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Prediction of QoS Data for Various Sensors Using AI Algorithms

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Abstract: Wireless environment monitoring is performed by spectrum sensors and network sniffing in wireless networks. By this, we will get a set of spatially distributed measurements. In this work, we show how machine learning algorithms can be used to generate probabilistic forecasts rather than point estimations using data from numerous sensing devices. In this respect, the QoS data from the pressure sensor is taken and based on that, univariate models were constructed. Feed Forward Neural Network (FFNN) and Gaussian Process (GP) artificial intelligence algorithms were used for the construction of the models. The algorithms are applied to model measurements data collected from a heterogeneous wireless testbed environment. To evaluate the constructed model, throughput has been predicted and examined for the Gas, Humidity, Pressure, and Temperature sensors. The results of various error metrics are used to assess the performance of models like NRMSE, MASE, sMAPE, WQL, and MAE, and based on the error metrics values, it is observed that both the FFNN and GP algorithms provide good results for the different sensors QoS values prediction, but the GP algorithms performs slightly better than FFNN. The results indicate that GP machine learning approach provides accurate results as compared to the FFNN approach for QoS values prediction in the wireless environment. The results will lead to secure message delivery in the network.

Keywords: *Feed Forward Neural Network; Gaussian Process; Sensor Data; Error Metrics; QoS Prediction.*

1. Introduction

Wireless Sensor Networks (WSNs) gather data and constantly supervise atmospheric data like temperature, gas, humidity and pressure. The continuous data broadcast in the network entirely depends on the energy-constrained sensor nodes. A reliable wireless connectivity service requires good QoS. Artificial intelligence and machine learning algorithms are becoming popular for various applications in WSN. These algorithms are used for understanding the data like gas, humidity, pressure, and temperature obtained from several sensors placed across the network and based on the received data; the algorithms will be helpful for predicting the QoS data, which enhances the performance of the WSN. In this work, we have taken the data from open source QoS data originating from IoT devices. The primary contribution of this paper is threefold: (1) Prediction for all the time series data involved using a model of a feed-forward neural network based on the sensor data collected. (2) The implementation of Gaussian process algorithms for creating probabilistic predictions of the time series data is the next step. (3) The performance of the created models is analyzed by using the performance metrics to select the best model for the QoS prediction for WSNs.

2. Review of related work on QoS Prediction in WSNs

In recent years, dynamic spectrum management has been developed to use the available wireless networks without congestion and user interference. Several algorithms were developed to analyze and predict the QoS data based on the data taken from the wireless sensor testbed. A new cluster-based routing protocol is designed, and it is compared with other cluster-based routing protocols. The performance is measured by network lifetime and coverage number of packets transported to the base station. The proposed protocol is used to build low power clusters, and it has experimented with various topologies

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in different networks [1]. The authors discussed the introduction of WSN and various types of adhoc networks. A detailed literature review on WSNs was outlined, and available research problems in WSN were discussed. It also gives about the several problems still require improvements, like security, energy-efficient routing, etc. [2]. A detailed study was presented by the authors during 2010–2019 in the Mobile WSN field. The outcome of the paper gives future insight into the WSN field [3]. The authors applied the swarm intelligence in mobile WSN. They have analyzed and summarized the key technologies of Mobile WSNs and problems in the performance optimization process of Mobile WSNs [4]. The authors used the Prophet model to predict the electricity requirement for a house, office, or any building and compared it with ARIMA [5]. The authors have used two new parameters like adaptivity coefficient and arithmetic crossover rate in ABC algorithm for image processing and resource scheduling and found that the ABC algorithm converges better [6]. A framework that accurately forecasts sales in the retail industry was given in this paper. The authors have used the Prophet and back testing approach for sales prediction [7]. Prediction of quality of service based on the history of web services has been achieved with neighborhood-aware deep learning algorithm [8]. Hybrid Ensemble LSTM-FFNN model is developed to accomplish the prediction of photovoltaic generation, and the results specify that the proposed model increases the forecasting accuracy [9]. User traffic forecast is significant for WSN operators. Forecasting of client traffic by using Prophet and Gaussian algorithms was planned and applied to predict the high and low-frequency components. The predicted results were compared with the experimental results [10]. The authors provided a complete evaluation of 5G communication employing deep learning and addressed the problems of resource allocation, LDPC coding, MIMO, NOMA, and security [11]. In the networking field, the researchers applied deep learning models for network traffic supervising and investigation [12]. PSO based technique in a cluster-based WSN to resolve hot spot problems produced by multi-hop communication. The authors also provided a prevention method that extends network lifetime through the removal of traffic load available in the gateways [13]. The authors put an effort to give a view to the recent research on machine learning methods that were used in WSNs to manage several problems; also, they have given special interest on to routing problems [14]. Various WSNs challenges and systems based on machine learning techniques were discussed by the authors [15]. The authors present a Content, Device, and QoS aware forecast in small cell networks, which utilizes a Multilayer Perceptron neural network for prediction [16]. FFNN and Facebook Prophet algorithms were used to forecast the passengers traveling on the train each month. The MAPE of FFNN and Prophet is 4.27 % and 3.36% [17]. The prophet prediction model was implemented to forecast Seoul air pollution in both the long and short term. The air pollutants were predicted and cross-validated with 2017 and 2018 data. For comparing the predicted and actual values, statistical indicators like MSE, MAE, and RMSE were used [18]. PSO algorithm and topology structure, selection of parameters, Parallel and Discrete PSO algorithm, multi-objective PSO, and its applications in the engineering field were discussed by the authors. They found that PSO algorithms were easy to implement, high precision and fast convergence [19]. The authors developed a new method for SH selection denoted as EERSS, which is supported by Cat Swarm Optimization algorithm and its performance is validated with traditional and non-traditional based EERSS. They found that SH selection performance of the developed method is superior than the traditional algorithms [20]. The authors predicted the cash flows in many companies like airlines, transport, retail, and e-commerce. They have used the ARIMA, Prophet, and LSTM methods to predict the accounts receivable cash flows [21]. LSTM-based neural network to predict QoS values for IoT applications was proposed by the authors and the results were compared with the ARIMA method [22]. The authors used the Bluetooth signals for indoor navigation applications. MLP and RNN AI algorithms were used by the authors [23]. The authors used the AECC method in UAV's for data collection by using 6G technology and also they have applied the QOSSO method for improving the performance of the chosen method [24]. The authors applied ant colony optimization algorithms in NP-hardness problems like resource scheduling traveling salesman. The merits of the algorithm are distributed calculation, positive feedback mechanism, and diversity [25]. The authors proposed ML-fresh in the Oppnets based on ML algorithms for better performance while transmission of data in WSN's [26]. Based on the above works of literature, it is clearly seen that there are only a few papers dealing with the QoS prediction by using the AI and ML algorithms, and also no significant contribution or research was conducted to predict the QoS data based on the data obtained from four different sensors. This paper mainly focused on the prediction of QoS data from gas, humidity, pressure, and temperature sensors using FFNN and GP Artificial Intelligence algorithms.

3. Methodology

This part elucidates the methodology used for QoS forecasting. The schema for QoS prediction and validation is bestowed in Fig. 1.

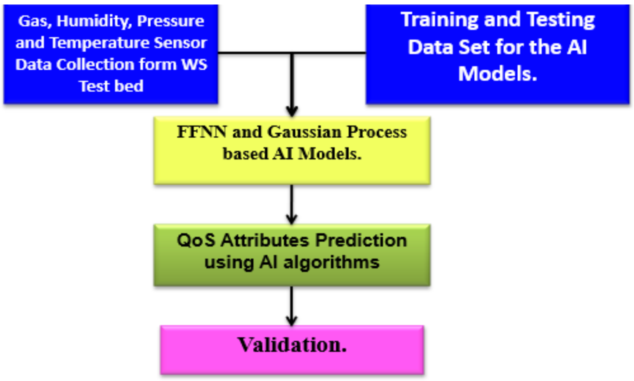

Fig.1. Flow chart for QoS prediction and Validation

4. Data Collection

In this work, different sensors data like Gas, Humidity, Pressure, and Temperature values obtained from a wireless sensor testbed are used for forecasting QoS data [27]. The performance of WSN depends upon the Quality of Services of the network. Throughput, data delivery latency, and consumption of energy are a few QoS of the network. A wireless sensor testbed receives the changes from the randomly placed Humidity, Temperature sensor nodes, Gas and Pressure. In this paper, we have taken the data from the WSN testbed for the month of June 2016 to train the FFNN and GP machine learning algorithms, which is given in Fig. 2.

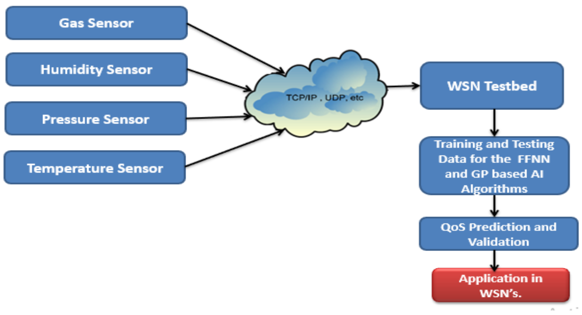

Fig.2. Data Collection for FFNN and GP ML Algorithm

One month of sensor throughput with five-minute intervals is considered for forecasting by using machine learning algorithms. The last one day of the time-series data is used as testing data, and the left-over data were used as training data. Figs. 3, 4, 5, and 6 demonstrates the difference between the training and the testing dataset. The variable QoS data from different sensors will be used as the target time series. Thus, the machine learning models will be trained in order to model the gas, humidity, pressure, and temperature sensors variables.

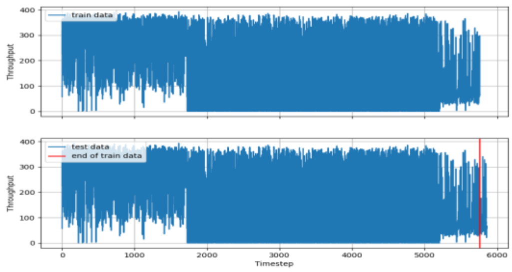

Fig.3. Gas Sensor dataset

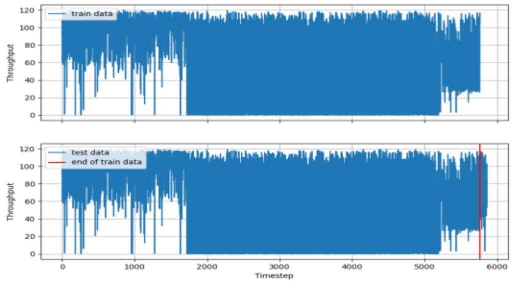

Fig.4. Humidity Sensor dataset

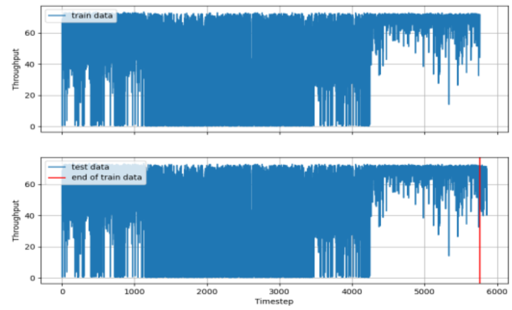

Fig.5. Pressure Sensor dataset

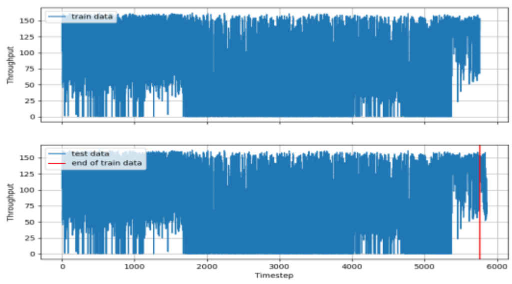

Fig.6. Temperature Sensor dataset

The primary motivation behind the Fig. 3-6 is to visually demonstrate the dynamics of the data emanating from sensor devices over time. Besides, it may be feasible for the machine learning community to immediately recognize the ratio of the training and the testing data needed to train and validate the models for such sensor data effectively.

4.1. Model Error Metrics

Various error metrics can be utilized to estimate the machine learning models built. The following error metrics (Normalized Root Mean Square Error, Mean Absolute Error, Symmetric Mean Absolute Percentage Error, Mean Absolute Scaled Error and Weighted Quantity Loss), are used in this work in order to measure the robustness and the reliability of the machine learning models built.

Table 1. Error Metrics to analyze the performance of prediction models

S.NO	Error Metrics
1	NRMSE
2	MASE
3	SMAPE
4	WQuantileLoss
5	MAE

$$NRMSE = \frac{\left(\sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}}\right)}{(y_{i_{max}}-y_{i_{min}})} \quad (1)$$

$$\text{MASE} = \text{mean}\,(|q_t|), \text{ Where } q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i-y_{i-1}|} \quad (2)$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{y}_i|}{(\hat{y}_i+y_i)/2} \quad (3)$$

$$WQL = 2\frac{\sum_{i=1}^{n}\left[max\left(y_i-\hat{y}_i^{(T)},0\right)+(1-T)max\left(\hat{y}_i^{(T)}-y_i,0\right)\right]}{\sum_{i=1}^{n}|y_i|} \quad (4)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \quad (5)$$

Where, y_i represents forecasted values, $\hat{y}_i$ represents the observed values, y_{max} is the maximum predicted value, y_{min} is the minimum forecasted values, e_t = Forecast Error, $t= 1\ldots n$ is the set of forecasting sample points, and T= 0.9 is the quantile value.

5. Results and Discussion

The essential key point is that we need to have 'probabilistic predictions' over 'point-estimate' predictions. Probabilistic predictions will allow us to have an uncertainty (or being able to quantify the confidence of the forecasted values) over the forecasts which we generate. This allows us to be able to extract various 'forecast paths' representing multiple levels of confidence over forecasts. The estimates in this work are generated by performing 'back-testing' using the machine learning models which we built. Back-testing is a process where a certain amount of the data is kept out of the training stage and is used only during the testing stage. The ability of the machine learning models can be evaluated on the data kept out as the models might not have seen that particular data during their training stages. Neural Networks are some of the most effective machine learning algorithms used in various sectors to model data exhibiting a lot of dynamics. On the other hand, the Gaussian Processes are traditionally used to model the data emanating from experiments and simulations. Our intention was to compare these, rather very different, approaches to present the limitations and the possibilities of modeling data emanating from sensor devices. For more information on the mathematical implementation and the APPs of the FFNN approach, the users are referred to "https://ts.gluon.ai/api/gluonts/gluonts.model.simple_feedforward.html

5.1. Feed Forward Neural network

One of the basic types of artificial neural networks is an FFNN. In these networks, the flow of information takes place in the forward direction [28]. During the process, the hidden layers carry out the estimation by using Equation 6 and changing the results to the next layer. Equation 8 is used for activating the nodes in the output layer [29, 30].

$$O_h = h_{Hidden}\left(\sum_{p-1}^{P} i_h\, w_h + b_c\right) \quad (6)$$

$$h_{Hidden}(x) = \frac{1}{1+e^{-x}} \quad (7)$$

Where, O_h - output of hidden layer, p - network inputs, i_h - input to the hidden layer, w_h - weight function, b_c - bias, $h_{Hidden}(x)$ - sigmoid function.

$$O_o = h_{Output}\left(\sum_{p-1}^{P} i_{c,p}\, w_{c,p} + b_c\right) \quad (8)$$

$$h_{Output}(x) = x \quad (9)$$

O_o- output of c, P - different nodes available in output layer, $i_{c,p}$ - input to node c, $w_{c,p}$ – weight, $h_{Output}(x)$ – activation function.

Fig. 7 depicts the comparison of original gas sensor data values taken from the testbed with forecasted values by using FFNN. In Fig. 7, the light-red and the strong-red shaded areas show the 90% and the 50% confidence intervals of the model predictions, respectively. The accuracy of the FFNN model is demonstrated in the form of error metrics values in Tab. 2.

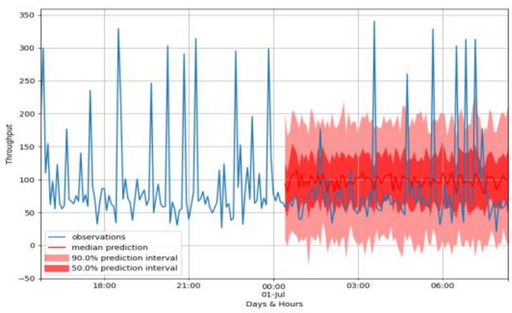

Fig. 7. QoS values from gas sensor based on FFNN Algorithm

Table 2. Error Metrics values of FFNN prediction model based on gas sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.77710
2	MASE	0.36874
3	sMAPE	0.47031
4	WQuantileLoss	0.14177
5	MAE	0.15347

Fig. 8 depicts the comparison of original humidity sensor data values taken from the testbed with forecasted values by using FFNN. The accuracy of the FFNN model is demonstrated in the form of error metrics values in Tab. 3.

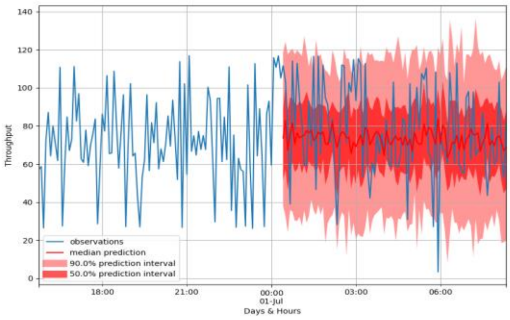

Fig. 8. QoS values from humidity sensor based on FFNN Algorithm.

Table 3. Error Metrics values of FFNN prediction model based on humidity sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.31607
2	MASE	0.55742
3	sMAPE	0.27559
4	WQuantileLoss	0.11594
5	MAE	0.04513

Fig. 9 shows the comparison of original pressure sensor data values taken from the testbed with forecasted values by using FFNN. The accuracy of the FFNN model is demonstrated in the form of error metrics values in Tab. 4.

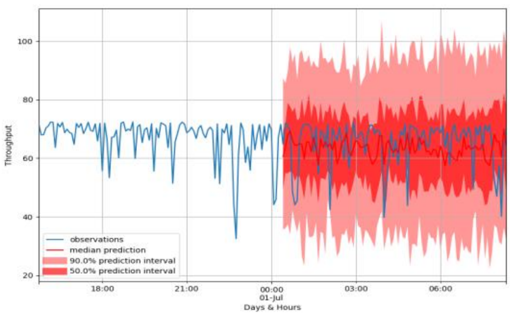

Fig.9. QoS values from pressure sensor based on FFNN Algorithm.

Table 4. Error Metrics values of FFNN prediction model based on pressure sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.13530
2	MASE	0.35193
3	sMAPE	0.11683
4	WQuantileLoss	0.08155
5	MAE	0.12916

The comparison of original temperature sensor data with forecasted values by using FFNN is given in Fig. 10. The accuracy of the FFNN model is demonstrated in the form of error metrics values in Tab. 5.

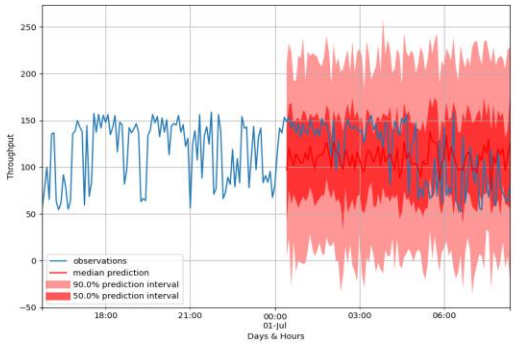

Fig.10. QoS values from temperature sensor based on FFNN Algorithm

Table 5. Error Metrics values of FFNN prediction model based on temperature sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.31254
2	MASE	0.62159
3	sMAPE	0.30978
4	WQuantileLoss	0.15589
5	MAE	0.10486

5.2. Gaussian Process

The Gaussian process algorithm is used to create local time series models, and if multiple models are available, each time series will have a Gaussian process with its own set of hyper-parameters. The four sensors data set is used in this paper, and the S is given as.

$$S = \{(a_i, b_i)\}\ i = 1\text{-}\ n, \tag{10}$$

Where, a indicates input training values taken from the 4 sensors. Thus, $a_i \varepsilon R^d$ refers to input data. $b_i \varepsilon R$ refers to corresponding output. The association between output and input values is given by

$$y = f(a) + c\,. \tag{11}$$

The Gaussian process f(a) is specified by,

$$Mean\ (m(a)) = \mu = E[f(a)]$$

The Gaussian Process is given by [31],

$$f(a) \sim GP(m(\mathrm{a}), k(\mathrm{a}, \mathrm{a}')) \quad (12)$$

The predictive distribution with mean and covariance are specified by,

$$\mathrm{m}(\mathrm{a}_*) = \mathrm{k}_*^{T} \mathrm{k}_b^{-1} \mathrm{b} \quad (13)$$

$$\sigma^2(\mathrm{a}_*) = \mathrm{K}_{**} - \mathrm{k}_*^{T} \mathrm{k}_b^{-1} \mathrm{k}_* + \sigma_n^2 \quad (14)$$

where k_y is kernel matrix and the results of GP are obtained by Equations 13 and 14. The Fig. 11 illustrates comparison of original gas sensor data with predicted values by using GP. The accuracy of the GP model is demonstrated in the form of error metrics values in Tab. 6.

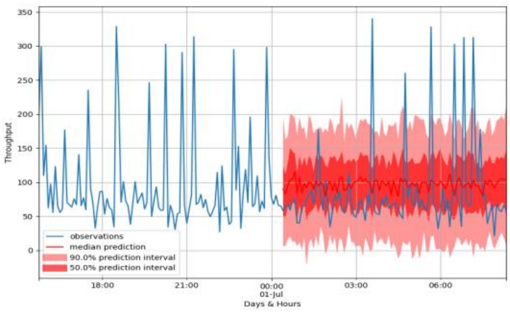

Fig.11. QoS values from gas sensor based on GP Algorithm.

Table 6. Error Metrics values of GP prediction model based on gas sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.77328
2	MASE	0.35850
3	sMAPE	0.45739
4	WQuantileLoss	0.13919
5	MAE	0.15347

Fig. 12 describes the comparison of original humidity sensor data with forecasted values by using the GP algorithm. The accuracy of the GP model is verified in the form of error metrics values in Table. 7.

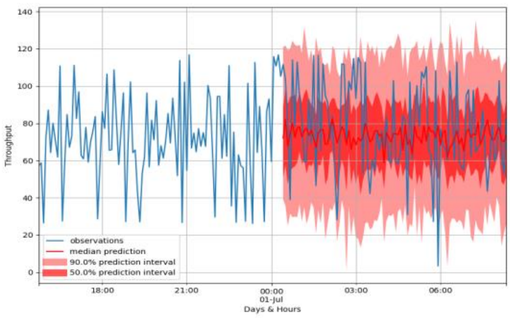

Fig.12. QoS values from humidity sensor based on GP Algorithm

Table 7. Error Metrics values of GP prediction model based on humidity sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.31281
2	MASE	0.55364
3	sMAPE	0.27448
4	WQuantileLoss	0.11671
5	MAE	0.04861

Fig. 13 represents a comparison of original pressure sensor data values taken from the testbed with forecasted values by using GP. The accuracy of the GP model is evaluated in the form of error metrics values in Tab. 8.

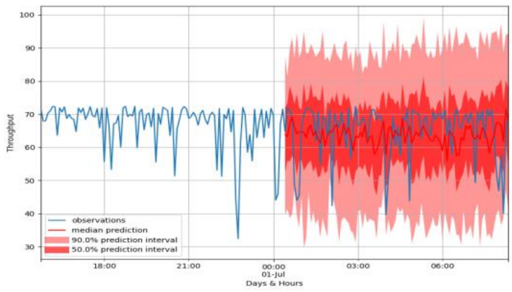

Fig. 13. QoS values from pressure sensor based on GP Algorithm

Table 8. Error Metrics values of GP prediction model based on pressure sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.13182
2	MASE	0.33988
3	sMAPE	0.11298
4	WQuantileLoss	0.06994
5	MAE	0.12569

Fig. 14 depicts the comparison of original temperature sensor data values taken from the testbed with forecasted values by using GP. The accuracy of the GP model is demonstrated in the form of error metrics values in Tab. 9.

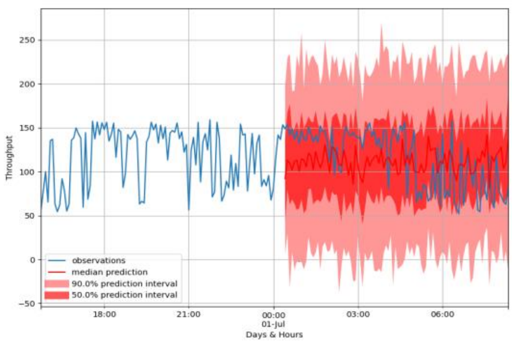

Fig.14. QoS values from temperature sensor based on GP Algorithm

Table 9. Error Metrics values of GP prediction model based on temperature sensor data

S.NO	Error Metrics	Value
1	NRMSE	0.31861
2	MASE	0.62075
3	sMAPE	0.30859
4	WQuantileLoss	0.15295
5	MAE	0.09791

In this paper, GP algorithms perform slightly better than FFNN. Based on the predictions, the GP and FFNN shall be implemented in WSN for better results.

6. Conclusion

Using data from various sensing devices, we showed how machine learning algorithms may be used to provide probabilistic forecasts as opposed to point estimations in this paper. The algorithms have been developed and validated for predicting QoS data. The Gas, Humidity, Pressure and Temperature sensor throughput data is taken from a wireless testbed. FFNN and GP algorithms are developed to predict QoS data. From the results, it has been observed that both the algorithms forecasted well, but the GP performs slightly better than the FFNN algorithm. The GP algorithm provides NRMSE of 0.77328, 0.31281, 0.13182, and 0.31861 for the gas, humidity, pressure, and temperature QoS values, respectively. From the results, it is found that GP and FFNN outcomes are better and have fewer errors. These results indicate that the proposed AI algorithms will be appropriate for wireless network QoS data studies. However, we have built univariate models for the data related to each sensor. In our extended work, we intend to demonstrate Deep Neural Networks used to create models that combine various time-series data data and generate forecasts for all of the time-series data involved. Further, we are also working on demonstrating the effect of various state-of-the-art optimizers on building accurate Deep Neural Networks based models in making probabilistic forecasts involving multiple time-series data.

Disclosure Statement

The authors declare that no potential conflict of interest was reported in this work.

Funding Statement

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