# Prediction Based Data Reduction and Controlled Transmission in Wireless Sensor Network for Weather Forecasting

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***Abstract:*** Weather forecasting is a challenging and complex field of modern research; it has gained significant attention of researchers now a day as it directly effects the global community specially the agriculture and farming. Wireless Sensor networks (WSNs) with the integration of IoT are implementing very commonly for collecting, storing and analyzing the weather information such as temperature, pressure, humidity and wind speed. The major challenge in weather forecasting using wireless sensor networks is to efficiently utilize the energy resource and to deal with low availability of spectrum resource of wireless sensor networks. These challenges can be overcome if the control over the data of WSN nodes can be taken without effecting the system accuracy. This paper describes the weather forecasting with an energy and spectrum efficient technique for WSNs by applying predictive data reduction algorithms and controlled transmission on WSN nodes maintaining the 80% of system accuracy.

***Index Terms***- Adaptive Filter, Data Reduction, Least Mean Square, Weather forecasting, WSN

## I. Introduction

Weather forecasting is an interesting and growing research field, it is used to predict the future weather conditions and involves the monitoring and reporting of the rapid changes in weather conditions. These weather updates needs to be monitored and analyzed by the meteorologists. It is challenging for meteorologists to observe, gather, analyze and distribute the updated and accurate weather information to the other fields or departments such as agriculture and farming. The problem can easily be resolved by the use of Wireless Sensor Networks.

WSN networks with the integration of IoT are implementing very commonly for collecting, storing, and analyzing the environmental data such as temperature, pressure, humidity and wind speed. A wireless sensor node can be defined as a maintenance entity for the wireless network with some major components such as a sensing unit to get the sensed data from the surroundings, a processor, and an RF transceiver to transmit the processed data back to the surroundings. They are usually deployed in such areas which are difficult for human being access.

While working with the wireless system or subsystem, its power source has always the battery constraints and hence energy deterioration occurs with time similarly wireless sensor node is highly power-constraint entity. Its battery cannot be replaced or charged once it is deployed. To use the sensor node with constrained resource, its processing abilities, level of security, coverage and lifetime all the factors will be compromised [1]. Hence the limited battery range and complexity in battery replacement and regarding made the power resource in wireless sensor networks is a is major constraint and precious resource. It's the main goal of many researchers to lessen the energy utilization during the system operation preserving the life of sensor node [2]. For this purpose, we need to have an energy conservation technique in the system model while designing a weather forecasting system using WSN.

Many energy conservation techniques to increase the lifetime of WSN nodes has been addressed in [3]. It is observed that the communication part of the transmission usually takes more energy as compared to the sensing block so greater part of the energy is wasted during the transmission of data instead of the actual sensing [3]. Energy can be saved if the control over the data generation of WSN nodes can be taken by only predicting major amount of sensed data without actually transmitting them over nodes keeping the system accuracy maintained.

There are many data gathering Energy-efficient schemes which are designed to reduce the amount of energy that is being used by sensing subsystem but instead of reducing energy consumed by sensing system it is also possible to save the energy by decreasing or eliminating the frequency of unnecessary sensing. This process can be done by decreasing the number of intermediate nodes and the sampling [4]. But we only can reduce the sampling frequency and number of nodes through this method, if the WSN is spread over a very tiny geographical area.

For energy conservation data reduction techniques can also be used which are very efficient for energy and bandwidth conservation. Data reduction can be achieved through multiple techniques as discussed in [1] but the most robust techniques is prediction method through adaptive filters. Data prediction make it easy for the wireless sensor-based systems to save energy by reducing the amount of information sent by transmitter for unnecessary transmission [1]. The data reduction approaches instead of data eliminating techniques are more robust to save the energy and life of WSN node.

Dias et al, explained in [5] different data techniques that may lower the number of transmissions, but not all of them involve predictions. Data reduction techniques can be divided into further categories as mentioned in Fig. 1.

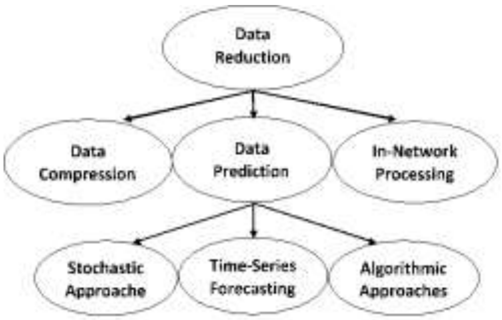


**Fig.1** Data Reduction Techniques

In [6] a complete weather forecasting system using WSN's and Arduino Uno has been discussed with predictive models but it has the same problem of energy and power degradation because of the having data load on WSN node.

Many Machine learning and deep learning based predictive algorithms has been addressed in [7], [8] and [9] for weather forecasting, but all these algorithms require prior knowledge of sensed data to be predicted which is very difficult to maintain.

There are a lot of adaptive prediction algorithms present, the choice of algorithm for the system with greater accuracy is totally dependent upon the convergence rate, accuracy rate and hardware complexity level. Because of the simplicity and goof performance LMS is one of the most suitable and efficient algorithms for adaptive filtering and widely used in large spectrum applications [2]. There are many variants available for LMS algorithm like standard MS, variable step size LMS and normalized LMS. All of the variants of LMS algorithm provide convergence with greater efficiency and accuracy.

In this paper we proposed a time series based adaptive dual prediction scheme that will be used for wireless sensor networks placed in weather forecasting system. The proposed scheme will use three LMS techniques for data prediction and compare them for greater values of convergence and accuracy. The main benefit of using this algorithm is that it doesn't require any prior information for the observed signal for future prediction.

The rest of the paper is organized as: Section II explains the proposed methodology, Section III describe the hardware and software details of the system, Section IV discuss the results and Conclusions while in future work is presented in Section V.

## II. METHODOLOGY

We have proposed dual prediction methodology for data reduction in weather forecasting system, that will apply on WSN nodes that is on both transmission and reception side. In this section our proposed methodology is explained through the flow chart and pseudocode.

### *A. Dual Prediction Scheme (DPS) Model:*

The model of the dual prediction scheme is represented in Fig. 2 as following:

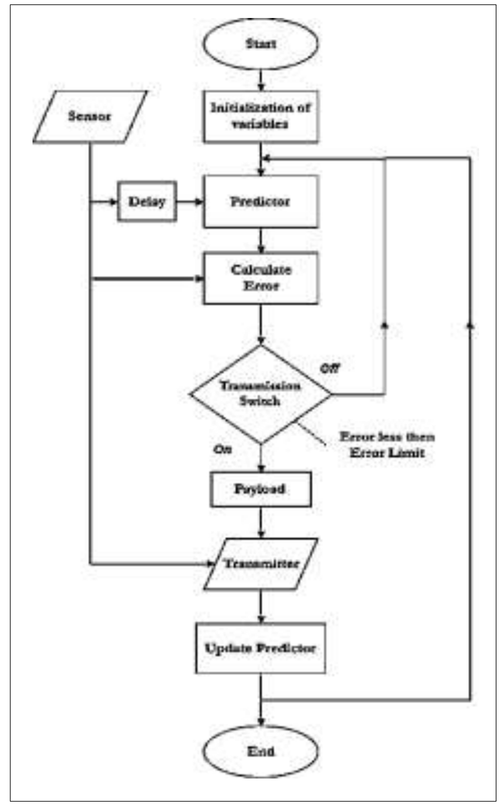


**Fig. 2a** DPS Model (Source Node)

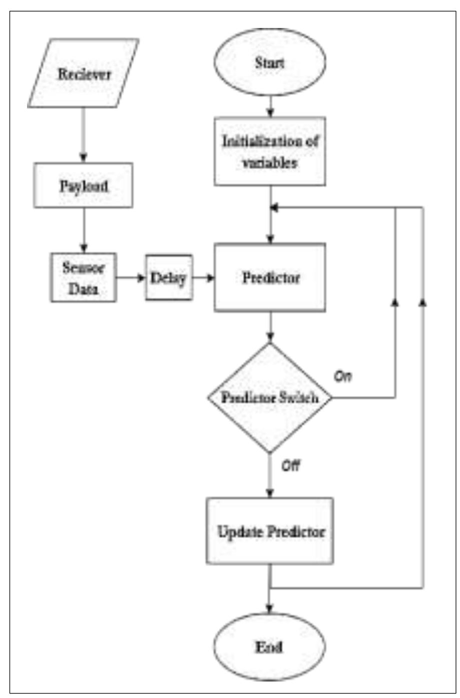

**Fig. 2b** DPS Model (Sink Node)

Dual prediction scheme will follow the three steps during every transmission. **Data acquisition** will be performed by the sensors, it involves the data (Temperature, Humidity and Air-Pressure) collection through the sensor unit and is forwarded to the main controller unit for **data prediction** which involves the training of the algorithm at both source and sink nodes in synchronous fashion by processing the data and estimating the future values through its error feedback. Once the future data is predicted instead of the direct transmission, predicted and actual data is compared during data control process, the error value is then compared with an error bound to maintain accuracy of predictions. If the error value is within the error bound (lesser than), the actual data will not be transmitted and instead the predicted value is used as output at sink node. **Data transmission** is done only when the error is greater than error bound by opening the transmission switch and it's turned off when the predicted data is accurate, error within the error bound.

## III. SYSTEM DESCRIPTION

The overall weather forecasting system is consist of a sensor BME-280 to acquire the environmental data (temperature, humidity and air pressure), an Arduino Uno for data prediction and controlling, and a NRF24L01+ wireless transceiver for transmission. The designed system's block diagram is presented in Fig. 3 and circuit diagram of the system is presented in Fig.4

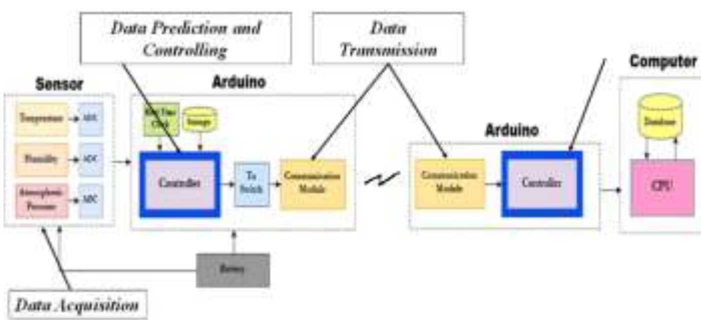


**Fig. 3** Block Diagram of System

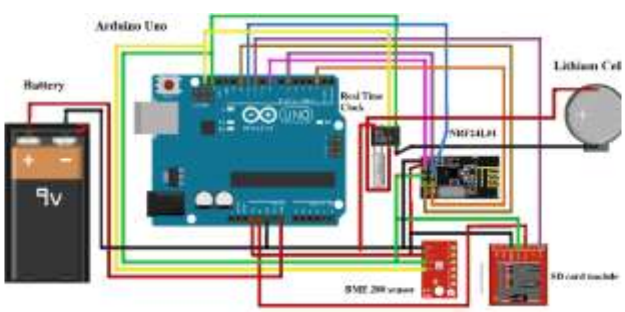


**Fig. 4** Circuit Diagram of System

*A. Implementation of Dual Prediction Scheme (DPS) Using Adaptive Filter:*

After the acquisition of data through sensors, dual prediction is done by adaptive filter using LMS, variable step LMS and normalized LMS algorithms to achieve the faster convergence and greater accuracy. The all three algorithms for adaptive filter based prediction are discussed in this section.

Adaptive filter can be used as the predictor as the delayed version of desired signal is used to constitute the predicted signal. The Adaptive filter based predictor model is shown in Fig.5

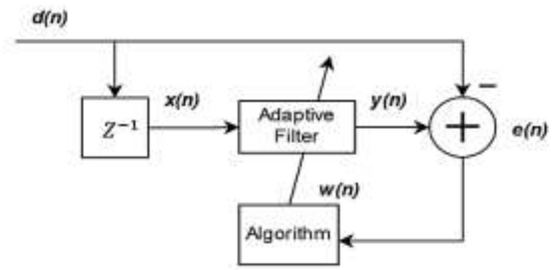


**Fig.5** Adaptive Filter Based Predictor Model

Where,
d(n) =desired Signal
x(n)= Delayed version of desired Signal
y(n)= Predicted Signal
w(n)= Adaptive filter Co- efficient
e(n)= variation between the y(n) and d(n)

*B. LMS Based Prediction:*

LMS algorithm is used for the weight adjustments of adaptive filter based predictor. It is widely used algorithm due to its simplicity. The predicted value from the adaptive filter using LMS algorithm at any instant 'n' is defined as the linear combination of last n samples of filter Co-efficient or weights. It can be written as:

$$y(n) = w^T(n)x(n) \ldots\ldots.\text{(i)}$$

The predictor calculates the error at 'n' sample between the desired and predicted value and adjust its Co-efficient or weights accordingly after each iteration. The error value determines how the filter coefficients and weights will be updated. According to the Least Mean Square algorithm (LMS), The estimation of filter Co-efficient or weights after 'n' samples can be written as:

$$w(n+1) = w(n) + 2\mu x(n)e(n) \ldots\ldots.\text{(ii)}$$

Where,

0<μ<0 $< \mu < \frac{2}{E_x}$ , $E_x = \frac{1}{N}\sum_{n=1}^{N}|x(n)^2|$ ,

**μ** is defined as the step size or convergence factor that describe the relationship between the desired and predicted signals, the value of μ must be small to achieve stable prediction with slow convergence as the largest values of μ leads towards unstable prediction but with faster convergence.

*C. N-LMS Based Prediction:*

The scaling of the delayed version of desired signal x(n) is a very sensitive topic for the "pure" LMS algorithms which makes it quite difficult to obtain a convergence factor(μ) from which the stability of the system can be certainly achieved. The problem can be resolved by varying the convergence factor after each iteration. As NLMS algorithm minimizes error by taking instantaneous error value for weight adjustments and normalizing its input power. The achieved convergence speed is much faster than the actual LMS Algorithm.
According to the Normalized Least Mean Square algorithm (N-LMS), The estimation of filter Co-efficient or weights after 'n' samples can be written as:

$$w(n+1) = w(n) + \frac{\mu_n}{\gamma + x^T(n)x(n)}\, x(n)\, e(n) \ldots\ldots (iii)$$

Where,

**γ**=small positive constant

**$0<\mu_n<2$** = Fixed convergence factor/Step Size

γ is introduced for the preservation of stability in the system, while $\mu_n$ is used to control the weights adjustments impaired by using instantaneous values and must be kept in between 0 and 2

*D. VSS-LMS Based Prediction:*

The variable convergence factor/step size algorithm provide the fast convergence and robust accuracy with low complexity level. The variable step size algorithm updates the convergence factor after each iteration or sample in parallel to the filter weights. By applying VSS Least Mean Square algorithm on equation (ii), the new filter weights will be updated as:

$$w(n+1) = w(n) + 2\mu_{n+1}\, x(n)\, e(n) \ldots (iv)$$

Where,

$$\mu_{(n+1)} = \frac{\mu_n}{M}, \quad M \le n \le M^2$$

To provide the faster convergence with proper stability $\boldsymbol{\mu_v}$ is bound by the upper and lower limits in the prediction model.

## IV. RESULTS

In this section, detailed results and comparisons have been explained for the data reduction in weather forecasting system using WSN networks by applying proposed dual prediction scheme with three different adaptive filter algorithms. The proposed Dual Prediction Scheme provide data reduction and energy consevation upto 82% with VSS-LMS Algorithm, 78% with N-LMS Algorithm and 68.33% with LMS Algorithm.
This section provides detailed analyses of the performance of each algorithm for its convergence and data saving capability in weather forecasting application.
All the algorithms were initially applied for the prediction and data reduction of temperature values, for that data set of temperature values is generted from self created sensor mode (during the period of four months) and a vector is formed containing the temperatures values at a constant time period gap of 2-3 minutes. This vector is applied as the input signal of all three algorithm on both sides of transmission. After obtaining 80 percent savings in transmission from atleast one of the algorithm, same scheme is applied to other predicting quantities of the system.

*A. System Stability and Data Reduction in DPS Using LMS Algorithm*

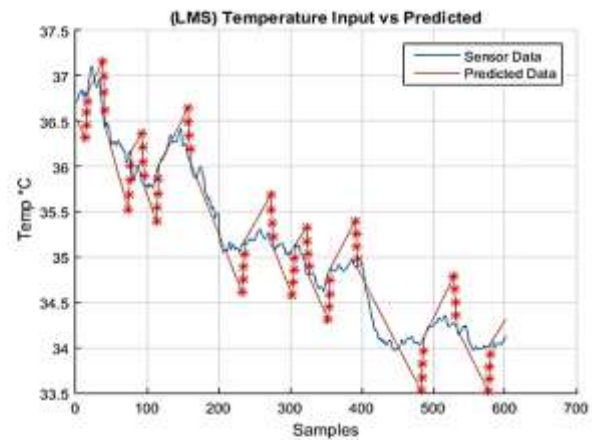


**Fig. 6a** Temperature Predictions using LMS

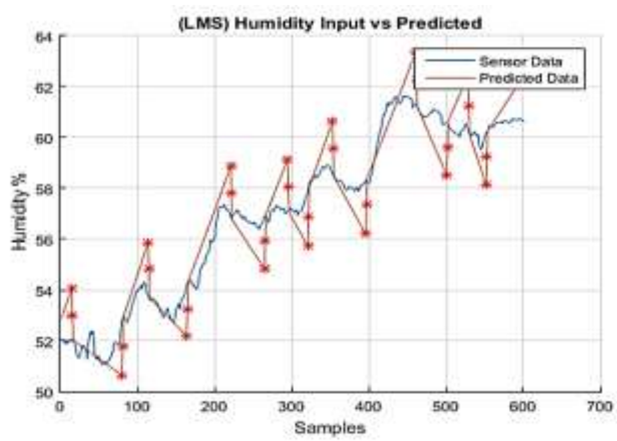


**Fig. 6b** Humidity Predictions using LMS

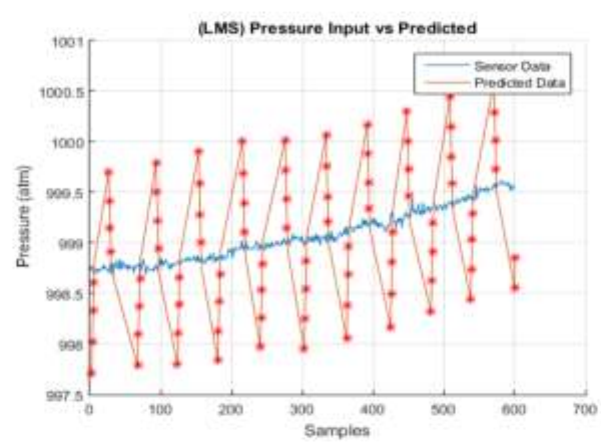


**Fig. 6c** Pressure Predictions using LMS

According to the simulation and hardware results shown in Fig. 6a, Fig. 6b and Fig. 6c, LMS was found to be converged after transmitting 91 samples that will take almost duration of 45.5 mins to be stable and meaningful predictions. Table. 1 explains that by implementing Dual prediction scheme with LMS algorithm upto 68% energy can be saved.

**Table.1** Data Reduction and Energy Consevation using LMS for Weather Predictions

| | Tranmission Energy | Saved Energy | Converging Sample | Initial Converge Time |
|---|---|---|---|---|
| Temperature | 17.01% | 82.99 % | 57 | 91 samples*0.5 mins per sample =45.5 mins |
| Humidity | 5.77% | 94.23 % | 83 | |
| Air Pressure | 13.74% | 86.26 % | 91 | |
| Overall | 31.67% | 68.33 % | 91 | |

*B. System Stability and Data Reduction in DPS Using N-LMS Algorithm*

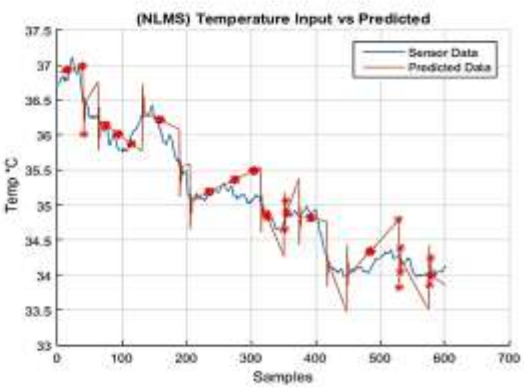


**Fig. 7a** Temperature Predictions using N-LMS

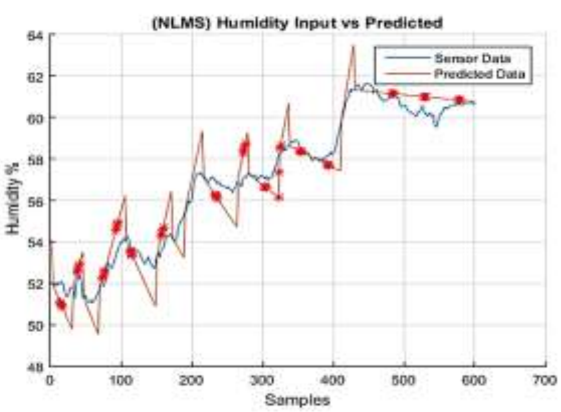


**Fig. 7b** Humidity Predictions using N-LMS

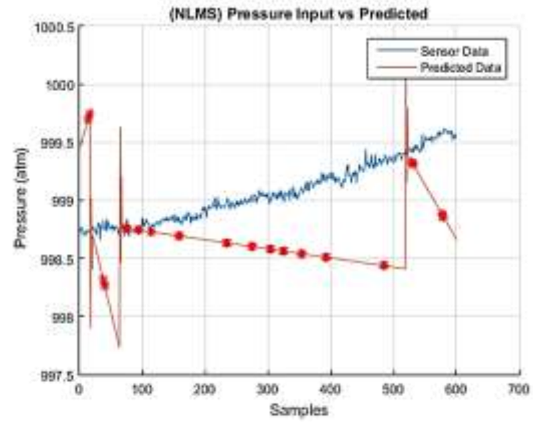


**Fig. 7c** Pressure Predictions using N-LMS

According to the simulation and hardware results shown in Fig. 7a, Fig. 7b and Fig. 7c, N-LMS was found to be converged after transmitting 38 samples that will take almost duration of 19 mins to be stable and meaningful predictions. Table. 2 shows the data reduction and energy consevation figures for Dual prediction scheme with N-LMS algorithm which is achieved upto 78%.

**Table.2** Data Reduction and Energy Consevation using N-LMS for Weather Predictions

| | Tranmission Energy | Saved Energy | Converging Sample | Initial Converge Time |
|---|---|---|---|---|
| Temperature | 14.68% | 85.32% | 17 | 38 samples *0.5 mins per sample =19 mins |
| Humidity | 6.34% | 96.66% | 34 | |
| Air Pressure | 3.23% | 96.77% | 22 | |
| Overall | 31.67% | 78.05% | 38 | |

*C. System Stability and Data Reduction in DPS Using VSS-LMS Algorithm*

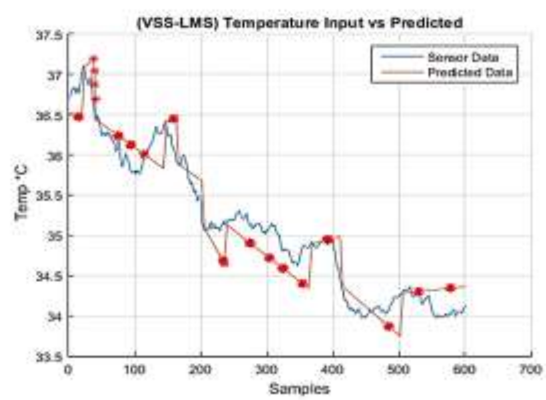


**Fig. 8a** Temperature Predictions using VSS-LMS

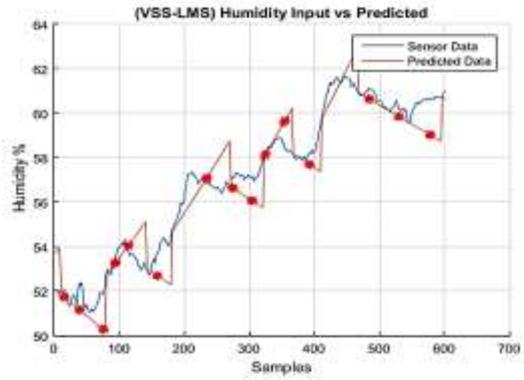


**Fig. 8b** Humidity Predictions using VSS-LMS

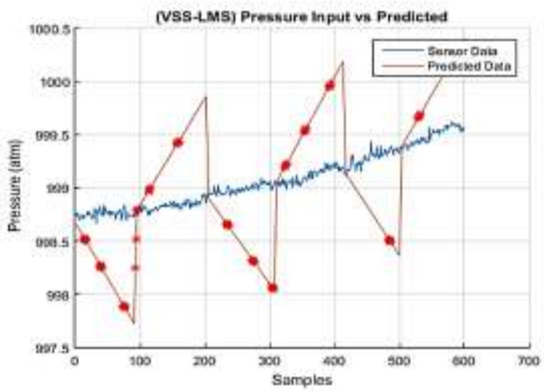


**Fig. 8c** Pressure Predictions using VSS-LMS

According to the simulation and hardware results shown in Fig. 8a, Fig. 8b and Fig. 8c, VSS-LMS was found to be converged after transmitting 91 samples that will take almost equal duration of 45.5mins that was of LMS algorithm for stable and meaningful predictions because the step size is not fixed throught the tranmission, it changes with predefine time periods. Table. 3 shows the data reduction and energy consevation figures for Dual prediction scheme with VSS-LMS algorithm. By applying DPS with VSS-LMS Algorithm on wheather forecasting system, upto 82% WSN node's energy is saved.

**Table.3** Data Reduction and Energy Consevation using VSS-LMS for Weather Predictions

| | Tranmission Energy | Saved Energy | Converging Sample | Initial Converge Time |
|---|---|---|---|---|
| Temperature | 13.33% | 86.67 % | 57 | 91 samples *0.5 mins per sample =45.5 mins |
| Humidity | 3.54% | 96.46 % | 83 | |
| Air Pressure | 4.15% | 95.85 % | 91 | |
| Overall | 18.38% | 81.62 % | 91 | |

*D. Convergence Period:*

Above tables shows that the Convergence Period of predicted values of all three environmental parameters by WSN based weather froecasting system using LMS and VSS-LMS was found to be the same but it is different with N-LMS Algorithm. Figure 9a, figure 9b and figure9c and Table. 4 shows the comparison between the convergence period of both LMS/VSS-LMS and N-LMS algorithms to explain the stability of system using both algorithms.

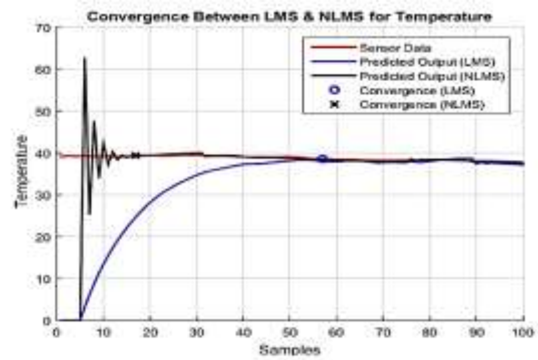


**Fig. 9a** Convergence gap for Temperature

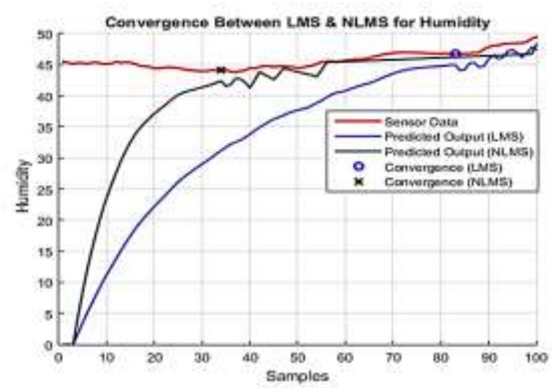


**Fig. 9b** Convergence gap for Humidity

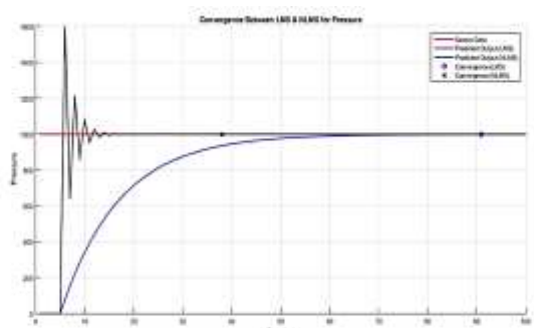

**Fig. 9c** Convergence gap for Pressure

**Table. 4** Stability Comparison among LMS/VSS-LMS and N-LMS

| | Converge after nth samples | Converge after nth samples |
|---|---|---|
| Temperature | 57 | 17 |
| Humidity | 83 | 34 |
| Air Pressure | 91 | 22 |
| **Total** | 91 samples x 0.5 mins = **45.5 mins** | 38 samples x 0.5 mins = **19 mins** |

## V. CONCLUSION

This paper proposed a dual prediction scheme for the data reduction and controlled transmission in wireless sensor networks used for wheather forecasting system. The technique is implemented to forecast the temperature, humidity and pressure values using adaptive filter with three algorithms (LMS, N-LMS and VSS-LMS). Overall System is designed to work with all three algorithms to achieve maximum stability and data reduction for energy conservation of WSN node. The proposed technique provides upto 68% energy saving with LMS algorithm, 78% energy saving with N-LMS Algorithm and upto 82% with VSS-LMS algorithm. The overall system performance with all three algorithm is concluded through the figure. 10.

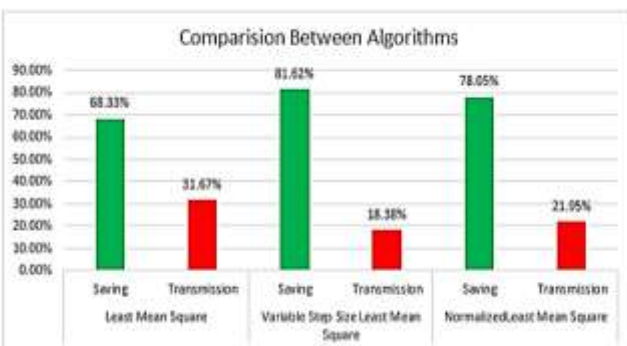


**Figure.10** Comparison of Algorithms for Overall system Performance

The above figure represents the analytics of the overall system peerformance. Above figure explains that the VSS-LMS can be the best option for data reduction but its convergence period is 45.5 mins (table. 2) that is much greater than NLMS whose convergence period is only 19 mins (table.3). So NLMS provides balanced output for both in data reduction as well as for stability of the wheather forecasting system, as the savings are greater than LMS and its convergence is also very quick.

## VI. FUTURE WORK

The designed system utilizes a low cost radio transceiver which can be replace with much efficient Xbee transceiver module. Also the Xbee transceiver module adds an additional network layer to the system as The IEEE 802.15.4 standard (ZigBee). Although the network has a capacity of only 6 nodes transmitters, the Xbee transceiver module will enable it to create more complex network topologies. Along with the hardware changes, diverse predictive algorithms like Kalman Filter or dual kalman filter can also be used that can provide more stability with greater data savings.

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