown in Table 2 contains the advantages of proposed approach.

Table 2: Compensations of the proposed methodology

Wireless Sensor Networks	
Challenges issues can be solved	**Major areas where it can be solved**
Data Redundancy	Reduce the energy consumption
Data Computation	Reduce the energy conservation
Security	Improve the battery life time
High Sensing and Flexibility	Improve the memory space while transmission

III. PROPOSED APPROACH

Sensor is a small low battery power device which has the ability to collecting information, gathering data and transmitting to the base station, due to low battery power and the low computational speed we cannot utilize all features of a sensor node to overcome its drawback [1]. The level of data aggregation decides by the deep learning approach [23], it improves the depth of the network by using deep learning approach [24]. The more number of layers are used while RSA encryption and decryption algorithm provides end-to-end confidentiality for collecting and aggregating the data. The entire data collection it performs the individual data operation as follows [25].

$$\sum E(D_1 + D_2) = \sum E(D_1) + \sum E(D_2)$$
$$\sum E(D_1 \times D_2) = \sum E(D_1) \times \sum E(D_2)$$

It performs addition and multiplication of encrypt the data without the need of individual decrypted data, the pseudo code for key generation as shown in Algorithm 1.

Algorithm 1: Pseudo code for Key generation procedure for RSA algorithm:

Step 1: Consider two different random prime numbers P1 and P2 where P1 $\neq$ P2

Step 2: Calculate the Value M=P1 $\times$ P2, N value will be calculate the modulus

operation of both P1 and P2

Step 3: Find the (M)=(P1 -1) (P2-1)

Step 4: Find an integers values 1<i< (M), and calculate i, (M), no divisors until

GCD (i, δ (M))=1

Step 5: Finally compute the value of private key based on Pr=1+k (M)

Step 6: Repeat the step 1 to Step5 until private key is obtained

After generating the key it is useful to find encryption and decryption as follows, Public key is obtainable for entire cluster data, it can be represented as (δ , M). Private key is existing to moreover sink nodes the, the pseudo code for encryption and decryption as shown in Algorithms 2 & 3.

Algorithm 2: Pseudo code for RSA Encryption Algorithm

Step 1: Sensor node contains public key Pu(i,M)

Step 2: En=(Ni) mod (M)

Step 3: The data is encrypted

Algorithm 2: Pseudo code for Decryption Algorithm

Step 1: sink nodes or base stations have private key such as P_r (Pr_i ,M)

Step 2: N= (En^{Pr}) mod (M)

Step 3: The data decrypted.

Kalman Filter [15] is ancient approach (1960), later the model is updated with Gray model and Dual Kalman filter etc, while data processing, Neel Arm Strong used in to predict earth surface , moon suface, satellite navigation system[16] LMS method is also proposed Widrow-Hoff rule (1960) used in adaptive circuit switching method for high data transmission in AT&T-bell laboratories, in this proposed methodology the same LMS algorithms has implemented with the feed-forward filter as shown in Figure 3.

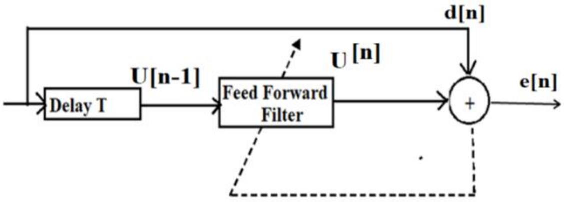


Figure 3: Feed-forward filter for data prediction approach [16].

At each instance of time the value one layer output process to the next layer, it has ‘n’ layers for deep learning approach (input layer, out layer, and many number of hidden layers) feed-forward adaption filter send the input signal ‘i’ , and it represented as U[n] becomes the output signal of the feed-forward filter and produce the predicted data rate value. The prediction is applicable to conclude missing value applying estimation of future value as per the deep learning approach on previous value. Let consider a WSN for a star topology network one node can act as head node, tree network the root can act as head node, where cluster network various number of nodes the primary root node can act as head node.

Each node can process the data to the next node, each and every sensor node have equal time period, the prediction technique is applicable to each and every node in the network. To compute the energy consumption in wireless sensor networks *Ec* , it receive the data *D* bits per second per unit of time , the energy consumed to transmit the data *T* bits per second per unit of time, E_{elc} the amount of energy required for feed forward filter, E_{fs} is the relay activation energy then it follows

$$E_c = D * T * E_{elc} * E_{fs} \tag{1}$$

The distance between one sensor node to another sensor node *di* then it calculate the distance function as follows.

$$d_i = \sqrt{\frac{E_{Elc}}{E_{fs}}} \tag{2}$$

The LMS algorithms works with the three major techniques such as i) Filter output ii) Estimation error iii) weight or input adaption as shown in Algorithm 4.

Algorithm 4: Least Mean Square (LMS) Algorithm

Step 1: Compute the filter output where F[n] be the output signal, $a^T[n]$ be the adjective sensor weights and input coefficient, the current input signal μ[n] used as follows.

$$\mathrm{F}[n] = a^T[n].u[n]. \tag{3}$$

Step 2: Then it calculate the estimated error, where e[n] is the estimated error occurrence has been given to the feed forward filter, C[n] is the expected output signal that subtracted from the given input signal F[n] as follows.

$$e[n] = C[n] - F[n] \tag{4}$$

Step 3: Adjust the weights as per the input adaption from equation 2, μ is the step size coefficient which can help to calculate the filter length, step size coefficient, it can adjust the weights as follows.

$$\mathrm{a}[n+1] = a[n] + \mu.u[n].e[n]. \tag{5}$$

In Feed forward b is the input signal at k number of iterative steps and the summation input is b[k] to calculate the output function F[K] the following formula which can be defined as

$$\mathrm{F}[k] = \sum_{j=1}^{p} a_i(n) \times b_j(n) \tag{6}$$

The final adjustments of A and B In feed forward filter adjustment of weights has follows.

$$A_{in} = [\mathrm{a}_1(n) + a_2(n) .... \mathrm{a}_k]^T \tag{7}$$

$$B_j(n) = [\mathrm{b}_1(n) + b_2(n) .... \mathrm{b}_k(n-M)]^T \tag{8}$$

The feed forward filter length M where μ is the input signal of feed forward filter, u[n] is the current input signal d[n] be the desired out signal, n be the iterative signals to adding the iterative data, the feedback can be obtain the adjustment of the desired input signal, it give the error it can adjust signal then obtain accurate feedback of feed forward filter, the auto correlation η can be obtained from n number of layers, the predicted signal obtained from desired output signal which gives error as feedback to adjust input signal. The total input signal IP_{Total} is devisable n layers matrix that is obtained by learning rate coefficient.

$$\eta = \frac{n}{IP_{Total}} \tag{7}$$

The total input power IP_{Total} obtained by the largest eigenvalue of autocorrelation matrix η. The step size variable μ lies in between the 0 and autocorrelation matrix .

$$0 < \mu < \frac{n}{IP_{Total}} \tag{8}$$

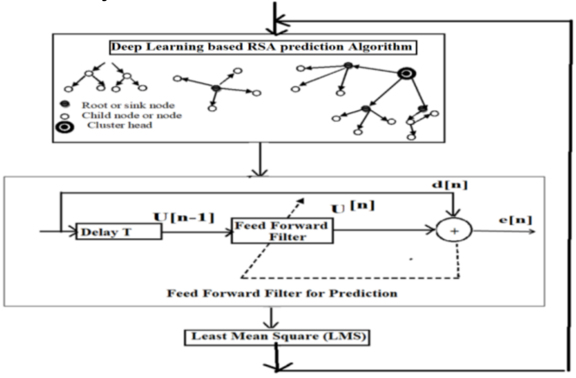
Where IP_{Total} it can be compute through mean value as follows

$$IP_{Total} = \sum_{n=1}^{n} \frac{\mu_n}{n} \tag{9}$$

n denotes the total number of iteration as per the deep learning based RSA approach, the iteration train the feed forward filter, it obtain the step size μ_{new} multiplied with filter length M and it division value of μ_{old} , it determine the absolute step size variable the provides the error value as per the equation given below.

$$\mu = \frac{\mu_{old}}{\mu_{new} \times M} \tag{10}$$

In the WSN the data collection by using deep learning-based RSA at the application layer, first sensor node collects data from the physical layer and sends data to the sink node, the sink node sends data to the sensor node, the sensor node checks the redundant data and remove the useless data and it sends to the data center [20] and it reduces the memory space as well as increase the data transmission rate, and it improves battery life. The overall proposed methodology has been described in Figure 4. In Below Figure 4, it performs three different stages, first stage decides the topology tree, star and cluster based widely used in WSN, while data transmission stage feed-forward filter used to collect data for each topology and compare the value of step size variable μ with the threshold value, it contains variable length M and calculate the error rate and it reduced to 'n' number of hidden layers. The third stage LMS value used to collect the data from each sensor and transmit to respective sink node at that time same algorithm is synchronously work and effective transmission of data to



the sensor nodes, the aforementioned approach continually work until whole data transmission in the entire network.

IV. EXPERIMENTAL EVALUTION

The proposed architecture, data collection using deep learning RSA prediction is implemented ns2 tool kit, the iterate approach after obtaining the LMS vale with variable step size given to the network for transmitting to the data than given to the network such as tree, star and cluster.

The feed-forward filter provides the prediction value μ, the IntelBerkeley Research Lab [17] provides the data set as follows.

Table 3: Intel Barkeley Research Lab resultant data set [17]

Topology	Sink node	Child node	Filter length (M)	Step Size
Tree	19	20,21,22,23,26,27	6	4
Star	4	2,3,5,6,7	6	5
Cluster	14,19	17, 18,20,21,12,13,15,16	2.4	6

In tree topology where sink node 19 the appropriate child nodes are 20, 21, 22, 23, 26, the feed forward filter length value M=6 (1.2×10^{-5}) and step size 4, it provides the data prediction rate 95%. In star topology the sink node becomes 4, the intermediate nodes are 2, 3, 5, 6, 7 the M value 6, the step size and filter length are same as tree topology. It considered sink nodes are 14 and 19 in cluster topology, the intermediate nodes are 17, 18 and 19 , the filter length M =2.4 (1.2×10^{-8}).

The aforementioned data set values with mathematical models are simulated with MatLab tool kit evaluated the results, it obtains the error rate results on the humidity sensor and temperature sensor, the effective results are carried out by the cluster topology compared to a tree and star topology, the highest error rate is measured on tree topology because it contains the maximum number of sink nodes, the following Figure 5 for error rate is measured on temperature sensor and Figure 6 error rate is measured on humidity sensor.

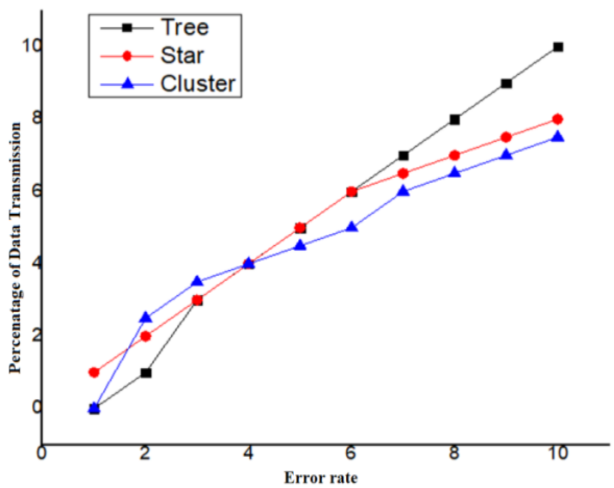


Figure 5: Temperature Sensor error rate

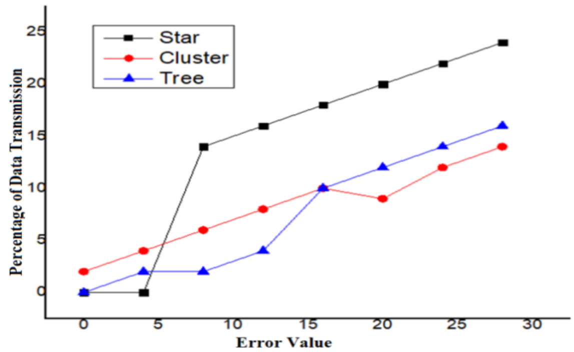


Figure 6: Humidity sensor error rate

The proposed model has been tested with the ns2 tool kit version2 open source event driven simulator and given the data set as input and obtain the effective results are carried out by the deep learning-based approach as shown in Figure 7 energy consumption not more than 92KWH when sensor nodes are 70 and Figure 8 lifetime of the battery is not more than 500 seconds when sensor nodes are 300.

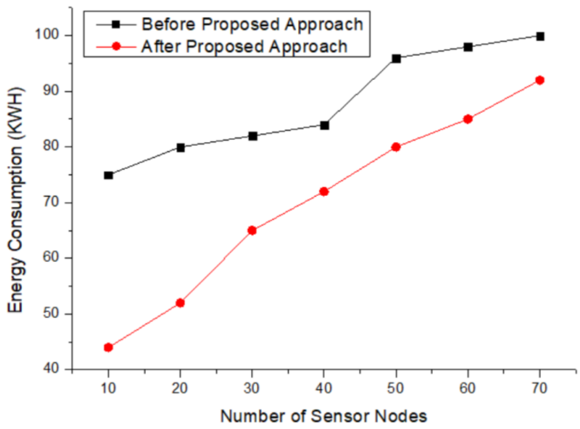


Figure 7: Performance of Energy consumption

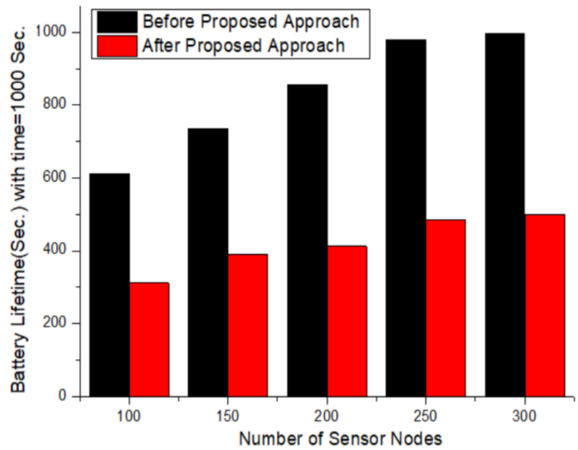


Figure 8: Performance of Battery life time.

To evaluate the data prediction approaches by using LMS algorithms for variable step-size method in networks such as tree, star, and cluster, the MALAB simulator evaluated the results, the average data rate of humidity and temperature sensor assumed as per topology as a tree, star and cluster on as per the data set [17] as shown in the Table 3.

Table 3: Obtained average data rate as per the topology

S.No.	Topology	No. of nodes for topology	Average temperature	Average humidity	Average data transferring rate	Step size
1	Star	2,3,4,5,6	18.9594	39.9742	43.24	4
2	Tree	20,21,22,23,26,27	19.0864	39.054	41.18	5
3	Cluster	17,18,20,21,15,16,17,19	18.7681	39.8245	42.94	6

Average data rate of humidity and temperature sensors, cluster network provides the higher performance rate compared to tree and star topology that is it gives approximately 98% of data reduction and transmitting rate because data transmit between a minimum numbers of sink nodes as shown in Table 4.

Topology	Sink node	Child node	Filter length (M)	Step Size	Data Prediction
Tree	19	20,21,22,23,26,27	6	7	95%
Star	4	2,3,5,6	4	7	92%
Cluster	14,19	17,18,20,21,12,13,15,16	4	4	98%

V. CONCLUSION

The experimental evaluation as per the Intel lab measured temperature humidity sensors, the valuations of results by using the proposed architecture by using the deep learning RSA prediction algorithm using the LMS method and variable step size approach implemented in ns2 tool kit, it obtains the result as implanted in MATLAB R2016b shown in Table 5.

Table 5: Star, Tee, Cluster corresponding type of sensor Prediction rates

Topology	Type of Sensor	Amount of Data Transfer (MBPS)	Prediction data rate
Star	Temperature	18.59	94.9%
	Humidity	36.64	95.01%
Tree	Temperature	43.24	92.01%
	Humidity	44.12	91.96%
Cluster	Temperature	36.64	97.89%
	Humidity	43.24	98.01%

It provides the 95% prediction rate in start topology on step size 4, the data transfer rated 18.59 MBPS on the temperature sensor and 95 MBPS in humidity sensor. In the tree, topology obtains 92%, and cluster topology obtain 98% higher prediction data rate when compared to the tree and star topologies. Tree and star topology needed less prediction rate due to the various sink and intermediate nodes and moreover it contains parent nodes, but the cluster network shows better performance when compared to tree and star topology.

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AUTHORS PROFILE

Anand Dohare, Research scholar in SHAUTS, University, Allahabad, India, Published various research paper in top journal, research area is WSN and cloud computing.

Dr. (Mrs) Tulika Assistant professor in the department of Computer Science and Information technology in Sam Higginbottom Institute of Agriculture Technology and Sciences, Allahabad Since November 2006. She received her Ph.D degree in Computer Science from Thapar University Patiala in Vehicular Network field. Her areas of interests are Vehicular Ad hoc network, Ad hoc network and Peer-to-peer network, she Published various book and research paper in renowned journals.

Dr. Basetty Mallikarjuna currently works at the Scool of Computing Science & Engineering, Galgotias University, Greater Noida. Dr. Basetty does research in Cloud computing, Internet of Things, Green Computing, Blockchain and 'Health care Applications'

Mrs. Sweta Sachan pursuing M.Tech from MDU, Rohtak in Computer Science & Engineering. Research area is AI & ML.