Towards Prediction Model For IoT-Wireless Sensor Network Packet Transmission Using Soft Computing Technique

James Agajo
Computer Engineering Department
Federal University of Technology
Minna, Nigeria
james.agajo@futminna.edu.ng

Sadiq Thomas
Computer Engineering Department
Nile Univerisity of Nigeria
Abuja, Nigeria
sadiqthomas@nileuniversity.edu.ng

Najashi Gafai
Electrical & Electronics/Computer Engineering Department
Baze University, Abuja, Nigeria
najashi.gafai@bazeuniversity.edu.ng

Ajao Adewale Lukman
Computer Engineering Department
Federal University of Technology
Minna, Nigeria
ajao.wale@futminna.edu.ng

N. Ali Obadiah
Computer Engineering Department
Nile University of Nigeria
ali.obadiah@nileuniversity.edu.ng

K. C. Okafor
Mechatronics Engineering Department
Federal University of Technology,
Owerri, Nigeria
kennedy.okafor@futu.edu.ng

2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS) | 978-1-6654-3493-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICMEAS52683.2021.9692316

Abstract— Packet transmission is a function of signal strength and distance in a wireless sensor network (WSN). The interval between the source node and sink node is of high significance in a wireless sensor network. This work developed a soft computing model that relates distance, signal strength, packet received and packet transmitted. An experiment was carried out using the CC2430 module for data acquisition. A learning process is carried out using the neural network (NN) tool toolbox. The entire datasets for training, testing, and validation are 60%, 25%, and 15% respectively. Regression result from training, testing, and validation was realized with *R* yielding 0.99972, 0.99974 and 0.99954 respectively. The summation of *R* gave 0.99869 in the work. The significance of the *R* value is that when it tends towards 1, the result demonstrates the accuracy of the model. This means that when the output of the trained and the test data are compared, it shows closeness symmetry. The closeness depicts how well the model performs. At convergence, the result shows that the coefficient for transmitted packet, distance and signal strength are predicted as 0.9969, 1.10800, and 0.7 respectively.

Keywords—Wireless Sensor Network, Machine Learning, Quality of Service (QoS), Artificial Neural Network, IoT

I. INTRODUCTION

In smart Internet of Things (IoT) powered networks, packet transmission largely depends on the signal strength and distance. In such a wireless sensor network, the interval between the source and sink nodes is very significant for deterministic applications [1]. The last decades have witnessed researchers focusing more on large-scale sensor networks having wireless communication capabilities [2]. The majority of the IoT-based apps are aimed at gathering data from the physical world, performing rudimentary processing on it, and sending it to the remote cloud for orchestration and analytics [3]. Most IoT-based applications only demand a minimal amount of bandwidth for data stream propagation. This, therefore, makes transmission delay less of an issue especially when the Fog layer is involved [1] – [8].

A wireless sensor network (WSN) is a sensor network comprising sensor nodes that are typically deployed in a field within a specific coverage area while serving a particular interest [9]. WSN is made up of a large number of small sensor nodes and a few powerful nodes known as central nodes or base stations which are battery-operated, low-cost, high-performance computing devices containing a variety of sensors without the Internet. WSNs are deployed in specific geographic areas and are organized into smaller supporting networks to sense and collect data [10]. The sensor and sink nodes communicate at 250kbps across the 2.4GHz ISM band. [11]. The nodes operate as a peer-to-peer network that employs multi-hop and cluster-based routing methods. Due to the huge area of WSN application, IoT-edge computing is one of the most popular research topics today. This is due to its wide application in the industrial sectors. With huge data transmission considerations, the major focus among researchers is to reduce the amount of power consumed the nodes. Considering its direct and indirect impacts, an important parameter to be addressed in any WSN taking cognizance of data transmission is the Bit Error Rate (BER). [12]. This is very significant since energy expended in transmitting incorrect or error bit information from a source node to a sink node can mask streams intelligence. This can equally lead to the complete waste of valuable resource. Also, the delivery of incorrect data by the network poses a threat to several battlefields and environment monitoring applications involving IoT WSNs [13].

There is a need to focus efforts on IoT WSN packet transmission optimization by understanding the complex variable composition in an operational network. In this case, traffic demand becomes necessary when applied in complex networks such as Fog Computing, Cloud and Big data, real-time demand.

The main aim of this work is to drive soft computing prediction models for IoT WSN packet transmission using machine learning techniques for quality of service optimization in IoT-WSNs.

The rest of this paper is organized as follows. Section II presents related works. Section III presents RSSI model and error analysis. Section IV presents model formulation. Section V presents neural network data fusion. Results and Analysis is discussed in Section VI while Section VII concludes the work with future direction.

II. RELATED WORKS

This section focused on WSN issues and research efforts by experts in the field. The paper in [14] focuses on identifying practical advantages for reducing WSN errors. Different parameters such as erroneous bits, frames missed, and total received packets are investigated, but average BER and the impact of distance on BER are given specific emphasis. The ratio of bits transferred with errors to total bits transferred is the BER. It's a widely used metric for calculating wireless network errors [14].

Various research publications have looked how impediments in the indoor environment affect RF signal strength. In some cases, obstacles that were considered are glass, walls, and steel. This is in addition to human activities between sensor nodes. The analysis had been carried out to discover how the signal was attenuated through walls and other obstacles [15]. Experiments had been done using Zigbee IEEE 802.15.4 Standards Transceiver [16]-[17]. IoT-based WSNs will remain popular since their research findings would probably reveal the optimized distances between RX and TX through walls and crowded areas. Human activities also impact signal strength to some extent. All of these factors had an impact on the RF signal strength.

Some researchers have worked on the Received Signal Strength Indicator (RSSI) [19]- [20]. This is a decibel (dBm) measurement of the signal strength at the receiver. Depending on the hardware platform, it is commonly a five, eight, or ten-bit value. In CC2430, the RSSI gives an 8-bit value. The RF signal strength parameter is commonly utilized in indoor tracking and localization [21]. It minimizes the cost by obviating the need for additional hardware and Time of Arrival (ToA). To estimate the position of unknown devices, many localization methods require a distance. Measuring the received signal strength of an incoming radio broadcast is one way to get a distance estimated. The RSS concept is that the transmitting device's (PTX) configured transmission power has a direct impact on the receiving device's (RDX) receiving power (PRX). A summary of related works is highlighted [22]-[32]. According to Friis' free space transmission equation, the detected signal strength decreases quadratically with the distance to the sender [33].

The use of soft computing techniques deals with the collection and harvest of artificial intelligence-focused computational schemes such as neural network, machine learning, fuzzy-logic, and organic-genetic algorithms to solve complex problems [32]-[33]. In this work, the received signal strength is converted into a received signal strength indicator (RSSI) in embedded IoT WSN devices. This is the ratio of received power to reference power (PRef).

The reference power is usually expressed as an absolute value of Pref=1mW [34] – [35].

$$\text{P } P_{RX} = P_{TX}.\mathrm{G_{TX}}.\ \mathrm{G_{RX}}\left(\frac{\lambda}{4\pi d}\right)^2 \qquad (1)$$

PTX = Transmission power of sender
PRX = Wave Power Remaining at receiver
GTX = Transmitter Gain
GRX = Receiver Gain
λ = Wave-length
d = Distance between sender and receiver

III. RSSI MODEL AND ERROR ANALYSIS

In this section, the radio mode consideration for RRSI is discussed. Now, RSSI measurements are the most widely used range-based technique. The primary idea is to use the received signal power, knowledge of the transmitted power, and a path loss model to estimate the distance between an IoT WSN transmitter and a receiver. free space propagation model, two-ray ground reflection model, long-distance path loss model, log-normal shadowing model, and Hata model make up the loss models [36].

In this paper, let us consider the log-normal shadowing model which is given (2).

$$PL(d) = PL(d_0) - 10nLog_{10}\left(\frac{d}{d_0}\right) + X \qquad (2)$$

where $PL(d)$ is the received signal power loss (expressed in dBm) and the distance between transmitter and receiver is denoted by d, the reference distance is denoted by (d_0), typically (d_0)= 1m .

distance. n is the path loss exponent, typically $n = 2{\sim}6$. X is a zero-mean Gaussian random variable that reflects the random variation in the path loss due to multipath and shadow fading. The experimental traffic patterns may consists of one packet per second transmitted by a node at one end of the line with each packet having a monotonically growing sequence number. In complex networks, all other nodes merely receive packets and record received packets in a local store.

IV. MODEL FORMULATION

Let's develop a model that will represent the sensor clusters within the cluster Personal Area Network (PAN) [37]. The model below is a matrix representation showing routing in a PAN for the IoT WSN model which factors errors ∈.

$$\begin{bmatrix} CH_1 \\ CH_2 \\ CH_3 \\ \vdots \\ \vdots \\ CH_n \end{bmatrix} = \begin{bmatrix} f_{11}(x) & f_{12}(x) \ldots\ldots & f_{1m}(x) \\ f_{21}(x) & f_{22}(x). \ldots\ldots & f_{3m}(x) \\ f_{31}(x) & f_{32}(x) \ldots\ldots & f_{3m}(x) \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ f_{n1}(n) & f_{n2}(n) & f_{mn}(x) \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ W_3 \\ \cdot \\ \cdot\cdot \\ W_n \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \vdots \\ \vdots \\ \epsilon_n \end{bmatrix}$$

(3a)

Let CH_1= Cluster Head 1
Let CH_2= Cluster Head 2
Let CH_3= Cluster Head 3
Let CH_n= Cluster Head 4
Let ϵ_1 = Error in data in Cluster 1
Let ϵ_2 = Error in data in Cluster 2
Let ϵ_3 = Error in data in Cluster 3
Let ϵ_n= Error in data in Cluster *n*

$f_1(x)$ is a function representing variable 1 in Base Sensor 1
$f_2(x)$ is a function representing variable 2 in Sensor Station 2
$f_3(x)$ is a function representing variable 3 in Sensor Station3
$f_n(x)$ is a function representing variable 4 in Sensor Station 4

A. Unique Cluster Models

The model for cluster head is split into (3b),(4),(5), and (6).

$$\begin{bmatrix} CH_1 \\ CH_2 \\ CH_3 \\ \vdots \\ \vdots \\ CH_n \end{bmatrix} = \begin{bmatrix} f_{11}(x) & f_{12}(x) \ldots \ldots & f_{1m}(x) \\ f_{21}(x) & f_{22}(x). \ldots \ldots & f_{3m}(x) \\ f_{31}(x) & f_{32}(x) \ldots \ldots . & f_{3m}(x) \\ \vdots & \vdots & \vdots \\ f_{n1}(n) & f_{n2}(n) & f_{mn}(x) \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ W_3 \\ \cdot \\ \cdot \\ W_m \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \vdots \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$CH_1 = W_{11}f_1(x) + W_{12}\, f_2(x) + \ldots . W_{1m}\, f_3(x) + \epsilon_1 \qquad (3b)$$

$$CH_2 = W_1 f_1(x) + W_2 f_2(x) + W_3\, f_{2m}(x) + \epsilon_2 \qquad (4)$$

$$CH_3 = W_1 f_1(x) + W_2 f_2(x) + W_3 f_{3m}(x) + \epsilon_3 \qquad (5)$$

$$W_n f_1(x) + W_n f_2(x) + W_N\, f_{nm}(x) + \epsilon_4 \qquad (6)$$

$W_1, W_2, \ldots . W_n$ are coefficient
f_1= Function for variable 1
f_2= Function for variable 2
f_3= Function for variable 3
f_n= Function for variable n

The equation at the base station is shown below

$$[E_{123\ldots m}] = [f_{1234\ldots n}(x) \quad (x) \quad \ldots . f_{1234\ldots\ldots n}(x)] \begin{bmatrix} W_1 \\ W_2 \\ \cdot \\ \cdot \\ W_m \end{bmatrix} + [\epsilon_{1234\ldots\ldots m}]$$

Base station= $E_{123\ldots\ldots\ldots m}$

The model for WSN fusion at the base station is given in (7)

$$E_{123\ldots m} = W_1 f_{1234\ldots\ldots m}(x) + W_2 f_{1234\ldots\ldots m}(x) + W_3\, f_{1234\ldots\ldots m}(x) + \epsilon_4 \qquad (7)$$

Further description will employ the use of the neural networks in realizing the predictive model for data transmission as shown in Fig. 1.

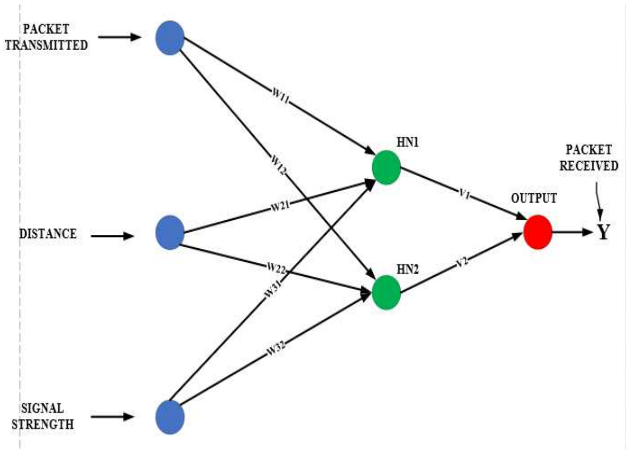

Fig. 1. Soft computing Neural model (Inner) Layer

The characteristic equation is given in (8) as follows.

$$aU + bX + cY + \cdots (input) = Z\ (output) \qquad (8)$$

where a, b and c are all coefficients. If U, X, and Y are considered as inputs variables, then a 2 layer artificial neural network equation from Fig. 1 can be represented as follows

$$Uw_{11} + Xw_{21} + Yw_{31} = HN1 \qquad (9)$$

$$Uw_{12} + Xw_{22} + Yw_{32} = HN2 \qquad (10)$$

Resolving the addition of entering into the output neuron gives

$$Z = V_1 HN1 + V_2 HN2 \qquad (11)$$

$$Z = V_1[Uw_{11} + Xw_{21} + Yw_{31}] + V_2[Uw_{12} + Xw_{22} + Yw_{32}] \qquad (12)$$

$$Z = U(V_1\, w_{11} + V_2\, w_{12}) + X(V_1\, w_{21} + V_2\, w_{22}) + Y(V_1\, w_{31} + V_2\, w_{32}) \qquad (13)$$

$$a = V_1 w_{11} + V_2 w_{12}$$
$$b = V_1 w_{21} + V_2 w_{22}$$
$$c = V_1 w_{31} + V_2 w_{32}$$

Table 1 shows the test result conducted. In this case, the experiments were carried out on our testbed several times. Date was recorded for the different receivers. For a four (4) variable input, the coefficients or synaptic weights from the equation are subjected to adjustments during the process of data training and learning. The eventual matrix model will be given as (14).

$$Output = \begin{bmatrix} W_{11}V_{11} \\ W_{12}V_{21} \\ \vdots \\ W_{1k}V_{k1} \end{bmatrix} P + \begin{bmatrix} W_{21}V_{11} \\ W_{22}V_{21} \\ \vdots \\ W_{2k}V_{k1} \end{bmatrix} T + \begin{bmatrix} W_{31}V_{11} \\ W_{32}V_{21} \\ \vdots \\ W_{3k}V_{k1} \end{bmatrix} H + \begin{bmatrix} W_{41}V_{11} \\ W_{42}V_{21} \\ \vdots \\ W_{4k}V_{k1} \end{bmatrix} SM \qquad (14)$$

This took cognizance of height and different transmission distances. For the WSNs, this work gathered RSSI values from various receivers, which are analyzed by MATLAB toolbox. Also, the various graphical representation of measured data is highlighted in Fig. 3. It could be deduced from the figure that signal quality of 1m is relatively strong and acceptable. Table 1. lists out the average value of RSSI of packet transmission, signal strength distance, and received packet the average value of RSSI is the maximal for the range of distance, Which leads us to the conclusion that signal quality vs. data sent and received

Table 1. Empirical data acquired from the field

SN	Transmitted packet	Received packet	Distance (m)	Signal Streng
1	12758	12758	5.0	-65
2	12758	12758	7.5	-66
3	12758	12758	10.0	-72
4	12758	12758	12.5	-73
5	12758	12758	15.0	-75
6	12758	12757	17.5	-77
7	12758	12757	20.0	--79
8	12758	12756	22.5	-80
9	12758	12753	25.0	-82
10	12758	12753	27.5	-83
11	12758	12608	30.0	-84
12	12758	12540	32.5	-84
13	12758	12248	35.0	-85
14	12758	12158	37.5	-85
15	12758	11656	40.0	-86
16	12758	11258	42.5	-86
17	12758	10748	45	-87

V. NEURAL NETWORK DATA FUSION

In this section, we highlight the application of soft computing neural network data fusion for data optimization. Fig. 2

shows the input layer's neurons which serve as buffers for dispersing input signals *(P, T, H, (SM)* in the hidden layer *(HN)* as inputs to the neurons in (14). Each neuron present in the hidden layer *(HN1, HN2)* sums up its input signals after weighting them for the strengths of the appropriate input layer connections (W_{ij}) and computes its output as a function.

$$HN1_{output} = f(TW_{11}+DW_{21} + SSTW_{31}) \tag{15}$$
$$HN1_{output} = f(TW_{12}+DW_{22} + SSTW_{32}) \tag{16}$$

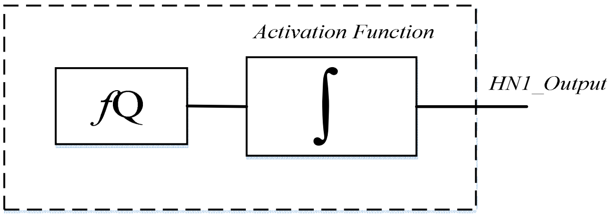

Fig. 2. Block diagram of Activation Function

VI. RESULTS AND ANALYSIS

A. Data Collection and Graph Discussion

In this section, the behaviour of all the data collected is presented graphically. Fig. 4 shows signal strength against distance, which explains that an increase distance leads to a decrease in signal strength. Fig. 5 is a graph of the packet received against signal strength. This explains that packet received decreases with an increase in distance, Fig. 6 is a graph of the packet received against distance. It is the combined graph of the packet received/packet transmitted against distance. Fig. 3 is the combined graph of the packet received/packet transmitted against signal-strength.

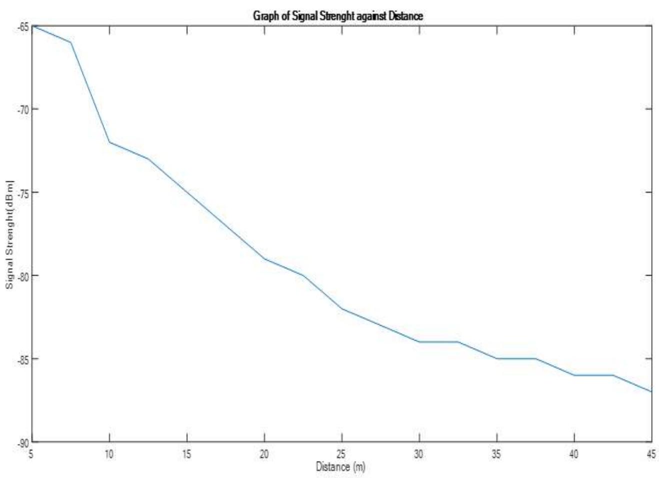

Fig 3. Graph of Signal Strength against Distance

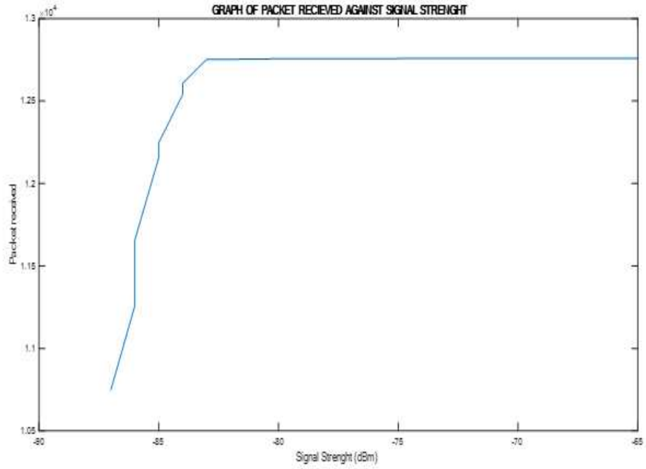

Fig. 4. Graph of Signal Strength against Packet received.

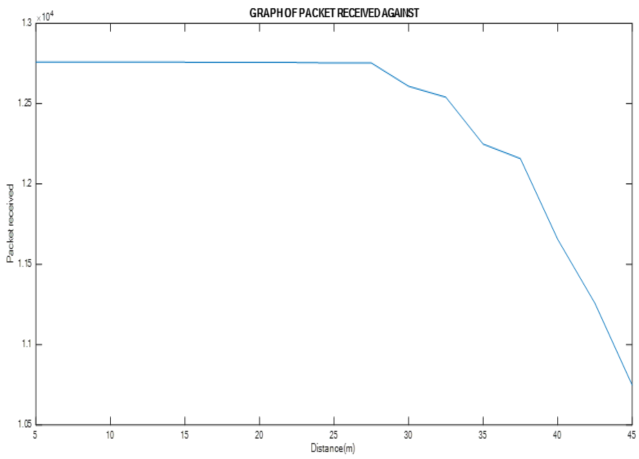

Fig. 5. Graph of Packet received against Distance

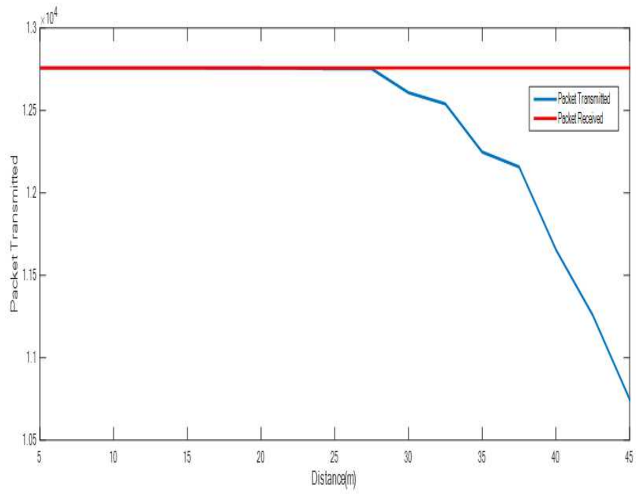

Fig. 6. Graph of Packet Transmitted/Received against Signal Strength 5

B. Analysis of Machine Learning Technique

One of the most prominent learning methods for learning from data is neural networks. This is created using decision units cascading chains. These is also known as perceptual and radial basis functions. Non-linear and complex correlations in data can be recognized using cascading chains of decision units. However, the learning process with several cascading chains, on the other hand, is computationally demanding.

Fig. 7 depicts the machine learning technique used to develop the models. Test performance and iteration using the neural network training tool was achieved. Now, the work explored a relationship between packet received, signal strength, and distance. The neural network engine is employed to realize the optimal convergent point for the IoT WSN.

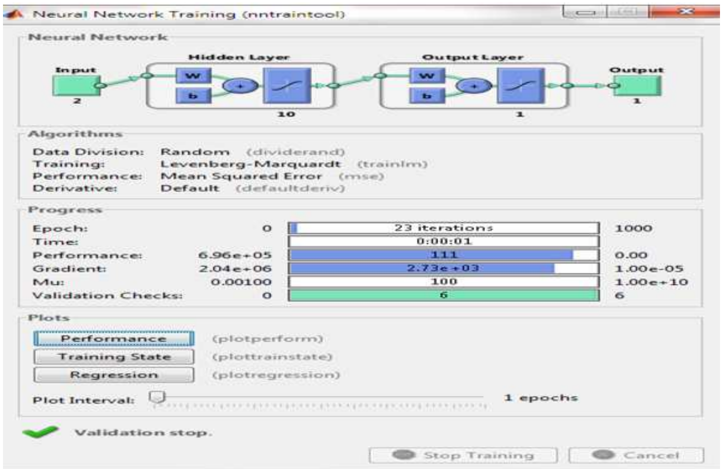

Fig. 7. Test performance and iteration using Neural Network Training tool.

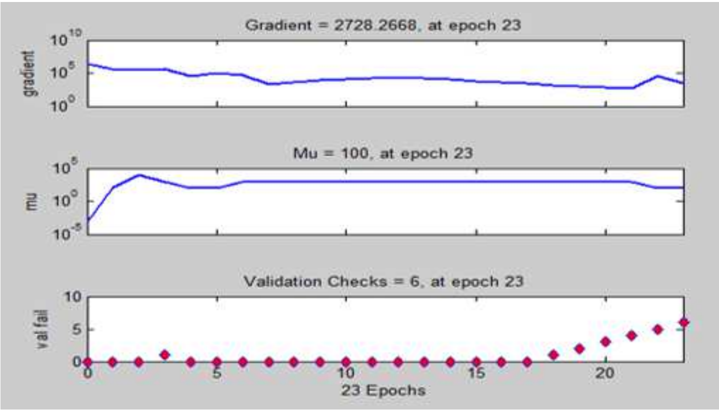

Fig. 8. Graph of Gradient Descent.

In developing the model the data collected was trained. Fig. 8 shows the gradient descent considering the neural performance in Fig. 9. The training, testing, and validation profiles are depicted in Fig. 9. For the variables been considered, the 3 inputs gave rise to the hidden layers. The processing is carried out while obtaining the output results. Fig. 9 shows the learning process using gradient descent shown in Fig. 8.

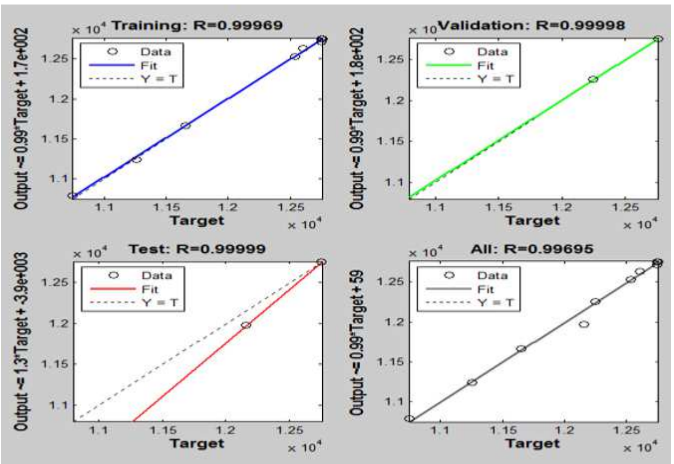

Fig. 9. Graph of Testing, validation, and Training.

Fig. 10 shows the process of training testing and validation with specific targets. The blue line is for training; the green line is for validation and the red line is for testing. At this point, the level of relationship between them is derived. The regression result for training testing and validation is shown in Fig.10 with R=0.99972, for validation R=0.99954 and Test R=0.99974, when we put all together *R*=0.99869.

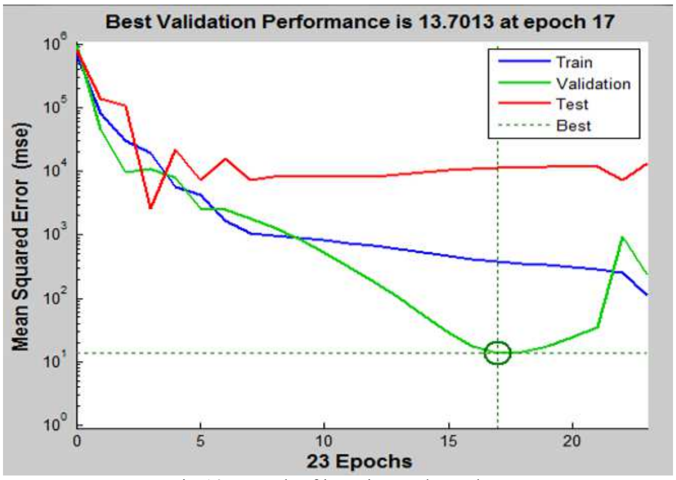

Fig.10. Graph of iteration and epoch

The significance of the value of *R* is that when it tends towards 1, this demonstrates the model accuracy. In this case, the output of the trained and test data are compared. Their closeness is a demonstration of how well the model performs. Recall that the *nntool* was used in generating the model after training, testing, and validation in Fig. 11. The model from the *nntool* was eventually generated. Now, the data show that after training, testing and validation, a model was developed for packet transmission as described by previous equations.

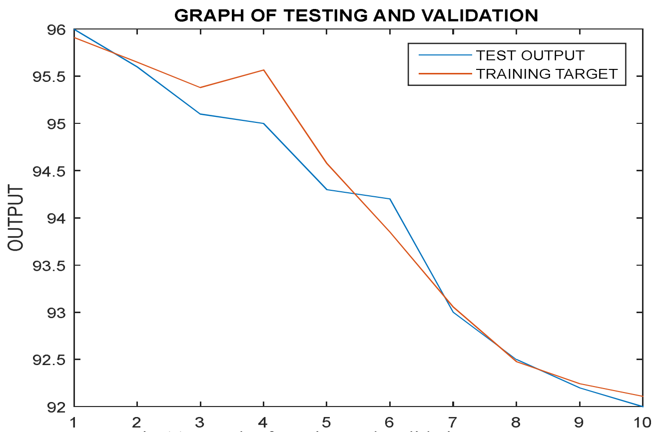

Fig 11. Graph of Testing and Validation

The work further optimized and fitted the model by training the data via the nntool MATLAB console interface. In this regard, 60% of the dataset was used for training while 25% was used for testing and 15% for validation.

From the neural network view, the data was further trained with more iterations to an optimal level until convergence was attained. The resulting most optimized model had an accuracy of *R*=0.99869. When further training was done, a point of convergence was attained. This further improved the initial coefficient earlier obtained. There was an improvement in what was obtained in Fig. 12. This gave rise to enhanced training and testing.

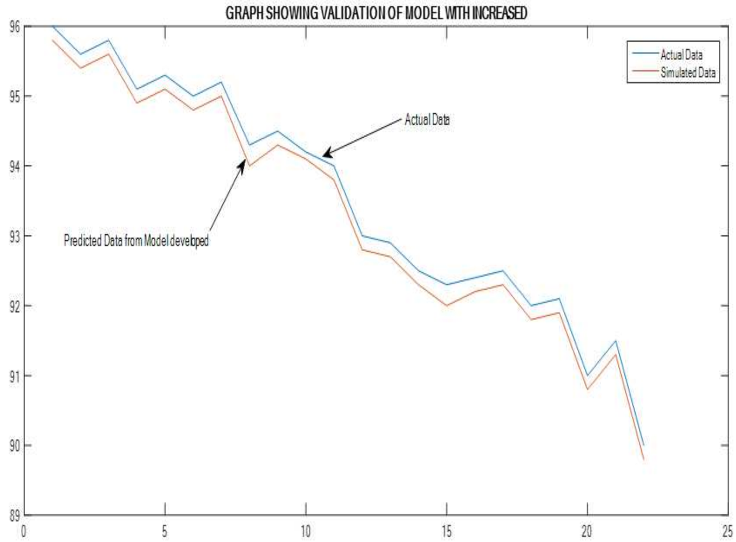

Fig.12. Plot of maximum model fitting.

The values of transmitted packet coefficient, distance, signal strength are summarized as follows. The packet transmitted, distance, signal strength, packet received, and packet transmitted gave 0.9969, -1.10800, 0.7, 0.9969 respectively. Future work will explore the use of field-programmable gate array (FPGA) design framework for IoT WSN [38]. Also, embedded neural switch [39], and software-defined radios [41], [42] in 5G relay networks [43] will be validated.

VII. Conclusion

In this paper, a computational model for predicting complex IoT WSN variables was developed. This is trained, tested, and validated using neural network soft computing technique. The model developed a relationship between signal strength, distance, received packet, and transmitted packet from the data collected. A point of convergence was achieved. Consequently, the model developed for packet transmission gave rise to the following prediction coefficients, namely packet transmitted, distance, signal strength, as 0.9969, 1.10800, and 0.7 respectively. The derived model could predict any datasets received from the data transmitting sources. This makes it very valuable for determining the optimal QoS for network providers/operators.

REFERENCE

[1] Deng, L., Li, D., Cai, Z. *et al.* Smart IoT information transmission and security optimization model based on chaotic neural computing. *Neural Comput & Applic* **32,** 16491–16504 2020

[2] J. -Q. Lin, H. -C. Wu and S. -C. Chan, "A New Regularized Recursive Dynamic Factor Analysis With Variable Forgetting Factor and Subspace Dimension for Wireless Sensor Networks With Missing Data," *in IEEE Trans on Instrumentation and Measurement,* vol. 70, pp. 1-13, 2021, Art no. 9509713,.

[3] C. Zhang, M. Yang, W. Zheng, Y. Zheng, Y. Wu and Y. Zhang, "Analysis of wavelength deployment schemes in terms of optical network unit cost and upstream transmission performance in NG-EPONs," *in IEEE/OSA J. of Optical Comm and Networking*, 13(9), pp. 214-223, 2021.

[4] H. Shin, D. Yoon, D. -Y. Na and Y. B. Park, "Analysis of Transmission Loss and Boresight Error of a Curved FSS Radome-Enclosed Antenna," *in IEEE Access*, vol. 9, pp. 95843-95852, 2021, doi: 10.1109/ACCESS.2021.3094526.

[5] J. Kawamoto, R. Shirato, T. Nakatogawa and T. Kurakake, "Remote Professional Media Production: Evaluation of Network Configuration That Satisfies Delay Requirements," *in IEEE Access,* vol. 9, pp. 100339-100351, 2021.

[6] C. Yi and J. Cai, "A Truthful Mechanism for Scheduling Delay-Constrained Wireless Transmissions in IoT-Based Healthcare Networks," in *IEEE Transactions on Wireless Communications*, 18(2), pp. 912-925, Feb. 2019.

[7] C. Ding, S. Xu, X. Chen, G. Zhou, P. Zheng and Y. Li, "A Delay and Load-balancing based Hierarchical Route Planning Method for Transmission Line IoT Sensing and Monitoring applications," *2019 IFIP/IEEE Symposium on Integrated Network and Service Management (IM),* 2019, pp. 207-215.

[8] H. B. Salameh and M. Al-Quraan, "Securing Delay-Sensitive CR-IoT Networking Under Jamming Attacks: Parallel Transmission and Batching Perspective," in *IEEE Internet of Things Journal*, vol. 7, no. 8, pp. 7529-7538, Aug. 2020.

[9] I. A. A. E. -M. And and S. M. Darwish, "Towards Designing a Trusted Routing Scheme in Wireless Sensor Networks: A New Deep Blockchain Approach," *in IEEE Access*, vol. 9, pp. 103822-103834, 2021, doi: 10.1109/ACCESS.2021.3098933.

[10] W. Yuanbing, L. Wanrong and L. Bin, "An Improved Authentication Protocol for Smart Healthcare System Using Wireless Medical Sensor Network," *in IEEE Access*, vol. 9, pp. 105101-105117, 2021, doi: 10.1109/ACCESS.2021.3099299.

[11] A. C. Lowaton and E. G. O. Tabacon, "A 2.4GHz ISM Band Application Low Noise Amplifier with Active Inductor Load Implemented on 65nm CMOS Process," IEEE *19th Int'l Symp., on Comm, and Info, Tech (ISCIT),* 2019, pp. 590-594.

[12] X. Peng, X. Liu, Y. Mei, J. Ren and H. Tang, "A Solution for Ultra-Low Bit-Error-Rate Interface of Superconductor-Semiconductor by Using an Error-Correction-Code Encoder," in *IEEE Trans on Applied Superconductivity,* vol. 29, no. 5, pp. 1-4, Aug. 2019, Art no. 1301604.

[13] F. Ertam, I. F. Kilincer, O. Yaman and A. Sengur, "A New IoT Application for Dynamic WiFi based Wireless Sensor Network," *Int'l Conf., on Elect., Eng., (ICEE),* 2020, pp. 1-4, doi: 10.09/ICEE49691.2020.9249771.

[14] M. S. Kumar and R. Ramanathan, "Impact of anchor position errors on WSN localization using mobile anchor positioning algorithm," 2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), 2017, pp. 1924-1928.

[15] S. Mizushina and A. Adachi, "A technique for wireless LAN connection through building concrete wall at 2.4GHz," 2010 *IEEE MTT-S International Microwave Symposium,* 2010, pp. 260-263, doi: 10.1109/MWSYM.2010.5514751.

[16] U. Pešović, D. Gliech, P. Planinśič, Z. Stamenkovic and S. Ranđić, "Implementation of IEEE 802.15.4 transceiver on software defined radio platform,"*20th Telecom Forum (TELFOR),* 2012, pp. 376-379,.

[17] J. Gil et al., "A Fully Integrated Low-Power High-Coexistence 2.4-GHz ZigBee Transceiver for Biomedical and Healthcare Applications," *in IEEE Trans on Microwave Theory and Techniques,* 62(9), pp. 1879-1889, 2014.

[18] Y. Kim, I. Hwang and D. Baek, "A Switchless Zigbee Frontend Transceiver With Matching Component Sharing of LNA and PA," *in IEEE Microwave and Wireless Components Letters*, 20(9), pp. 516-518, 2010.

[19] R. S. Rosli, M. H. Habaebi and M. R. Islam, "Characteristic Analysis of Received Signal Strength Indicator from ESP8266 WiFi Transceiver Module," *IEEE 7th Int'l Conf., on Computer and Comm Eng (ICCCE),* pp. 504-507, 2018.

[20] V. Sharma and M. Hashmi, "Received Signal Strength Indicator Analysis for Item Tracking using Chipless RFID," *IEEE 10th Int'l Conf on Consumer Electronics (ICCE-Berlin),* 2020, pp. 1-3, doi: 10.1109/ICCE-Berlin50680.2020.9352171.

[21] Z. Xin, H. Lu, L. Hu and J. Li, "Implementation of SPI and driver for CC2430 and C8051F120," *2nd Int'l Conf. on Consumer Electronics, Comm., and Net. (CECNet),* 2012, pp. 2638-2641.

[22] K. Lounis and M. Zulkernine, "Attacks and Defenses in Short-Range Wireless Technologies for IoT," in IEEE Access, vol. 8, pp. 88892-88932, 2020, doi: 10.1109/ACCESS.2020.2993553.

[23] H. Lee and K. Ke, "Monitoring of Large-Area IoT Sensors Using a LoRa Wireless Mesh Network System: Design and Evaluation," *in IEEE Trans on Instrumentation and Measurement*, 67(9), pp. 2177-2187, Sept. 2018,.

[24] Y. Yao, Z. Zhu, S. Huang, X. Yue, C. Pan and X. Li, "Energy Efficiency Characterization in Heterogeneous IoT System With UAV Swarms Based on Wireless Power Transfer," in IEEE Access, vol. 8, pp. 967-979, 2020.

[25] M. Ballerini, T. Polonelli, D. Brunelli, M. Magno and L. Benini, "NB-IoT Versus LoRaWAN: An Experimental Evaluation for Industrial Applications," in *IEEE Transactions on Industrial Informatics*, 16(12), pp. 7802-7811, 2020.

[26] H. Pirayesh, P. K. Sangdeh and H. Zeng, "Coexistence of Wi-Fi and IoT Communications in WLANs," in *IEEE Internet of Things J.*. 7(8), pp. 7495-7505, 2020.

[27] X. Zhang, X. Zhang and L. Han, "An Energy Efficient Internet of Things Network Using Restart Artificial Bee Colony and Wireless Power Transfer," in *IEEE Access*, vol. 7, pp. 12686-12695, 2019.

[28] Z. Xu, G. Hu, M. Jia and L. Dong, "Potential transmission choice for Internet of Things (IoT): Wireless and batteryless communications and open problems," *in China Communications*, 18(2), pp. 241-249, 2021.

[29] Z. Wang, Y. Shi, Y. Zhou, H. Zhou and N. Zhang, "Wireless-Powered Over-the-Air Computation in Intelligent Reflecting Surface-Aided IoT Networks," in *IEEE Internet of Things* Journal, vol. 8, no. 3, pp. 1585-1598, 1 Feb.1, 2021.

[30] A. Mahmoud, X. Yuan, M. Kheimi and Y. Yuan, "Interpolation Accuracy of Hybrid Soft Computing Techniques in Estimating Discharge Capacity of Triangular Labyrinth Weir," *in IEEE Access,* vol. 9, pp. 6769-6785, 2021.

[31] T. Chinnadurai, N. Prabaharan, S. Saravanan, M. K. Pandean, P. Pandiyan and H. H. Alhelou, "Prediction of Process Parameters of Ultrasonically Welded PC/ABS Material Using Soft-Computing Techniques," *in IEEE Access,* vol. 9, pp. 33849-33859, 2021

[32] X. Chen, Y. Liu, L. X. Cai, Z. Chen and D. Zhang, "Resource Allocation for Wireless Cooperative IoT Network With Energy Harvesting," in *IEEE Transactions on Wireless Communications*, 19(7), pp. 4879-4893, 2020.

[33]] J. Agajo , B. C. Okeke.,C. I. Awolo , O. M. Igbinosun, Efficient Routing Technique in a Wireless Sensor Network using Personal Area Network and Artificial Neural Method, *Int'l J. of Electronics and Telecom Sys., Research Electroscope , Electroscope J.* , Nnamdi Azikiwe University , 7(7) , No.2, pp7-13, 2015

[34] Q. Dong, F. Zhu, Y. Cai, L. Fang and M. Lu, "Analysis of RSSI Feasibility for Sensor Positioning in Exterior Environment," *IEEE Wireless Telecom Symposium (WTS),* 2021, pp. 1-7.

[35] M. Atashi, P. Malekzadeh, M. Salimibeni, Z. Hajiakhondi-Meybodi, K. N. Plataniotis and A. Mohammadi, "Orientation-Matched Multiple Modeling for RSSI-based Indoor Localization via BLE Sensors," 2020 *28th European Signal Processing Conference (EUSIPCO),* 2021, pp. 1702-1706.

[36] J. Blumenthal, F. Reichenbach., Timmermann D., "Position Estimation in Ad hoc Wireless Sensor Networks with Low Complexity", *Joint 2nd Workshop on Positioning, Navigation and Communication 2005 (WPNC 05) & 1st Ultra-Wideband Expert Talk* 2005 (05), S.41-49, 2005.

[37] N. Choudhury, R. Matam, M. Mukherjee and J. Lloret, "A Performance-to-Cost Analysis of IEEE 802.15.4 MAC With 802.15.4e MAC Modes," *in IEEE Access*, vol. 8, pp. 41936-41950, 2020, doi: 10.1109/ACCESS.2020.2976654.

[38] K. C. Okafor, E. C. Genevera and O. O. Akinyele, "Hardware description language (HDL): An efficient approach to device independent designs for VLSI market segments," *3rd IEEE Int'l Conf. on Adaptive Sci and Tech (ICAST 2011),* 2011, pp. 262-267.

[39] K. C. Okafor, G.C. Ononiwu, Sam G. V.C Chijindu, C. C. Udeze "Towards Complex Dynamic Fog Network Orchestration Using Embedded Neural Switch", *In Int'l J. of Computer and App, (IJCA) SI- Internet of Everything, Networks, Application, and Computing Systems,* 43 (2), Pp.91-108, 2021.

[40] Z. Htay, Z. Ghassemlooy, M. M. Abadi, A. Burton, N. Mohan and S. Zvanovec, "Performance Analysis and Software-Defined Implementation of Real-Time MIMO FSO With Adaptive Switching in GNU Radio Platform," *in IEEE Access*, vol. 9, pp. 92168-92177, 2021.

[41] R. M. Narayanan and C. F. Handel, "Vehicle Length Estimation Using an LTE Transmitter Combined With a Software-Defined Receiver," in *IEEE Sensors Letters,* 5(6), pp. 1-4, Art no. 3500704, 2021.

[42] M. U. Ndubuaku K. C. Okafor, C.C Udeze, O. Salih, "Intelligent Symbiotic Relay Selection Technique for 5G networks", *Int'l J., of Eng., Res., in Africa,* Vol.43. Pp.84-100. 2019.