# Data Imputation Model for Internet of Medical Things (IoMT) Using Nonlinear Autoregressive Exogenous (NARX) network Model

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**Research Article**

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# Abstract

The objective of this paper is to propose a data transmission reduction approach using Nonlinear Autoregressive Exogenous (NARX) network based prediction model to minimise energy consumption in sensor nodes (SNs) and base stations (BS). The NARX based prediction model is used to impute the missing sensor values by the base station. The imputation of missing transmitted sensor data is compensated by the base station using historical sensor data and sensor values of the interrelated sensor data in Internet of Medical Things (IoMT). The purpose of this paper is to achieve energy conservation by reducing the amount of redundant sensor data transmitted over the IoMT when data is not received at Time stamp‘t’.

# 1. Introduction

IoMTs are a special type of wireless sensor networks that are used for health and biomedical areas. In recent years, they have attracted more attention from the government, businesses and academics. However, there are limitations such as number of sensors and the amount of energy available in IoMT, and the two sensors are more sophisticated and expensive. Several studies have been conducted to improve the energy efficiency and longevity of IoMTs (Hsu Myat 2017).

Data prediction is the most efficient way to reduce the number of data transmissions in between sensor and base station by using the predicted values instead of the real ones without compromising the quality of information to be generated. It focuses on how to minimize the number of data transmissions from the sensor nodes to base station. However, the accuracy of the prediction within an error bound is one of the major issues. The numerous prediction models predict the future data in appropriate or accuracy level based on the environment (Silverman, 2014).

Normally, base station uses a prediction model to suggest a new data transmission that reduces the amount of data reported to the sink. Unlike other similar techniques, with this model have a low computational cost and a small recollection path while remaining robust and efficient. This approach allows the body sensor to collect temperature and pulse rate measurements to obtain an optimal energy by reducing the amount of transmission.

Data transmission is generally much more expenses in them of energy consumption than data processing and sensing. The energy spends in transmitting one bit is hundreds to thousands of times that spend in executing one instruction. Give this fact it is possible to achieve overate energy sharing by making there of between computation and communications. Never this should be done with adequate carefree less because wireless sensors are always limited in computational energy, which is more pronounced for body sensors (Uma Jasawat, Nisha Pandey 2014).

Data reduction methods include different techniques that may lower the number of transmissions, but not all of them involve predictions. Through sensor nodes that are collecting data at a certain time and paths that can aggregate more information to the data similarity. Hence, IoMTs is optimized in favour to reduce their energy consumption and number of transmissions.

All of these application types can reduce the number of transmissions, but prediction-based data reduction methods are not restricted to only one of them within the years and hardware evolution, some works started shifting the paradigm of avoiding complex algorithms. Wireless body area network constraints to adopt prediction techniques aiming to find patterns in the sensor data to improve its collection and delivery. For instance, if nodes that measure similar information integrate the same cluster, redundant data can be efficiently suppressed, increasing the overall data delivery and improving the IoMT's energy efficiency (Guo et al. 2009). The energy efficient IoMT is designed and simulated using a single NARX prediction model. The performance of NARX should be evaluated using the quality metrics due to the unique characteristics of the "physical sensors" in the IoMT and the special requirements of the health functions.

The main contribution of this paper is stated as below:

- For BS operations, design and develop NARX neural network-based prediction model using time-series IoMT data.
- Identify the best values for the parameters of the NARX Neural Network such as learning algorithm, activation algorithms, initial weights and bias
- BS detects the missing values of IoMT sensor data and imputes it using the NARX based data prediction model.

# 1.1. Problem formulation

The base station directly communicates with every sensor present on the body. The sensors may be assumed to work independently. There are no redundant sensors. The followings are basis assumption of the proposed NARX based simulation model.

- It consists of two sensor body temperature, pulse rate which are connected to the base station and both are synchronized with the clock.
- There is no latency in this communication model.
- There is very little delay or delay in predicting the sensor data.
- The sensor values of the body temperature sensor and the pulse rate sensor are interrelated.

The rest of this article is planned as follows. To review the background study for identifying the research gaps in section 2. Section 3 lists the methods and materials. Section 4 elaborate the proposed work. Section 5 explains the result and discussion. In section 6 presents conclusion with possible future work.

## 2. Review Literature

This section discussed the related work relevant to the energy efficient models in sensor network. It discussed energy efficient data transmission models in sensor network; Prediction based data transmission for sensor network and the various Energy model in sensor network.

In the Table 1, it describes the data transmission for sensor network is compared to sensor network type and prediction algorithm. Here the prediction based method is efficient to predict the actual sensor data using the past sensor data. The efficiency of the predicted data is known by its error value. Therefore different authors highly suggested the root mean squared error (RMSE) measure is better to evaluate the prediction based ANN data transmission.

**Table 1**

**Prediction based data transmission sensor network**

| Reference | Wireless sensor network type | | | Measure | | Prediction algorithms | |
|---|---|---|---|---|---|---|---|
| | IOT | Industrial IOT | WBAN | RMSE | MSE | Statistical | ANN |
| Huaijin Liu, Yonghong Chen (2018) | | √ | √ | √ | | | √ |
| Feng Xia, Zhenzhen Xu (2012) | | √ | | √ | √ | | √ |
| Xiaohui Liang , Xu L (2015) | √ | | √ | √ | √ | | √ |
| Fasee Ullah, Abdul Hanan Abdullah (2012) | √ | | | √ | √ | √ | |
| Marwa salayma, ahmed(2016) | √ | | √ | √ | | | √ |
| Amira Meharouech(2011) | √ | | | √ | √ | √ | |
| Yangzhe Liao, Mark S. Leeson(2016) | √ | | √ | √ | | √ | |
| Anum Talpura, Natasha Baloch(2015) | | √ | | √ | √ | | √ |
| Rehman, N. Javaid (2014) | √ | | √ | √ | √ | | √ |
| Omar ahmed fujiren (2014) | | √ | | √ | √ | √ | |
| Yangzhe Liao Mark (2012) | √ | √ | √ | √ | | √ | |
| Aleksandar Milenković (2011) | | √ | √ | √ | √ | | √ |
| Shilpa vikas shinde | √ | √ | | √ | √ | √ | |
| Osman, Ahmed mehaoua | √ | | √ | | √ | | √ |
| Gopal Krishna, sunil kumar singh. | | √ | √ | | √ | √ | |
| Noor hafizah hassan | √ | | √ | | √ | | √ |
| Siddhartha bhandari | √ | | √ | √ | | √ | |

The various studies related to prediction based data transmission techniques for sensor network. It has observed neural network based prediction techniques performed well then statistical techniques. Therefore neural network based prediction techniques for sensor network have been proposed in paper.

# 3. Methods And Materials

**Prediction Algorithm: NON-LINEAR AUTOREGRESSIVE WITH EXOGENUS INPUT (NARX) NEURAL NETWORK**

To reduce the error between the actual sensor data and the predicted data, choose the best performing neural network-based prediction technique for the data transmission reduction problem in IoMT. These types of prediction algorithms work well for slow changes in sensor values, especially when it handles time-series data well.

NARX is a type of artificial intelligence system made up of simple processing units called neurons. Each neuron can renew itself in learning eras with weighted connections attached to its neighbour. The stored knowledge gained by the network is characterized by the weight status of all connections. Neurons are made up of input connections stored at one end, which have an activating function and a threshold value, which ultimately determines whether the passing data should be sent to the output connection or not.

In this paper, dynamic neural network with time delay lines is used to perform non-linear autoregressive prediction with external time-series input vector. This type of network contains multi-neurons in the hidden layer with a delay factor connected to an output layer. The training of this network can be done using several learning algorithms such as Levenberg-Marquardt (LM), Bayesian Regularization (BR), Scaled Conjugate Gradient (SCG). Bayesian Regularization algorithm is always preferred to be used with noisy input time-series data but it will take more training epochs.

The NARX must be trained with past values of sensors in IoMT that are received by the BS. The NARX network is trained in an open loop, using the real target values as feedback and thus ensuring greater accuracy in training. After training, the network converted into a closed-loop, and the predicted values are used to supply new feedback inputs to the network. The output is the series of prediction values that will be used by the BS to impute the SN's missing data and store it in the memory. The architecture of the NARX-NN illustrated in Fig. 1.

As a result, the prediction of sensor values within an acceptable error rate for imputation will definitely save the transmission energy of the SNs in IoMT. This suggests that the predictive accuracy of the NARX method will directly help to improve the lifetime and conserve the energy of SNs.

## 3.1 Simulation parameters

Table 2
Initial values for simulation parameters

| Parameter | Symbols | Value |
|---|---|---|
| Initial energy | $E_O$ | 100 J |
| Prediction error | [illegible] | 0.5 and 1.0 |
| Number of sensor node | N | 2 |
| Network field length | L | 500 m |
| Control packet | - | 50 bytes |
| Data packet | - | 100 bytes |
| Simulation time interval | T | 35 Seconds |
| Transmission energy | $E_{TX}$ | 150mJ |
| Received energy | $E_{RX}$ | 50 mJ |
| Prediction energy | $E_{DP}$ | 10 mJ |

Table 2 shows the Initial values for simulation parameters which contain the various parameters with its symbols and values. The communication performance of this model is evaluated in terms of Packet loss ratio, Throughput, End to End delay using the sensor data of Pulse rate and Body Temperature.

### Packet loss ratio

It is defined as “the ratio of the number of loss packets to the total number of sent packets”.

$$packetlossratio = \frac{numberofpacketreceived}{numberofpacketsent}$$

### Throughput

Throughput refers as “how much data can be transferred from the source to the receiver in a given amount of time”.

$$Throughput = \frac{Numberofpacketsent}{TimeTaken}$$

### End to End delay

Maximum delay between source and destination.

$$EndtoEnd = 2D\frac{1+(f+r)/m)+f/r}{\sqrt[1\mu]{\mu^2+2\pi(f+r)}}$$

# 3.2 Predicted data quality

The mean squared error (MSE) and root mean squared error (RMSE) are used to determine of the quality of the predicted data by the LRNN prediction model for WBAN. if the time series at the BS is likely to be consistent. MSE is defined as in Eq. 6. RMSE is defined as in Eq. 7.

$$\mathrm{MSE} = \mathrm{X}\frac{1}{D}\mathrm{X}\sum_{i=1}^{D}(\mathrm{sensor}_x - \mathrm{sensor}_y)$$

$$\mathrm{RMSE} = \mathrm{X}\frac{1}{D}\mathrm{X})\sum_{i=1}^{D}(\mathrm{sensor}_x - \mathrm{sensor}_y)$$

${\text{s}\text{e}\text{n}\text{s}\text{o}\text{r}}_{x}$ is the “real sensed data”, and ${\text{s}\text{e}\text{n}\text{s}\text{o}\text{r}}_{y}$ is the data calculated using the “prediction model”, and D is the “number of data measurements”.

## 4. Proposed Work

Consider a WBAN scenario in which a BS is connected to a number of wireless SNs. In this model, there is a correlation between sensors that are connected directly with the base station for communication. Figure 2 shows a simple network with all the sensors directly connected with BS.

# 4.1. Base Station Operation

BS should have enough power and a classical processing unit with a large storage device. BS is responsible for continuously requesting data from sensors. To reduce the transmission process at the sensors, BS does not have to wait until the sensors send their missing data unnecessarily, especially when BS has a computational ability to predict the sensor data through the NARX prediction algorithm. The requested sensor data packet contains the captured value 'C', the accepted error value α, and other fields related to datalink and serial number. The predicted sensor value 'P' is calculated based on previous knowledge learned from the stored past sensor data and α is the accepted error, in which case the actual sensor data 'A' is approximately equal to P.

$A - \alpha \leq P \leq A + \alpha$

Where α can be selected according to the predictive accuracy, and smallest α value leads to greater predictive accuracy.

After requesting an actual sensor value from a SN, BS will wait for a while until the sensor responds. If there is no response from the SNs at 't', BS predicts value P using sensor values up to t-1 timestamp which is supposed to be approximately equal to the 'A' and will be stored in the BS as if it was collected data. Figure 3 shows the workflow of the base station. Figure 4 shows the Work flow for Data transmission reduction model in NARX.

| **Algorithm 1 Request_Algorithm for BS ( A, α)** |
|---|
| **START** |
| 1. Initialize the value for α and A = 0; |
| 2. BS request the actual sensor data from SNs |
| 3. BS waits for predefined duration Wt |
| 4. If Sensed_data is received then At = Sensed_data |
| 5. Stored the value of At + Variance of the predicted value in the St |
| 6. Predict Pt using NARX(St-n, St-1 ); |
| 7. Goto step 2 |
| **END** |

The algorithm 1 describes the process of the BS. The base station has to maintain the required quality (or accuracy) of the data to be recorded even when the sensor decides not to send the sample. In this situation, for example, if the sensor does not deliver xk, the base station will activate the predictor to produce the estimate xk and then records it.

**Algorithm 2 Sensor Data Imputation using NARX prediction model**

**START**

1 BS broadcasts request to all SNs

2 for SNs in IOMT

for each ‘t’ in T[n]

if the BS received the data from PR sensor

PR (t) = r[t]

Else

PR(t)=”NAN”

Trigger the impute phase

End if

if the BS received the data for BT sensor

BT (t) = r[t]

else

BT(t)=”NAN”

Trigger the impute phase

end if

end for

**END**

**Impute Phase: NARX(Stored_PR,Stored_BT],)**

**START**

For each SN in BS

For each timestamp ‘t’

If stored data(t)=”NAN” then

Predicted (t) = NARX(Stored_PR(1:t-1),Stored_BT(1:t-1)

Stored data(t) = Predicted (t)

End if

End for

End for

**END**

# 5. Result And Discussion

In this paper, three different simulation setup is carried out in matlab environment. They are Standard IoMT (S- IoMT), NARX-Tansig- IoMT and NARX-Logsig- IoMT models. To compare the above three models, five different set of transactions namely $T_{1,}$ T2, $T_{3,}$ $T_4$ to $T_5$ are carried out between base station and sensor nodes.

Table 3 describes the performance of the S-IoMT and LRNN-Tansig-IoMT in terms of energy saved for base station while it is communicating with pulse rate sensor node. For T1 transaction, there are 3 missed transactions identified for pulse rate sensor by BS. To recover these missed pulse rate sensor values, standard IoMT model sends the request to the sensor node which consumes total energy **34.20** micro joules. The prediction based IOMT model predicts the missed sensor value using NARX- Tansig- IoMT prediction model without requesting the data from the pulse rate sensor node; for that it consumed energy of 9.96 micro joules for predicting these value by base station.

Table 4 describes the performance of the S-IoMT and NARX-Tansig-IoMT in terms of total energy consumption for pulse rate sensor node. Therefore, the total energy consumption of S-IoMT nd NARX-Tansig- IoMT for T1 transaction is **524.24** micro joules and **512.40** micro joules respectively. Similarly, the total energy consumption for $T_{2,}$ T3, $T_{4,}$ and T5 are given in Table 4. Table 5 describes the performance of the S- IoMT and LRNN-Tansig- IoMT in terms of energy saved for pulse rate sensor node. Therefore, the total energy saved for S- IoMT and NARX-Tansig- IoMT for T1 transaction is 270.40 micro joules and 263.20 micro joules respectively. Likewise, the total energy saved for $T_{2,}$ T3, $T_{4,}$ and T5 are given in Table 7.

Table 3

**Energy Saved by Pulse Rate Sensor using NARX-Tansig- IoMT Model**

| No. of transaction | No. of missed transaction | Energy Saved for base station | Energy Saved for Sensor node | Total energy saved |
|---|---|---|---|---|
| $T_1$ | 3 | 9.96 | 15.60 | 34.20 |
| $T_2$ | 4 | 19.92 | 35.84 | 47.12 |
| $T_3$ | 7 | 43.16 | 71.68 | 64.31 |
| $T_4$ | 9 | 73.04 | 117.76 | 89.62 |
| $T_5$ | 13 | 116.20 | 184.32 | 109.11 |

Table 4
**Total energy consumption for pulse rate sensor using NARX-Tansig- IoMT**

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Tansig- IoMT |
|---|---|---|---|
| $T_1$ | 3 | 524.34 | 512.40 |
| $T_2$ | 4 | 1044.48 | 1031.20 |
| $T_3$ | 7 | 1571.84 | 1549.6 |
| $T_4$ | 9 | 2094.08 | 2064.20 |
| $T_5$ | 13 | 2626.56 | 2583.40 |

Table 5
Total energy saved for pulse rate sensor using NARX-Tansig- IoMT

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Tansig- IoMT |
|---|---|---|---|
| $T_1$ | 4 | 270.40 | 263.20 |
| $T_2$ | 6 | 533.60 | 522.80 |
| $T_3$ | 8 | 796.80 | 782.40 |
| $T_4$ | 10 | 1076.00 | 1058.00 |
| $T_5$ | 15 | 1334.00 | 1307.00 |

Table 6 describes the performance of the S- IoMT and NARX-Tansig- IoMT in terms of energy saved for base station while communicating with body temperature sensor node. For T1 transaction, there are 3 missed transactions identified for body temperature sensor by BS. To recover these missed body temperature sensor values, standard IoMT model sends the request to the sensor node which consumes total energy **32.12** micro joules. The NARX-Tansig-IoMT predicts the missed sensor value without requesting the data from the body temperature sensor node and for that it consumed energy of 10.52 micro joules for predicting these value by base station.

Table 7 describes the performance of the S- IoMT and NARX-Tansig-IOMT in terms of total energy consumption for body temperature sensor node. Therefore, the total energy consumption of S-IOMT and NARX-Tansig-IOMT for T1 transaction is 532.48 micro joules and 519.20 micro joules respectively. Similarly, the total energy consumption for $T_{2,}$ T3, $T_{4,}$ and $T_5$ are given in Table 7.

Table 8 describes the performance of the S-IOMT and NARX-Tansig-IOMT in terms of total energy saved for body temperature sensor node. Therefore, the total energy saved for S-IOMT and LRNN- Tansig-IOMT for T1 transaction is 276.48 micro joules and 263.20 micro joules respectively. The total energy saved using the above two models for $T_{1,}$ $T_{2,}$ T3, $T_{4,}$ and $T_5$ are given in Table 8.

Table 6
Energy Saved by Body Temperature Sensor using NARX-Tansig-IOMT Model.

| **No.of transaction** | **No .of missed transaction** | **Total Energy Saved** | **Energy Spent Sensor Node** | **Total energy saved** |
|---|---|---|---|---|
| $T_1$ | 3 | 10.52 | 15.24 | 32.12 |
| $T_2$ | 5 | 26.56 | 41.20 | 49.60 |
| $T_3$ | 8 | 53.12 | 82.16 | 64.00 |
| $T_4$ | 10 | 86.32 | 133.36 | 91.24 |
| $T_5$ | 12 | 126.16 | 194.80 | 112.56 |

Table 7
Total energy consumption for body temperature sensor using NARX-Tansig-IOMT

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Tansig-IOMT |
|---|---|---|---|
| $T_1$ | 4 | 532.48 | 519.20 |
| $T_2$ | 6 | 1054.72 | 1034.80 |
| $T_3$ | 8 | 1576.96 | 1550.40 |
| $T_4$ | 11 | 2104.32 | 2067.80 |
| $T_5$ | 14 | 2631.68 | 2585.20 |

Table 8
Total energy saved for body temperature sensor using NARX-Tansig-IOMT

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Tansig-IOMT |
|---|---|---|---|
| $T_1$ | 4 | 276.48 | 263.20 |
| $T_2$ | 6 | 542.72 | 522.80 |
| $T_3$ | 8 | 808.96 | 782.40 |
| $T_4$ | 11 | 1080.32 | 1043.80 |
| $T_5$ | 14 | 1351.68 | 1305.20 |

Table 9 describes the performance of the S-IOMT and NARX-Logsig-IOMT in terms of total energy saved for base station while communicating with pulse rate sensor node. For T1 transaction, there are 4 missed transactions for pulse rate sensor. To recover these missed pulse rate sensor values, standard IOMT model sends the request to the sensor node which consumes total energy **37.40** micro joules. NARX-Logsig prediction model predicts the missed sensor value of the SNs without requesting the data from the pulse rate sensor node and for that it consumed energy of 11.60 micro joules for predicting these value by base station.

Table 10 describes the performance of the S-IOMT and NARX-Logsig-IOMT in terms of total energy consumption for pulse rate sensor node. Therefore, the total energy consumption of S-IOMT and NARX-Logsig-IOMT for T1 transaction is 534.48 micro joules and 520.24 micro joules respectively. Similarly, the total energy consumption for $T_{2,}$ T3, $T_{4,}$ and $T_5$ are given in Table 10.

Table 11 describes the performance of the S-IOMT and NARX-Logsig-IOMT in terms of total energy saved for pulse rate sensor node. Therefore, the total energy saved for S-IOMT and NARX- Logsig-IOMT for T1 transaction is **271.40** micro joules and **260.22** micro joules respectively. The total energy saved for $T_{2,}$ T3, $T_{4,}$ and $T_5$ are given in Table 11.

Table 9
Energy Saved by Pulse Rate Sensor using NARX-Logsig-IOMT Model.

| No. of transaction | No. of missed transaction | Total Energy Saved for base station | Energy Spent Sensor node | Total energy saved |
|---|---|---|---|---|
| $T_1$ | 4 | 11.60 | 17.43 | 37.40 |
| $T_2$ | 6 | 28.32 | 46.56 | 49.12 |
| $T_3$ | 9 | 57.08 | 89.22 | 64.21 |
| $T_4$ | 13 | 91.03 | 141.67 | 94.65 |
| $T_5$ | 15 | 131.46 | 196.44 | 117.32 |

Table 10
Total energy consumption for pulse rate sensor using NARX-Logsig Model.

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Logsig-IOMT |
|---|---|---|---|
| $T_1$ | 4 | 534.48 | 520.24 |
| $T_2$ | 6 | 1054.72 | 1034.80 |
| $T_3$ | 8 | 1576.96 | 1550.40 |
| $T_4$ | 11 | 2104.32 | 2067.80 |
| $T_5$ | 14 | 263.68 | 2585.20 |

Table 11
Total energy saved for pulse rate sensor using NARX-Logsig-IOMT Model.

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Logsig-IOMT |
|---|---|---|---|
| $T_1$ | 4 | 271.40 | 278.22 |
| $T_2$ | 6 | 542.72 | 559.10 |
| $T_3$ | 8 | 808.96 | 818.44 |
| $T_4$ | 11 | 1080.32 | 1092.80 |
| $T_5$ | 14 | 1351.68 | 1362.20 |

Table 12 describes the performance of the S-IOMT and NARX-Logsig-IOMT in terms of energy saved for base station while communicating with body temperature sensor node. For T1 transaction, there are 3 missed transactions for body temperature sensor. To recover these missed body temperature sensor values, standard IOMT model sends the request to the sensor node which consumes total energy **39.24** micro joules. NARX-Logsig prediction model predicts the missed sensor value without requesting the data from the body temperature sensor node; for that it consumed energy of 12.40 micro joules for predicting this value by base station.

Table 13 describes the performance of the S-IOMT and NARX-Logsig-IOMT in terms of total energy consumption for body temperature sensor node. Therefore, the total energy consumption of S-IOMT and NARX- Logsig-IOMT for T1 transaction is **532.44** micro joules and **524.10** micro joules respectively. Similarly, the total energy consumption for $T_{2,}$ T3, $T_{4,}$ and $T_5$ are given in Table 13.

Table 12 describes the performance of the S-IOMT and NARX-Logsig-IOMT in terms of total energy saved for body temperature sensor node. Therefore, the total energy saved for S-IOMT and NARX- Logsig-IOMT for T1 transaction is **276.48** micro joules and **263.20** micro joules respectively. The total energy saved for $T_{2,}$ T3, $T_{4,}$ and $T_5$ are given in Table 14.

Table 12
Energy Saved by BT Sensor using NARX-Logsig-IOMT Model.

| No. of transaction | No. of missed transaction | Total Energy Saved | Energy Spent Sensor node | Total energy saved |
|---|---|---|---|---|
| $T_1$ | 3 | 12.40 | 18.24 | 39.24 |
| $T_2$ | 5 | 29.12 | 47.52 | 51.67 |
| $T_3$ | 8 | 59.20 | 91.30 | 67.52 |
| $T_4$ | 11 | 94.33 | 146.32 | 96.77 |
| $T_5$ | 14 | 134.57 | 198.78 | 119.61 |

Table 13
Total energy consumption for body temperature sensor using NARX-Logsig-IOMT Model

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Logsig-IOMT |
|---|---|---|---|
| $T_1$ | 4 | 532.44 | 521.10 |
| $T_2$ | 5 | 1049.60 | 1038.00 |
| $T_3$ | 7 | 1571.84 | 1559.60 |
| $T_4$ | 10 | 2099.20 | 2076.00 |
| $T_5$ | 15 | 2636.80 | 2587.00 |

Table 14
Total energy saved for body temperature sensor using NARX-Logsig-IOMT Model

| No. of transaction | No. of Missed Transaction | S-IOMT | NARX-Logsig -IOMT |
|---|---|---|---|
| $T_1$ | 4 | 276.48 | 269.20 |
| $T_2$ | 5 | 537.60 | 528.00 |
| $T_3$ | 7 | 803.84 | 786.60 |
| $T_4$ | 10 | 1075.20 | 1046.00 |
| $T_5$ | 15 | 1356.80 | 1307.00 |

Figure 5 depicts the comparison of total energy consumption for pulse rate sensor using S-IOMT, NARX-Tansig-IOMT and NARX-Logsig-IOMT models. It is clear that NARX-Tansig-IOMT performed well for all set of transactions namely because for these transactions NARX-Tansig-IOMT consumed lesser energy than S-IOMT, NARX-Logsig-IOMT.

Figure 6 depicts the comparison of total energy saved for pulse rate sensor using S-IOMT, NARX-Tansig-IOMT and NARX-Logsig-IOMT models. It is clear that NARX-Tansig-IOMT performed well for all set of transactions namely $T_{1,}$ T2, $T_{3,}$ $T_4$ and $T_5$ because for these transactions NARX-Tansig-IOMT saved higher energy than S-IOMT, NARX-Logsig-IOMT.

Figure 7 depicts the comparison of total energy consumption for body temperature sensor using S-IOMT, NARX-Tansig-IOMT and NARX-Logsig-IOMT models. It is clear that NARX-Tansig-IOMT performed well for all set of transactions namely $T_{1,}$ T2, $T_{3,}$ $T_4$ and $T_5$ because for these transactions NARX-Tansig-IOMT consumed lesser energy than S-IOMT, NARX-Logsig-IOMT.

Figure 8 depicts the comparison of total energy saved for body temperature sensor using S-IOMT, NARX-Tansig-IOMT and NARX-Logsig-IOMT models. It is evident that NARX-Tansig-IOMT performed well for all set of transactions namely $T_{1,}$ T2, $T_{3,}$ $T_4$ and $T_5$ because for these transactions NARX-Tansig-IOMT saved higher energy then S-IOMT, NARX-Logsig-IOMT.

Table 15shows the throughput value of NARX-Tansig prediction model for pulse rate sensor and body temperature sensor node. It is observed that the number of transactions increased, the throughput value is also increased.

Table 15
Throughput value for Pulse Rate and Body Temperature Sensor using NARX-Tansig-IOMT model

| No. of transaction | Pulse Rate | Body Temperature |
|---|---|---|
| $T_1$ | 97.00 | 97.33 |
| $T_2$ | 98.00 | 98.75 |
| $T_3$ | 99.22 | 99.11 |
| $T_4$ | 99.43 | 99.37 |
| $T_5$ | 99.88 | 99.52 |

Table 16
Throughput value for Pulse Rate and Body Temperature Sensor using NARX-Logsig-IOMT

| No. of transaction | Pulse Rate | Body Temperature |
|---|---|---|
| $T_1$ | 96.33 | 97.00 |
| $T_2$ | 98.20 | 98.46 |
| $T_3$ | 99.00 | 99.12 |
| $T_4$ | 99.21 | 99.44 |
| $T_5$ | 99.80 | 99.88 |

Table 16 shows the throughput value of NARX-Logsig prediction model for pulse rate sensor and body temperature sensor node. It is observed that the number of transactions increased, as well as the throughput value is increased.

Table 15shows the RMSE value of NARX-Tansig prediction model for pulse rate sensor and body temperature sensor node. It is observed that the number of transactions increased, the RMSE is decreased. It indicates that more number of inputs in the dataset increases the quality of the NARX prediction algorithm.

Table 17

RMSE Value for Pulse Rate and Body Temperature Sensor using NARX-Tansig-IOMT

| No. of transaction | RMSE for PR Sensor | RMSE For BT Sensor |
|---|---|---|
| $T_1$ | 0.92 | 0.87 |
| $T_2$ | 0.88 | 0.85 |
| $T_3$ | 0.85 | 0.83 |
| $T_4$ | 0.82 | 0.78 |
| $T_5$ | 0.78 | 0.76 |

Table 18

RMSE Value for Pulse Rate and Body Temperature Sensor using NARX-Logsig-IOMT

| No. of transaction | Pulse Rate | Body Temperature |
|---|---|---|
| $T_1$ | 3.08 | 4.07 |
| $T_2$ | 3.06 | 4.04 |
| $T_3$ | 3.05 | 4.02 |
| $T_4$ | 3.03 | 4.01 |
| $T_5$ | 3.01 | 4.00 |

Table 18 shows the RMSE value of NARX-Logsig prediction model for pulse rate sensor and body temperature sensor node. It is observed that the number of transactions increased, the RMSE is decreased. It indicates that more number of inputs in the dataset increases the quality of the prediction algorithm.

Table 19

**Residual energy for Body Temperature sensor and Pulse Rate sensor**

| No. of transaction | Total Residual Energy (BT) | Total Residual Energy (PR) |
|---|---|---|
| $T_1$ | 471.23 | 462.11 |
| $T_2$ | 430.78 | 418.36 |
| $T_3$ | 371.40 | 352.4 |
| $T_4$ | 286.87 | 262.76 |
| $T_5$ | 183.69 | 154.97 |

Table 19 represents the total residual energy for body temperature and Pulse rate sensor. The total residual energy for set of transactions in $T_1$ is 471.2 micro joules and 462.11 micro joules. From the Table 19, it is known that when number of transactions increased total residual energy decreased, due to more communication between base station and sensor node.
Figure 9 describes the total residual energy for the body temperature and Pulse Rate sensor. The value is decreasing at different transactions. The maximum residual energy is received at $T_1$ transactions and is represented in the form of micro joules.

Figure 10 shows the packet loss performance of LRNN-Tansig model for all transaction namely $T_{1,}$ T2, T3, $T_{4,}$ $T_5$. It is observed that packet loss is increased very meagrely as number of transactions increased. Therefore the proposed model is robust against packet loss.

Figure 11 shows the throughput performance of LRNN-Tansig model for all transaction namely $T_{1,}$ T2, T3, $T_{4,}$ $T_5$. It is observed that throughput is increased very neagerly as number of transactions increased. Therefore the proposed model is robust against throughput.

Figure 12 shows the end to end delay performance of LRNN-Tansig-IOMT model for all transaction namely $T_{1,}$ T2, T3, $T_{4,}$ $T_5$. It is observed that end to end delay is increased very negerly as number of transactions increased. Therefore the proposed model is robust against throughput.

# 6. Conclusion And Future Work

NARX Prediction-based data transmission approach has been proposed in this paper to address the problem of energy conservation in the context of wireless body area networks. The proposed NARX-based IOMT yield on effective approach for energy efficient data transmission. This approach has been designed particularly for wireless body area network by taking into account their unique characteristics as opposed to conventional WSN. Results on simulated datasets demonstrated the effectiveness and wide applicability of the approach NARX prediction based IOMT. This model has minimized energy consumption in sensor nodes (SNs) and base stations (BS) of WBAN. Here, NARX based model has been developed using body temperature sensor values and pulse rate sensor values. Its motive is to impute the missing sensor values by the base station. The advantage of using this model is that there is no frequent need to update the prediction model to enhance its predictive accuracy.

As future work, a sensor network prototype will be developed using the best forecast model to demonstrate the effectiveness of the proposed approach. At best, field tests are performed to obtain real-time data that enhances the predictive accuracy of the model.

# Declarations

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### Conflict of Interest

Authors have no conflict of interest

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# Figures

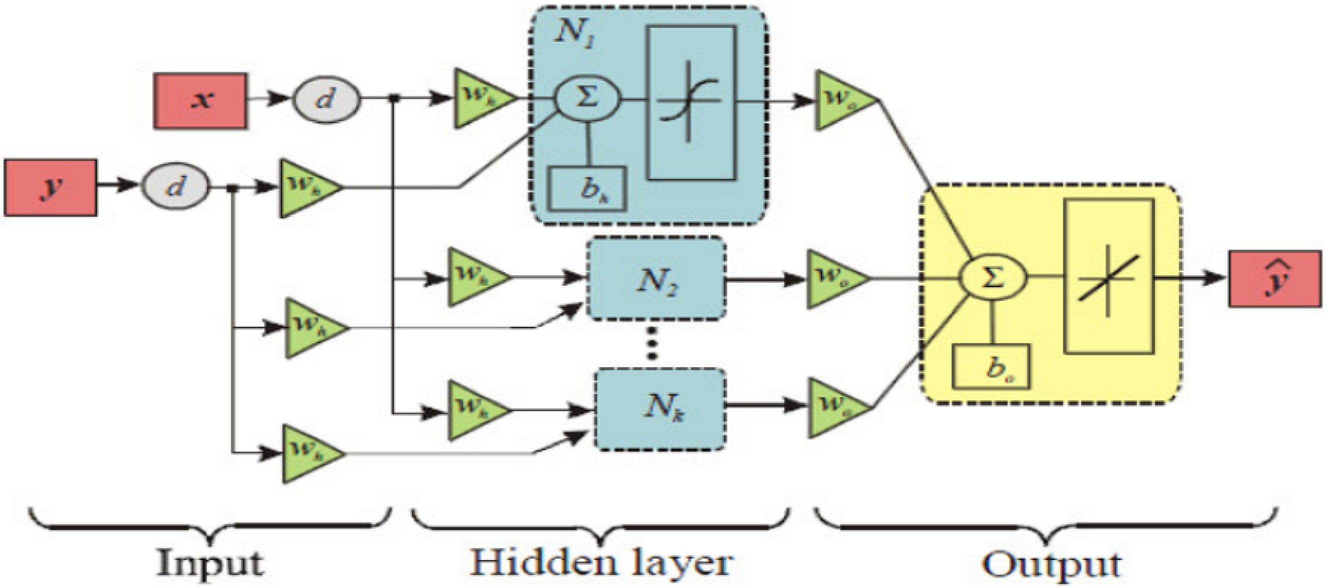


Figure 1

NARX Architecture

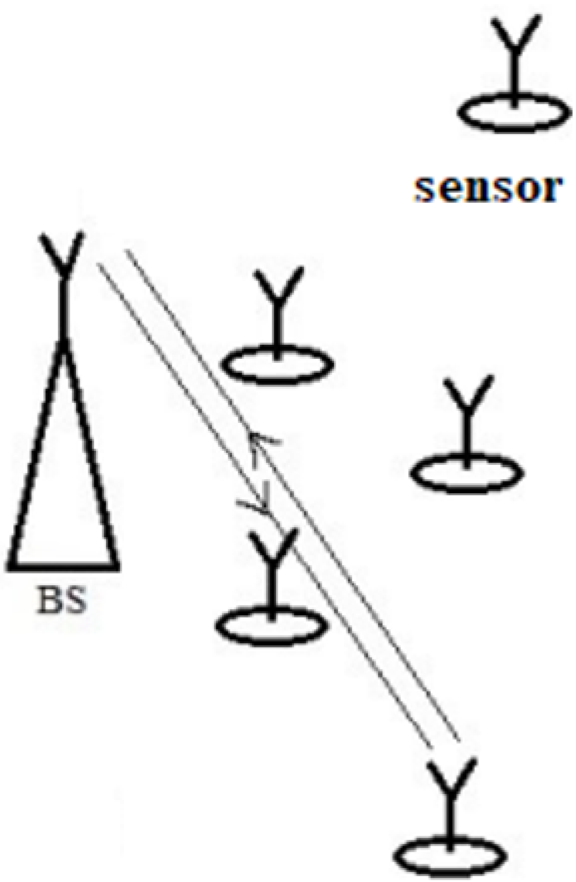

Figure 2

System Architecture

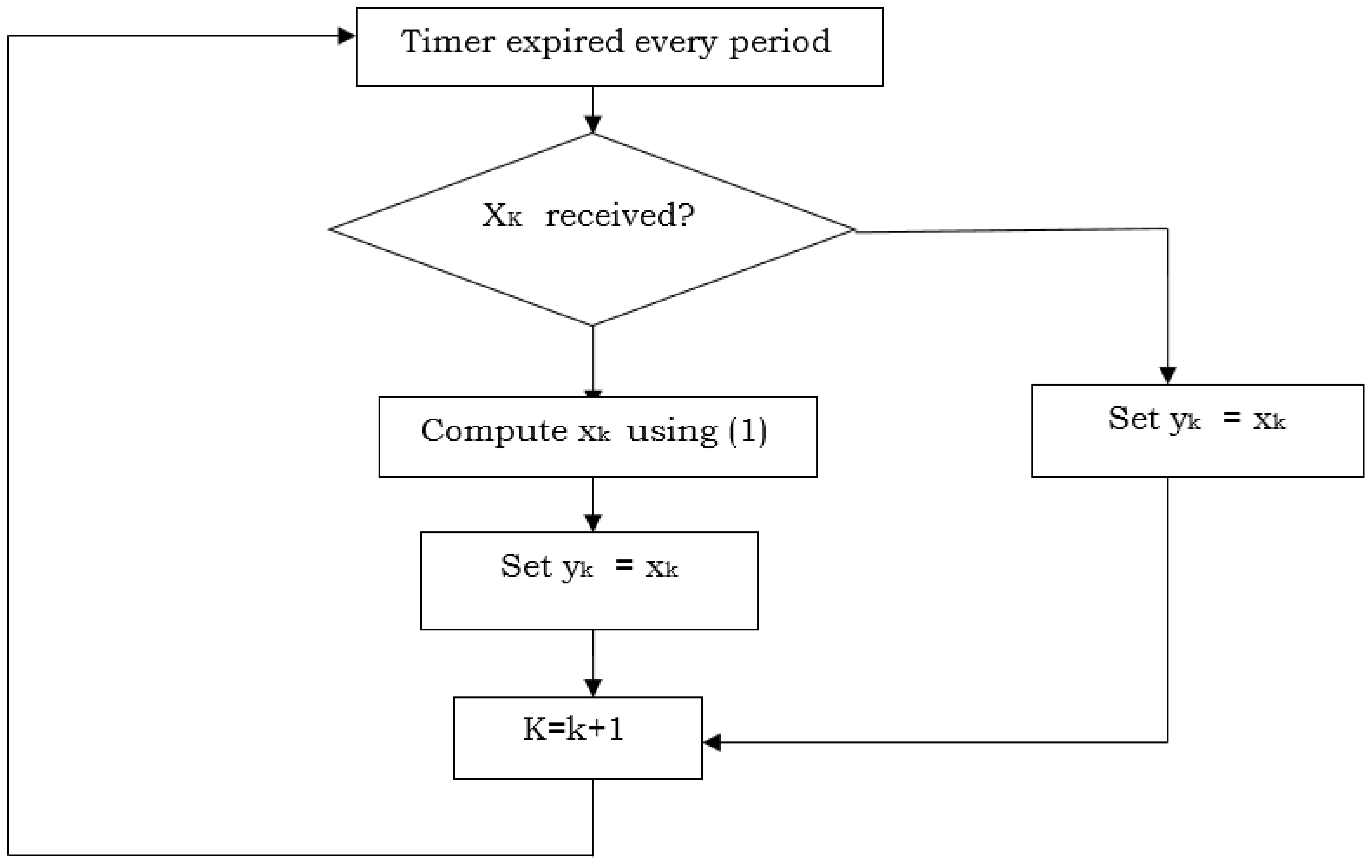


Figure 3

Workflow of the base station.

Figure 4

Work flow for Data transmission reduction model in NARX

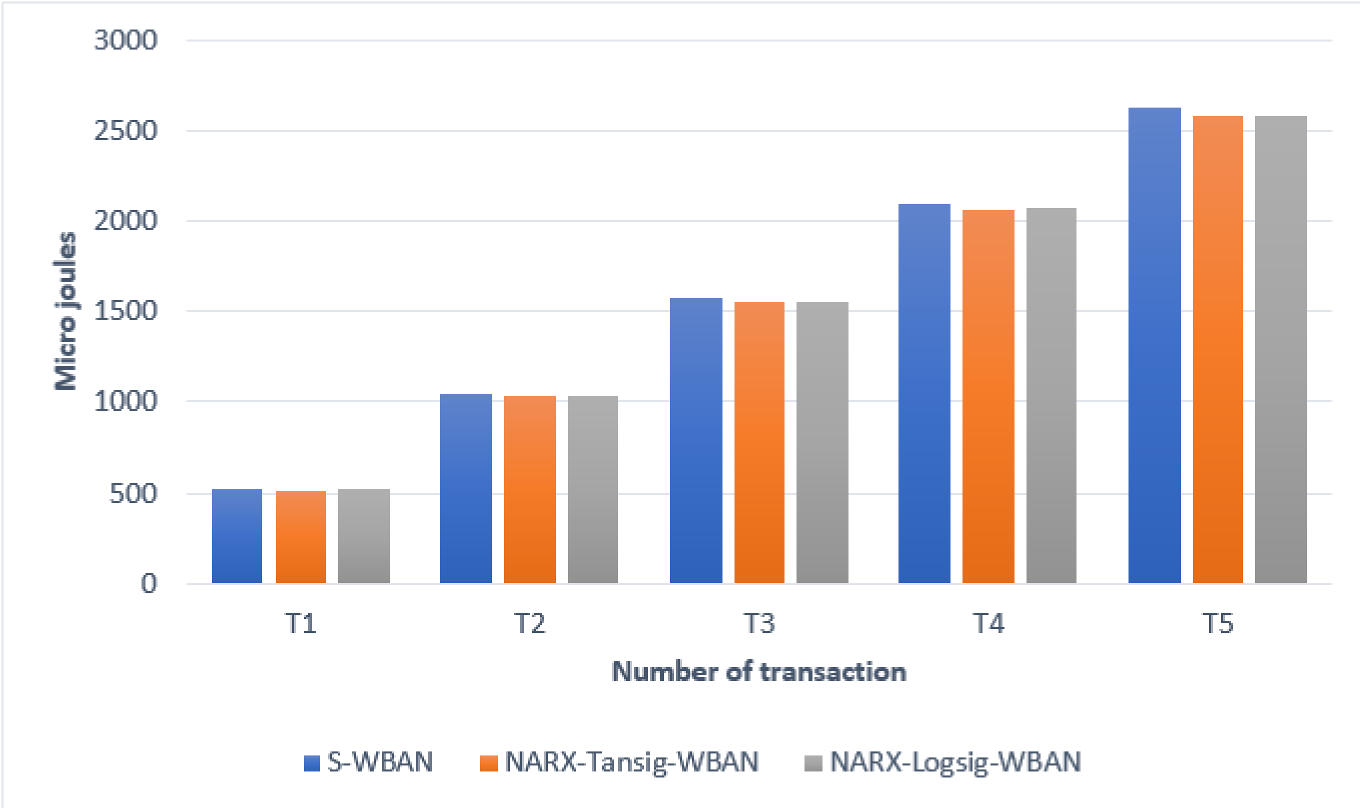


Figure 5

Total energy consumption based comparison for pulse rate sensor.

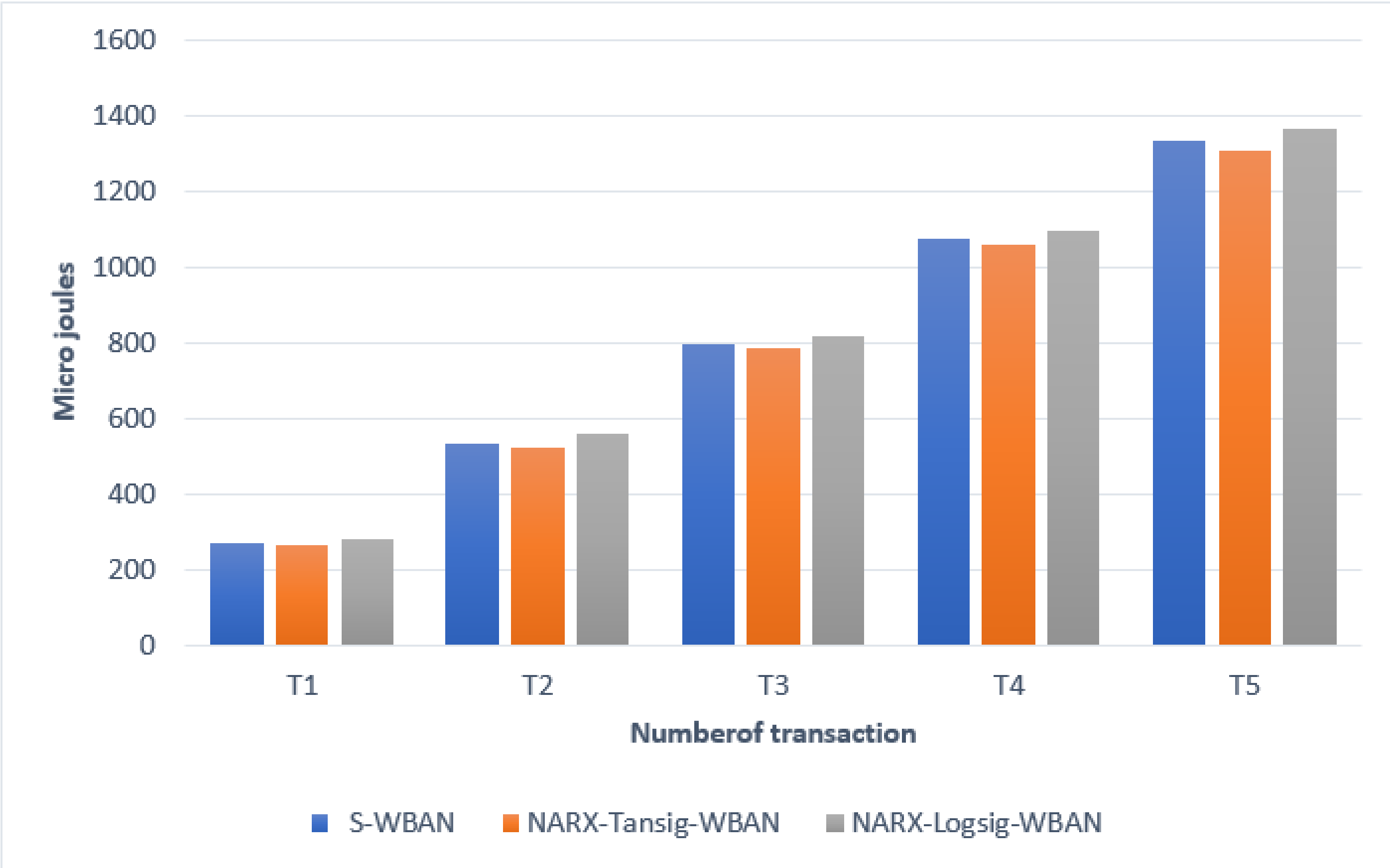


Figure 6

Comparison of total energy saved for body temperature sensor.

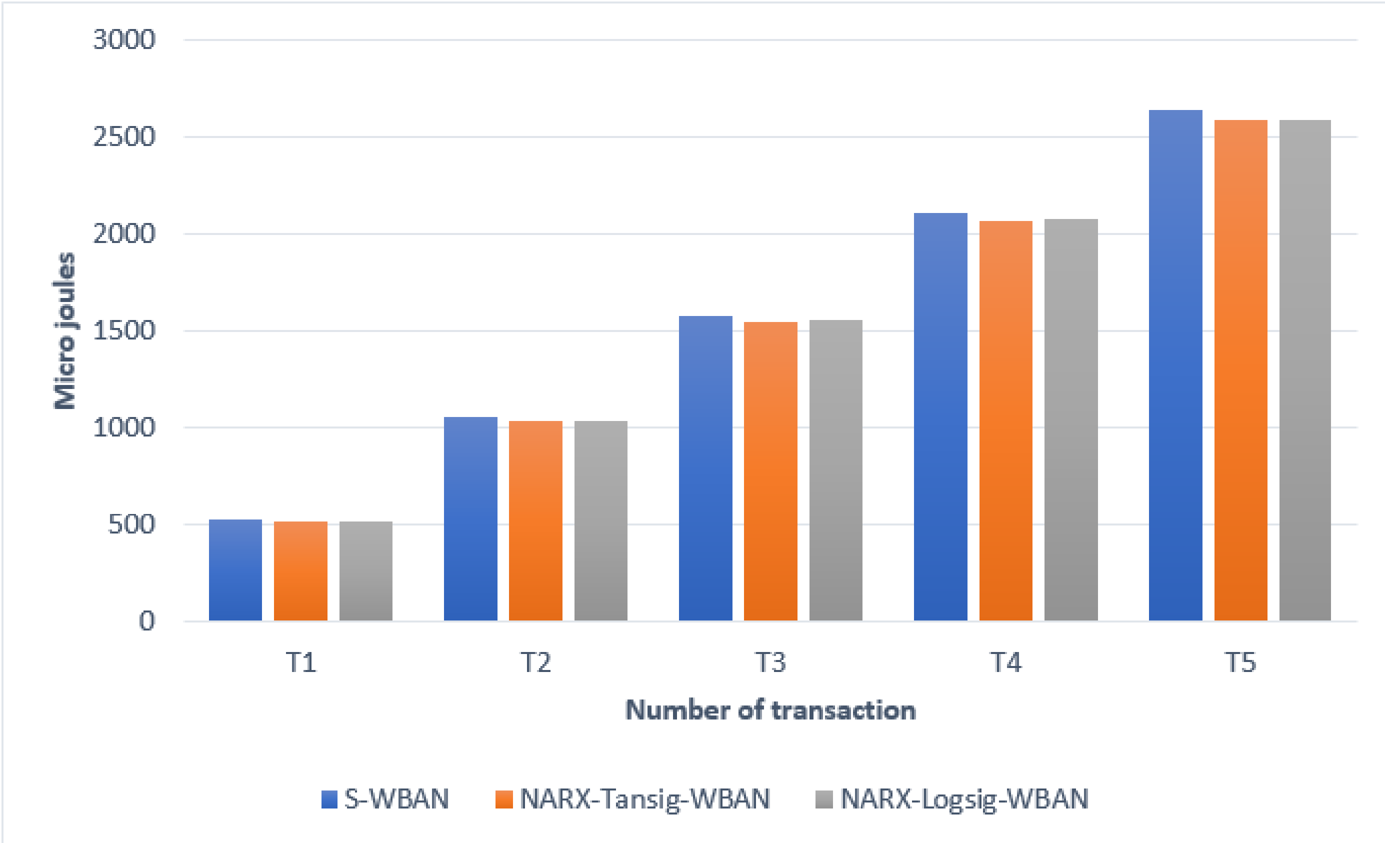


Figure 7

Total Energy Consumption Based Comparison for Body Temperature Sensor

Figure 8

Comparison of total energy saved based on body temperature sensor.

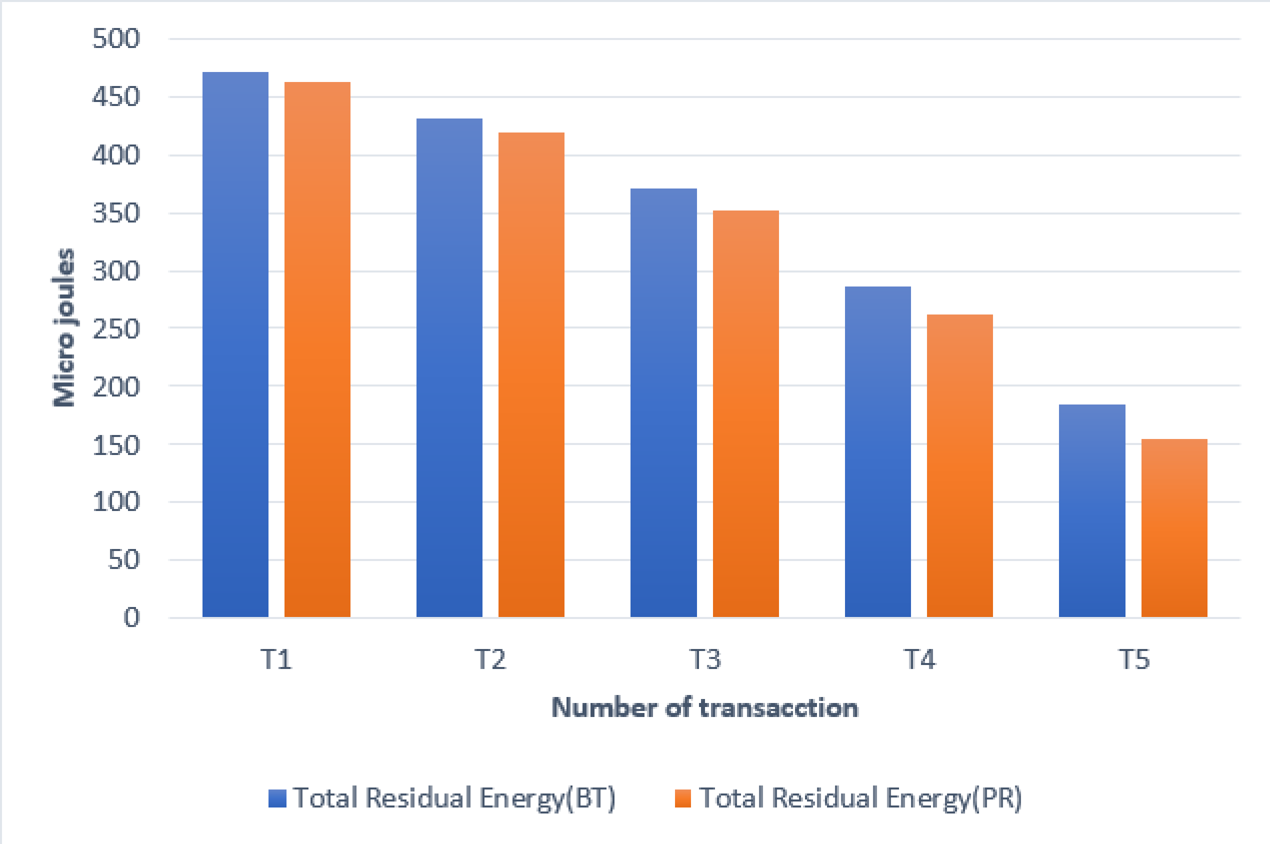


Figure 9

Residual Energy for body temperature and Pulse Rate sensor.

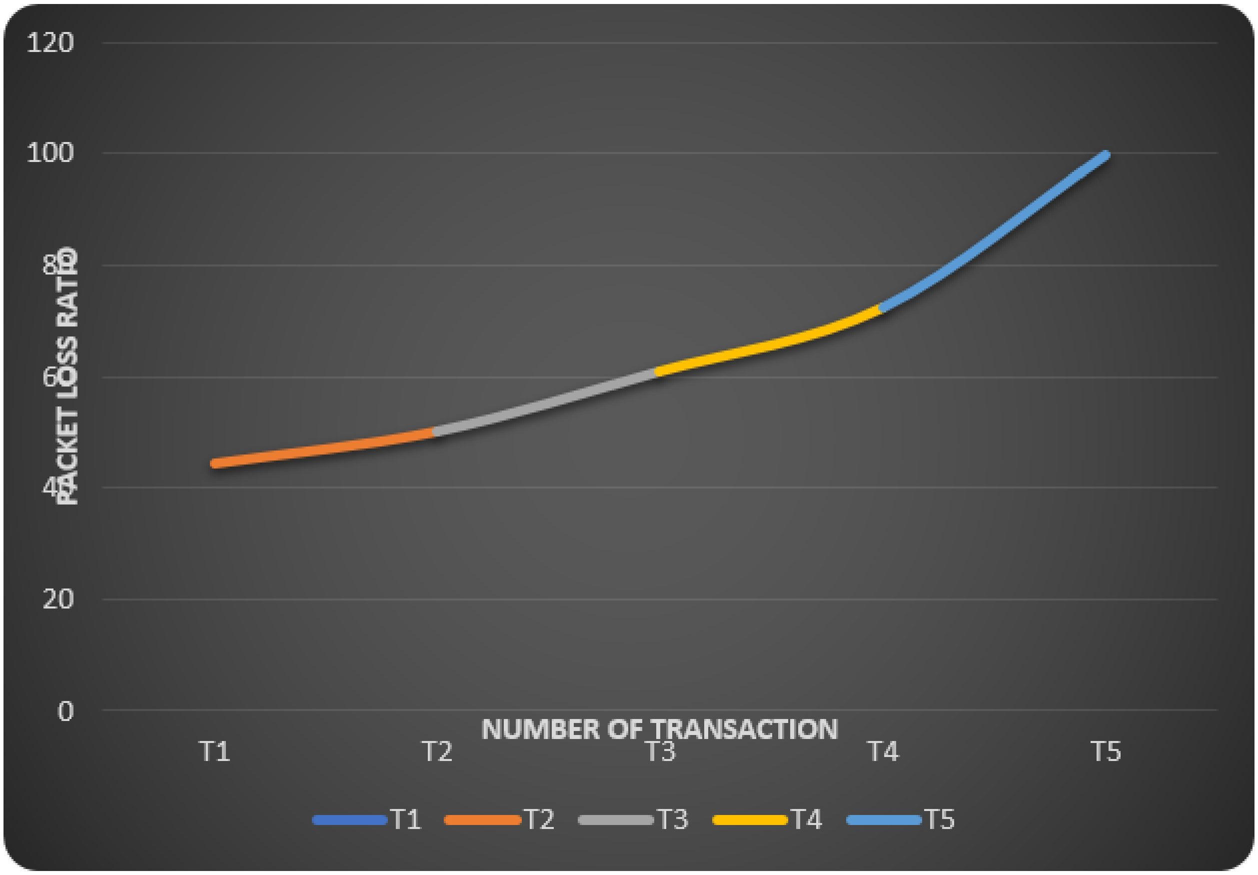


Figure 10

Packet loss performance of LRNN-Tansig-IOMT model

Figure 11

Throughput Performance of LRNN-Tansig-IOMT model

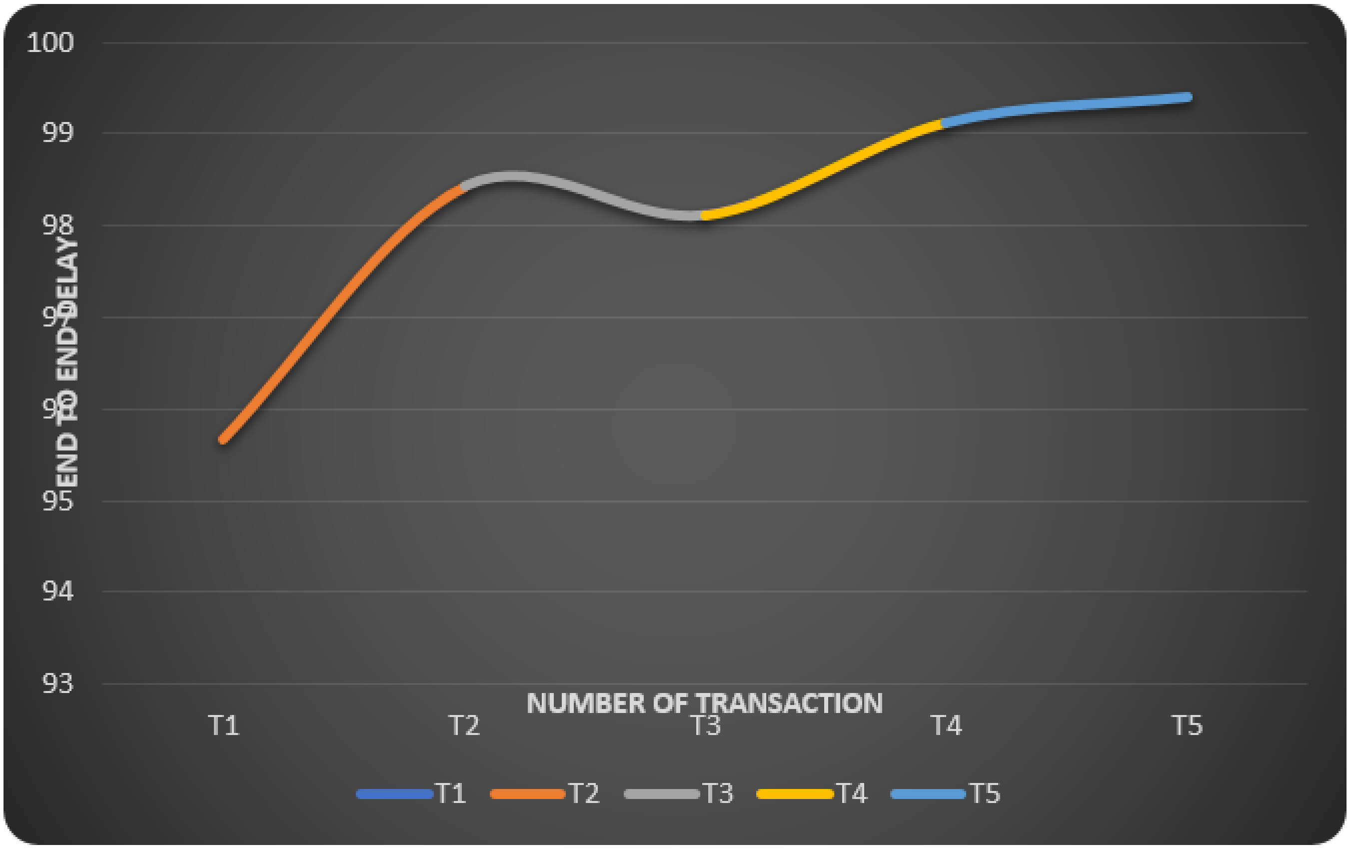


Figure 12

End to end delay performance of LRNN-Tansig-IOMT model.