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A Novel Energy-efficient Sensor Cloud Model using Data Prediction and Forecasting Techniques

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A Novel Energy-efficient Sensor Cloud Model using Data Prediction and Forecasting Techniques

Abstract

An energy-efficient sensor cloud model is proposed based on the combination of prediction and forecasting methods. The prediction using Artificial Neural Network (ANN) with single activation function and forecasting using Autoregressive Integrated Moving Average (ARIMA) models use to reduce the communication of data. The requests of the users generate in every second. These requests must be transferred to the wireless sensor network (WSN) through the cloud system in the traditional model, which consumes extra energy. In our approach, instead of one second, the sensors generally communicate with the cloud every 24 hours, and most of the requests reply using the combination of prediction and forecasting methods in the cloud system, which results in less communication and more battery life for the sensor. In our model, we used the ANN model initially, which had predicted the temperature for a given day with an accuracy of 92%. The results of ANN, together with the earlier real temperatures, are given as input to the ARIMA forecasting model, which provides an accuracy of 96% for one day in advance. Our simulation shows that the proposed method saves more energy compared to the traditional approach.

Keywords

Artificial Neural Networks, Sensors, Clouds, Prediction Method, Wireless Sensor Network.

1. Introduction

Many applications need Sensors in today's world. WSN formes using the combination of several sensors in which the sensors communicate with each other without wire. Cloud computing is a prominent technique in which the end-users need not have to worry about infrastructure requirements as the users have to pay and use the services given by the cloud service provider. Sensor-cloud is the integration of the sensor network with the cloud systems. Sensor-cloud must be energy efficient as the lifetime of the battery in the sensor is finite and more energy consumes in the data center for running the server. The consumption of power in WSN is proportional to the data rate directly. The requests to access sensors through the cloud system are generally frequently even once in a second. All the queries of the users transfer to the sensor network through the cloud. As a result, more energy consumes within the sensor networks. Therefore prediction method is suggested for implementation in the cloud system to predict future sensor data for a day in advance so that a single communication in 24 h between the end-user and the sensor is required, which would reduce the energy consumption.

Authors in Ref. [1] have proposed an algorithm based on the ANN to predict the temperature, which provides better results than the local official weather forecast system. Brain et al. [2] have proposed the ANN model, which predicts temperature throughout the year with fewer errors. The model was able to adjust its prediction quickly on the addition of new information and also was made publicly available on the internet. The research carried by Zahra et al. [3] had proposed a data-driven technique that predicts temperatures. The performance of the proposed model was the same as the existing weather-predicting websites. A comparison study made in Ref. [4] using data-driven techniques of various types of neural networks and the nearest neighbor approach to predict the temperature of stream water for a short time. The study showed better results by taking the mean, minimum & maximum temperature of the previous day and also considering the movement of the Sun from the past 2 day as input.The scheme proposed by Wang and Qiu [5] suggested a hybrid uncertain finite element method using parameters under certain conditions for predicting the unknown temperature field. The proposed method effectively solves the problems of heat conduction. Authors in Ref. [6] have proposed an approach named as chain structure for temperature prediction. Xiaojun Wang proposed the temperature model with the use of collected data [7]. The model produced better results than the other temperature models. In Ref. [8], authors have demonstrated a framework for thermal prediction for run-time management decisions. The model got better results than the earlier proposed Gaussian process, with improved accuracy in prediction results. In Ref. [9], authors have used neural network methods to study the ambient air temperature series. The results obtained from this model provide better accuracy in prediction than the autoregressive model. Lynn Houthuys et al. [10] have proposed a model to predict the temperature for the forecasting of weather. The model considered the past temperature data of a city and its surrounding towns to predict the temperature. The results obtained were quite improved compared to the earlier works and was at par with the existing prediction methods. Das et al. [11,12] proposed the data prediction based energy-efficient sensor cloud models in which the prediction method is used in the cloud system to save energy consumption for the sensors. Hamouda and Msallam [13] proposed the selection of variable sampling intervals for the monitoring of the parameters used in agriculture activities, which is energy efficient using WSNs. An optimization problem for coverage using the distributed and clustering methods for energy-efficiency proposed in Ref. [14]. Elshrkawey et al. [15] proposed a technique that balances energy consumption in the clusters by selecting the cluster head. An energy-efficient approach using the energy harvesting model to predict energy for harvesting and residual energy in advance discussed in Ref. [16]. In Ref. [17], the authors proposed a novel method for the maximization of the network lifetime. Vinitha et al. [18] proposed a multi-hop routing technique that is energy efficient. In Ref. [19], the authors analyzed the query processing technique's characteristics in the WSNs. In Ref. [20], the authors proposed a localization technique that provides accurate location of WSNs. Authors in Ref. [21,22] proposed an advanced communication technique that minimized the delay and increased throughput. Authors in Ref. [23] surveyed various

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issues addressed by multi-channel usage in WSNs. The authors in Ref. [24] proposed energy harvesting for rectifiers to maximize throughput for the system. The research carried out by Kamarei et al. [25] recommended a method that divided the WSN into four partitions logically, and the data is collected from the center of these partitions on time to make the nodes energy efficient. Authors in Ref. [26] proposed an optimization model to enhance the coverage of the area in the WSNs. The authors in Ref. [27−31] implemented various optimization models in various real-time applications. The research carried out by M. Rao et al. [32] designed an energy-efficient motion monitoring system of the ship using a Bayesian network. The structure of the paper is as follows. Section 2 explains the Sensor Cloud Model for Energy Efficiency using ANN and ARIMA models. Sections 3 describes the results of our simulation. The conclusion of the paper is in part 4.

2. System model

2.1. Energy efficient sensor cloud model

The combination of prediction and forecasting method uses ANN and ARIMA [33] in the cloud to predict the sensor data in advance. So all the user requests are answered by the cloud system. As a result, energy consumption minimizes as the cloud system replies to the user's requests. Fig. 1 shows our proposed novel energy-efficient Sensor Cloud model using ANN with a single activation function and ARIMA Technique.

In our model, initially, the ANN-based prediction method with a single activation is used. Then, forecasting using the ARIMA method uses to predict the temperature. Fig. 2 explains prediction using ANN and Forecasting using ARIMA Model.

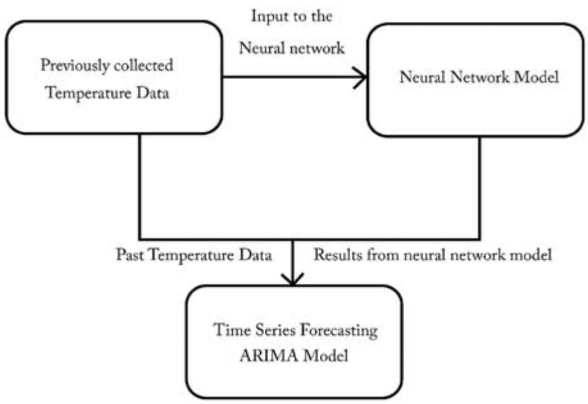

Fig. 2. Prediction Using Artificial Neural Network and Forecasting using ARIMA Model.

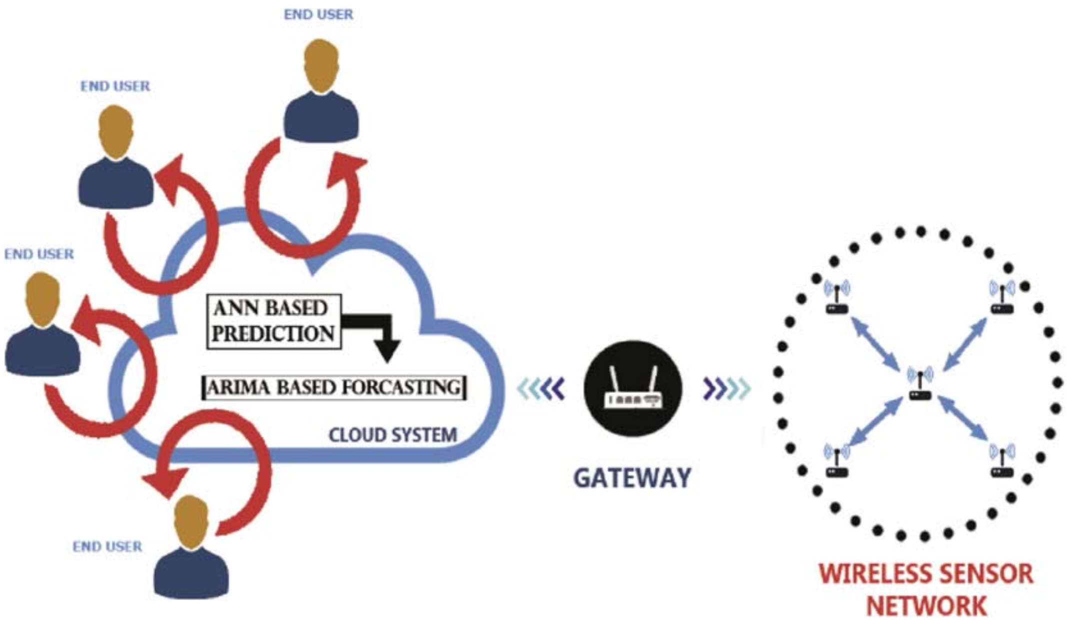

Fig. 1. Novel energy-efficient Sensor Cloud model using ANN and ARIMA Techniques.

2.2. Prediction using artificial neural network with a single activation

This section gives a description of the implementation for a model that uses ANN using back-propagation [34] algorithm for prediction combined with the forecasting using ARIMA within the cloud system. The meteorological dataset of "Kaggle" website from the year 1997 to the year 2015 of Madrid, Spain [35], is used for our simulation. For the training and testing purposes, we choose the data randomly with a ratio of 0.83: 0.17, respectively, from the dataset. This dataset contains 60,000 instances of measurements, which divides into 10,000 test samples and 50,000 training samples. Our simulation uses Mean temperature as the target parameter and nine other parameters as the predictors such as (a) Mean Dew Point (°C) (b) Mean Humidity (c) Mean Sea Level Pressure (hPa) (d) Visibility Mean (Km) (e) Mean Wind Speed (Km/h) (f) Precipitation (mm) (g)Cloud Cover (h)Events (i)Wind Dir (Degrees). We have used $\frac{e^x-1}{e^x+1}$ for the transfer function both in the output layer and in the hidden layer. We are using this activation function because it has a smooth curve, and the accuracy of the model can obtain from the first iteration or first epoch itself.

The steps of ANN-based prediction with a single activation are as follows:

1. The number of layers and neurons initialize. Other than the output nodes, the biases and weights generate for each node.
2. The output of the feed-forward network calculates using the activation function *f(x),* where $f(x) = \frac{e^x-1}{e^x+1}$, along with bias and the weight of neurons.
3. The neural network is trained randomly with batches of 30 tuples.
4. A gradient descent method updates the biases and weights with the introduction of backpropagation to a single mini-batch dataset.
5. The Cost Function is defined, and the value of the error function minimalizes using a gradient descent technique.
6. The gradient descent technique uses to obtain weight and bias, which minimizes the cost function. The minimum cost function acquires on repeating the above process.
7. By picking mini-batches from the training inputs in a random manner, the stochastic gradient descent applies to determine the deviation of the weight and biases.
8. Calculation of the errors in a layer.
9. A heuristic sense uses where the inaccuracy in the neuron is known.
10. The backpropagation algorithm applies to calculate the gradient.

2.3. Results of ANN-based prediction system with a single activation

Fig. 3 shows the results of the ANN-based prediction system with a single activation.

The x-axis displays the randomly selected date, and the y-axis shows the temperature in the scaling factor 1. The accuracy of this prediction using $\frac{e^x-1}{e^x+1}$ the transfer function both in the output layer and in the hidden layer is approximately 92%.

2.4. Forecasting using ARIMA model

In our model, the output of the neural network fed to a time-series forecasting ARIMA model. Our time-series temperature data contains seasonality and trend. Our ARIMA model consists of the 2nd order of the autoregression, the 1st order of differencing, and 1st order of moving average. First of all, we apply non-linear log transformation for making stationary. But the time series is still non-stationary. Then, the differencing method uses for creating this stationary. Fig. 4 shows the time series analysis for the temperature.

The x-axis of the graph shows the dates of the year. The y-axis shows the normalized temperature within a scale of [-2, 2]. In first-order differencing, we compute the differences between consecutive observations in the time series. From the above figure, we can see stationary by first-order differencing. To apply an ARIMA model to our time series, we need to get the optimal results for the following three model parameters (p,d,q):

The number of autoregressive (AR) terms (p): In this case, we have assumed the value of p = 2.

The moving average (MA) in terms of (q): In this case, we have assumed the value of q = 2.

The differences (d): In this case, we have assumed the value of d = 1, as you are modeling using the first order differenced time series.

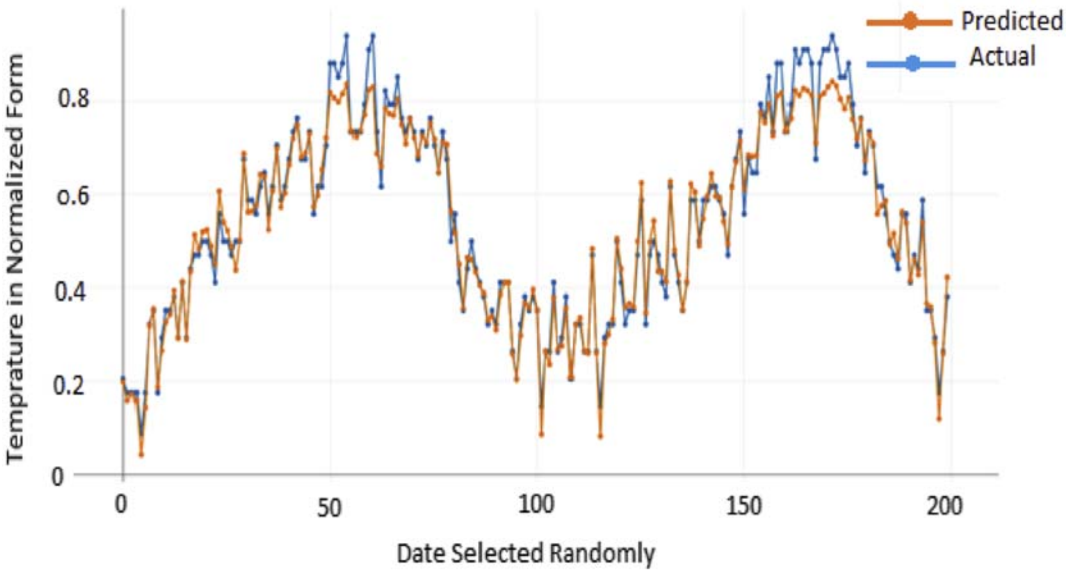

Fig. 3. The relationship between actual and predicted values for ANN-based prediction.

Figs. 5–6 show the partial autocorrelation function (PACF) and autocorrelation function (ACF) values respectively.

The x-axis of the graph shows the index selected randomly from the dataset for calculating the PACF and ACF values, and the y-axis shows the normalized temperature within a scale of 1.

Our assessment of the ACF and PACF plots differs from the values suggested by the arma_order_select_ic function. We test with different p and q values and use the fitting results of the model to study the Akaike information criterion (AIC) values and select the model with less AIC. The optimal values for the ARIMA (p,d,q) model are (2,1,2).

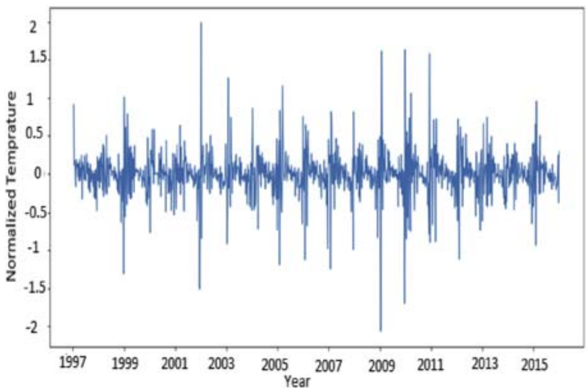

Fig. 4. The time series analysis for the temperature.

2.5. *Measure the variance between the data and the values predicted by the modeling*

Fig. 7 shows the residual Analysis of our model.

The x-axis of the graph shows the index from our dataset randomly, and the y-axis of the figure shows the highest number of temperature that lies in a particular region. The analysis of residual error values of the density plot indicates a normal distribution centered on zero means. There is no violation of the constant and scale assumptions of the residuals in the range (−1, 1).

2.6. *Visualization of time series forecasting*

Applying the combination of prediction technique using ANN with a single activation and forecasting technique using ARIMA, the predicted and the actual temperature is shown in Table 1. Fig. 8 shows observed values and the rolling one-step out-of-sample forecast. The x-axis of the graph shows the date starting from February 2015 to December 2015, and the y-axis of the figure shows the actual temperature within that period. From this graph, we can infer that the combination of ANN-based prediction and ARIMA forecasting model provides 96% accuracy. The projections scale is correct

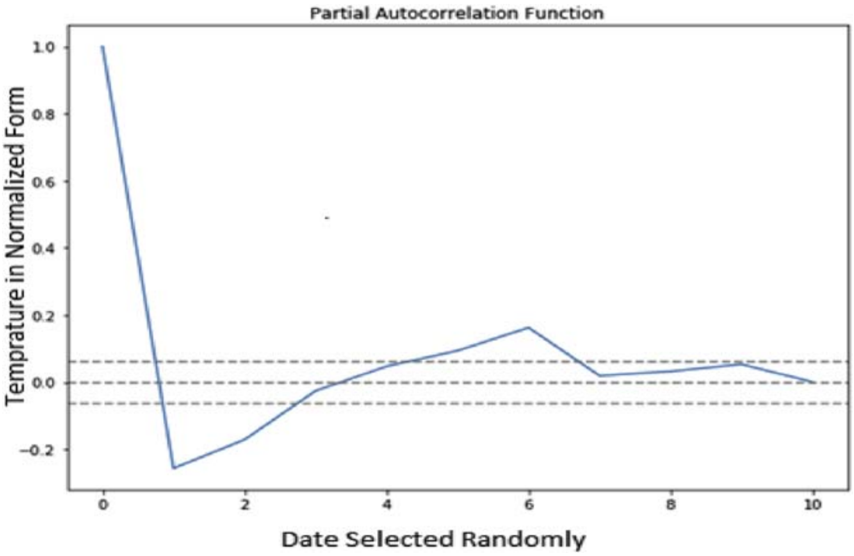

Fig. 5. Partial autocorrelation function values.

and is taking up the inclination in the primary time series.

3. Results and discussion

In our simulation, there is the distribution of hundreds of nodes uniformly in a square of side 50 m. The rate of data transfer for each sensor node is 1Mbps to the sink, which is at the square edge. Assuming that every node transfers data 5 s every hour, we calculate the total energy consumption of all 100 nodes. Fig. 9 displays the comparison of power consumption in the traditional approach and the proposed method. The proposed method consumes very less energy as

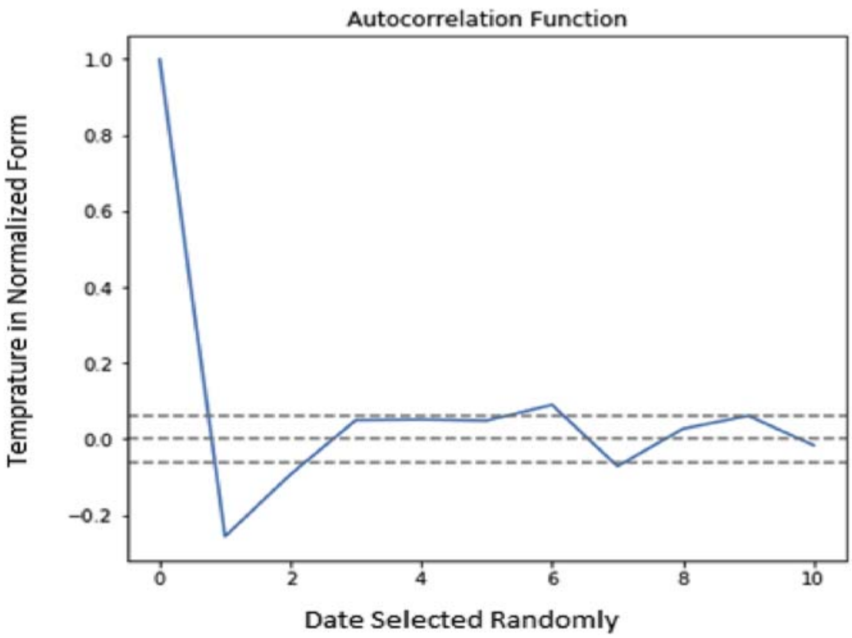

Fig. 6. Autocorrelation function values.

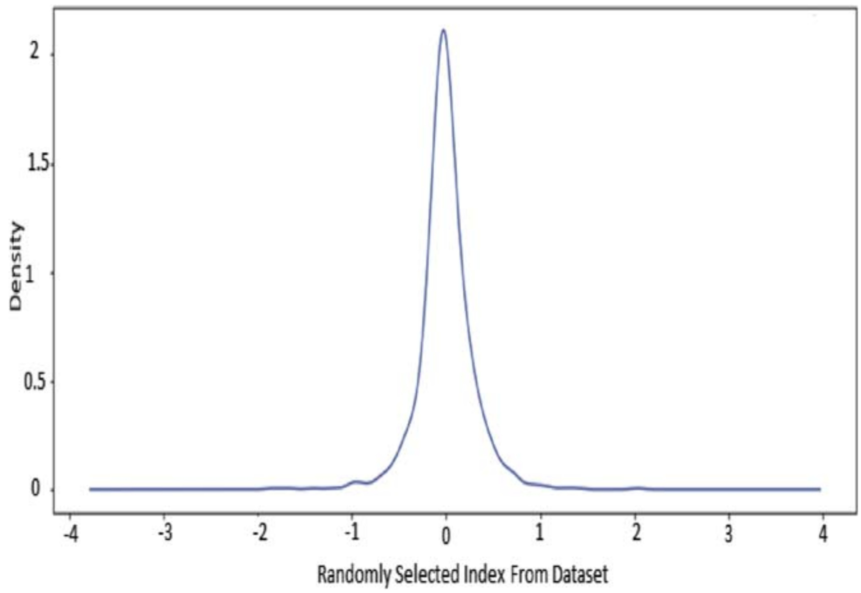

Fig. 7. Residual Analysis of the model.

Table 1
Predicted and actual temperature.

Predicted Value	Actual Value	Predicted Value	Actual Value
18.817615	19.857142	12.786874	10.063665
19.908139	18.285714	10.873247	8.679720
18.464407	16.767458	9.452142	7.423916
17.491207	14.395040	8.031289	7.290523
15.374788	14.466867	7.565879	9.285714
14.902348	13.837764	8.689195	6.394606
14.082206	13.165738	6.874709	8.500000

compared to the conventional approach. The accuracy of the prediction and also energy-saving goals attain using the proposed model in the sensor cloud environment.

4. Conclusion

In our approach, instead of 1 s, the user's requests are redirected to the sensor through the cloud generally

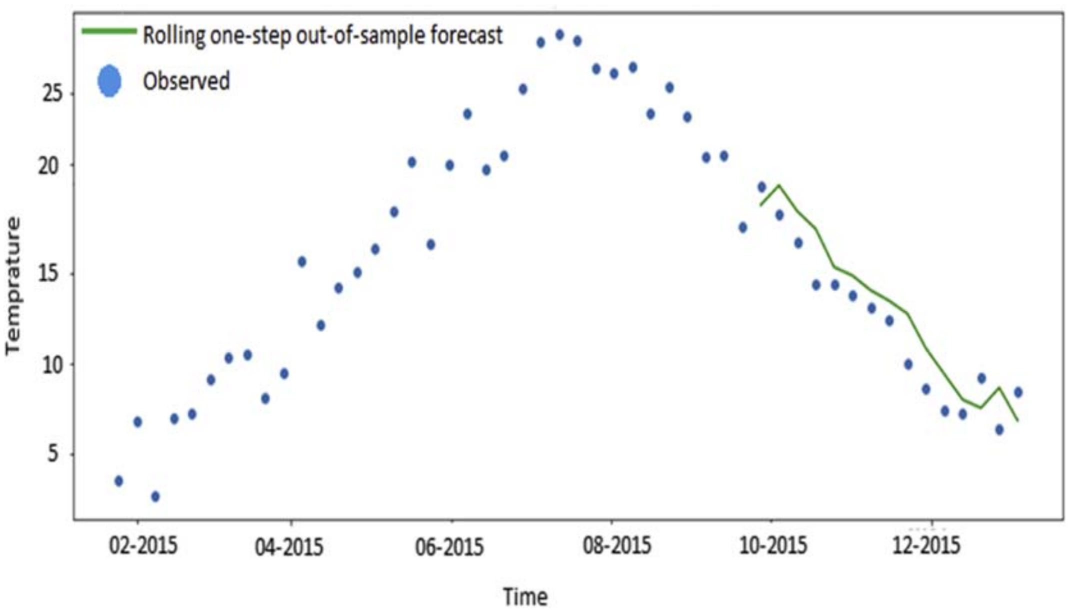

Fig. 8. The relationship between the observed values and the rolling one-step out-of-sample forecast.

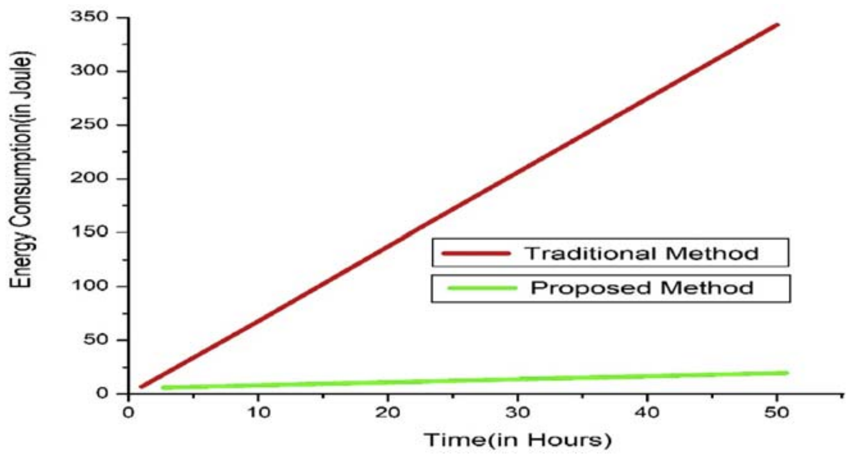

Fig. 9. Energy Consumption in the traditional approach and the proposed method.

every 24 h as all the user requests are answered by the cloud using the combination of prediction and forecasting method. So this results in less communication and more lifetime of the battery. Initially, the ANN-based prediction model with a single activation function was used to predict the temperature for a day in advance, which provides an accuracy of 92%, and these results of ANN along with previous real temperatures taken as input for the ARIMA forecasting model which provides an accuracy of 96%. Our simulation shows the proposed approach is energy efficient compared to the traditional method. In future accuracy of prediction may be further increased by the use of computational intelligence algorithms and also implement our model in large scale heterogeneous nodes environment.

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