Error Minimization and Energy Conservation by predicting data in Wireless Body Sensor Networks using Artificial Neural Network and Analysis of Error

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Abstract— **Wireless Body area Sensor Network (WBSN) is a recent concept that can dramatically benefit healthcare applications through advances in wireless technology. Physiological and biokinetic parameters that require continuous monitoring are sensed by small and lightweight body sensors that transmit the values of these parameters over wireless links for monitoring at the other end. The sensors employed in WBSNs are limited in resources, with battery power being at the premium. Conservation of energy used by the network has a direct bearing on the longevity of the network. Therefore, there is no need to send data periodically and need to transmit selectively when needed. This paper presents a dual framework for predicting when to transfer physiological parameters in such a network that could save energy consumption while maintaining error to minimum level. The framework utilizes an artificial neural network (ANN) for prediction that not only saves energy, but also does it with lesser error than popular prediction algorithms. A comparison of performance of five data prediction algorithms in predicting physiological data is presented. The amount of network energy saved as a result of prediction is also considered in detail.**

Index Terms—**Artificial Neural Network; Body Sensor Network; Energy Conservation; Error Analysis; Prediction.**

I. Introduction

THE CONCEPT of sensors is not new to human beings because of the five sense organs present in the human body. Monitoring of any physical quantity or parameter involves the use of sensors for providing qualitative and quantitative information which can also be used for control of such parameters. Complex mechanical systems or industrial units typically involve thousands of such sensors networked together in keeping track of the parameter values for information and control. Wireless Sensor Networks (WSNs) [1] are an extension of conventional sensor networks that involve multiple sensor nodes in monitoring an environment for parameters of interest, reporting all involved data communication and commands on wireless links.

Wireless Body area Sensor Networks (WBSNs) are special implementation of WSNs in the field of healthcare and fitness that focus on sensing and communication of physiological and biokinetic parameters, providing more precise values at better rates of sampling than conventional patient data systems [2]. They can support biofeedback and interactivity for modern human-centric diagnostic and fitness applications. WBSNs use wireless transceivers for transmission of data over wired or wireless links (illustrated in Figure 1), from body-mounted or implanted

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transducers to a coordinating and aggregating sink station (CSS) [3], usually worn externally by the human subject. The CSS can then forward the data to a central repository known as Base Station (BS) for analysis, archiving and decision on corrective action by the physician, if needed as well as to various receiving stations. Further, personal medical data networks can be combined to scale up to a much bigger network for telemetry purposes [4]. The transducers involved in WBSNs are very small in size, with limited computing power, have limited memory and run on small batteries that cannot generate a lot of power. The limited energy budget in WBSNs necessitates energy conservation to prolong the network lifetime. There can be several approaches to energy conservation, with the prominent ones being duty cycling, mobility and data driven approaches [5]. In this paper we focus on the last one, combining two approaches into the proposed framework.

There can be two basic approaches for routing of WSN data: proactive and reactive [6]. In the proactive scheme, data is transmitted by the CSS at a predetermined fixed rate and received by the BS, while in reactive approach data is sent if and only if it crosses some predefined threshold values [7]. Both these schemes have limitations. Too much energy is consumed in the proactive approach due to periodic transmission of data. In a reactive scheme, data is transmitted only when thresholds are crossed and very little information is received. In our proposed data driven approach, we suggest transmission of all needed data while minimizing data transmission by time series prediction from available samples

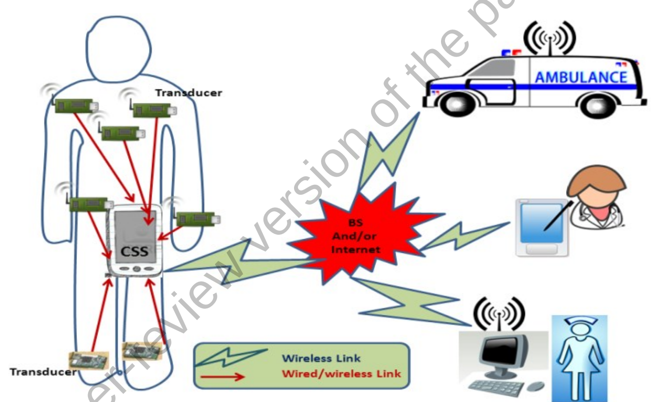

Figure 1: Communication from Body transducers via the Coordinating Sink Station (CSS) to the Base Station (BS)

at the CSS. This eliminates some of the data samples from the transmission sequence. The samples discarded would be those that can be reconstructed at the BS end using prediction, without an appreciable loss in reconstructing the information from predicted data. Any kind of data processing on the CSS would consume some power, but it would help in cutting down the data rate over the network and therefore the power required for transmission. Reducing the data rate has the potential to dramatically reduce the power consumption by the microprocessor and transceiver circuits, because data transmission consumes much more energy than data processing. This would help the WBSN save on a considerable amount of battery power. The resource constraints also advocate that the prediction algorithms involved should not be computationally too expensive. We have used an Artificial Neural Network (ANN) in modeling, fitting and predicting of physiological data for energy conservation in CSS and BS of a WBSN. It may be noted that ANN-based data prediction for WBSN has not been used in the literature.

II. WHY SELECTIVE TRANSMISSION?

Availability of accurate WBSN data can make the physicians better informed and prepared about patients' health condition which help predict faster and early diagnosis of problems, thereby has a potential of saving lives with reduced data set. Based on the selected transmitted values received, if a significant fraction of body parameter data can be predicted correctly at intermediate time, then data need not be continuously transmitted. Thus the prediction makes redundant part of data not transmitted. This would also help in conservation of battery power that would otherwise be used for supplying energy required for the transmission of redundant data.

A. Overview of Existing Schemes for Data Prediction

Chu *et al.* [8] suggested an approach based on stochastic characterization of the data involves mapping of the data into a random process as a probability density function. The result, when combined with the actual sample values can yield predicted values. Temporal and spatial correlations can be modeled as Markov processes combined with disjoint-clique [9]. Any aberrations or noise from prediction can be filtered out. The model can be replicated at the sensor as well as the sink end. Jain *et al.* propose a Kalman filter based model can also be used for data prediction [10]. The approach involves stream filtering using a Kalman filter. Tulone and Madden [11] propose that better prediction can be achieved if a trend component that keeps changing and evolving with prediction run time can be included in the forecast model. Such stochastic characterization based prediction techniques prove to be computationally demanding for the resources at the sensor end. None of these approaches have been applied to the WBSNs data or evaluated for performance and QoS satisfaction.

Le Borgne *et al.* [12] propose a dual prediction scheme for conventional sensor networks. The authors have suggested the use of a framework involving predictions at the sensor end as well as at the CSS end. It works on the basis that the sensor keeps comparing the sensed and predicted values if the values are within error bounds, and transmits a sample only if the difference exceeds the error bound. In the absence of a sample received, the CSS assumes the values predicted at its end to work fine and uses them to create the time series. These predictions end up in saving energy by reducing the number of transmission packets from the sensors to the CSS.

Another extension for the dual prediction in BSNs by Xia *et al.* [13] suggests the use of Proportional Integral Derivative (PID), a proven control algorithm at the sensor and the CSS ends for time series prediction. The authors propose the scheme for use in a WBSN.

All the approaches listed above except for the approach by Xia *et al.* [13] have been used for conventional wireless sensor networks. Smaller size of sensors and more constraints on computing and power resources combined with QoS limitations make WBSNs remarkably different from their WSN counterparts. Hence the approaches except for the approach by Xia *et al.* [13] could be questionable choices for WBSNs. Although the approach has been tried on WBSNs, we compared the performance of the algorithms used in the paper and found out that the prediction has some limitations. We suggest an improvised dual sensing framework that utilizes ANNs for prediction at the CSS end for predictions.

B. Accurate Value Prediction using ANN

ANNs are based on the human neuronal system that handles the job of communication and control in the human body. Human neurons form a communication network in which the information transmission is actuated by nerve impulses. ANNs have two basic architectures based on data flow; feed forward in which the flow of signals is in the forward direction only, and feedback which employs a component of the output being fed back so as to be combined with the input signal. The feedback or back propagation algorithms have proved to work very well with applications involving time series prediction.

Predicting future values or events is possible within reasonable limits of accuracy using mathematical calculations on the data from past and current states. Predictive models can be built using approximations involving mathematical calculations that could be computationally intensive. There are applications in the field of weather, stocks and shares, geological events, and in the field of healthcare where prediction could be useful.

Neural Networks employed for prediction at CSS/BS are able to use just the historical data for auto-learning. After the learning is complete, the network can discover hidden non-linear dependencies, despite the presence of noise in the historical data used to train the network. This approach is apt for value or trend prediction applications involving the time series because of the availability of discrete samples of historical data.

The difference between predicting a value or the full trend lies in our interest of value of the variable of interest versus the non-quantified behavior of the value going up or down, along with getting parameters like the change in moving average. The greater the density and length of the historical time series, the closer is the prediction of future values. Additional information like derivation, other related variables and intervention indicators containing details about the period into which the prediction is required, can improve the accuracy of prediction.

III. USED BASIC APPROACH

Control algorithms like PID and their variants have a long history of being used in industrial applications. They utilize the real-time values of physical parameters for generating a predictive control signal using simple mathematical calculations. ANNs are a relatively new technique that can be used for time series prediction.

A. PID Control Paradigm

The PID control paradigm has a long and successful history of use in regulation and dynamic control applications. The main advantage of PID control is that detailed or a-priori knowledge about the system is not required, but the controller can still be tuned very easily to meet the control requirements.

If $\varphi(t)$ and $u(t)$ define the input and output for a control system, the PID control equation can be laid down as

$$u(t) = -\propto \varphi(t) - \beta \frac{d\varphi(t)}{dt} - \gamma \int_0^t \varphi(s)ds \qquad (1)$$

and equivalently as

$$u(t) = K_P e + K_I \int_0^t e(\tau)d\tau + K_D \frac{de}{dt} \qquad (2)$$

The constant α in the first term marks the proportional feedback gain. The second term adds damping to the performance of the control by using a time derivative, while the third term offsets the nonzero steady state error and helps provide a low gain. The standard PID transfer function can be represented in terms of K_P, K_I and K_D, the constants of proportionality for the proportional, integral and derivative components in the original control equation in frequency domain. Chosen correctly, the constants can yield a stable control performance for the application.

Specific choices of values for the three constants result in the *Linear*, *Moving Average*, or the *PAST* algorithms. All of these algorithms can be used for time-series prediction, with differences in their performance in prediction.

B. Feedback or Back propagation in ANN

Physiological parameters with a trend involving nonlinear variations of a diverse nature can be modeled aptly by using ANNs. An ANN tries to function like the human brain, and models the nonlinear relationship between the input(s) and the output(s) using basic blocks called neurons that are interconnected. A typical model may involve multiple layers of neurons with weighted interconnections between them.

At each neuron, the weighted inputs, external as well as the ones from other neurons are summed together with an external bias, and a nonlinear activation function then acts on this sum to generate the neuronal output. The nonlinearity associated with each neuron remains fixed. Training the network on the complex relationship between input and output involves an iterative estimation of weights by nonlinear optimization using known input and output values.

A training data set is created from a part of input samples, while selecting different sets of samples for validation check and testing on training. In the gradient descent algorithm, the ANN takes in the training data set and the data set of desired outputs and trains itself while minimizing the cumulative mean square error between the calculated and desired outputs by adjusting the weights on interconnections for all neurons [14]. The neuronal nonlinearity can be made differentiable by the use of nonlinear sigmoid function giving us the feedback or backpropagation algorithm, which is a variant of the gradient descent.

The sigmoid function chosen for the training is suitable for continuously varying physiological parameters due to its differentiable nonlinearity.

$$f(x) = \begin{cases} = \frac{1-e^{-x}}{1+e^{-x}}, & for -1 \le f(x) \le 1, \\ = \frac{1}{1+e^{-x}}, & for\ 0 \le f(x) \le 1 \end{cases} \tag{3}$$

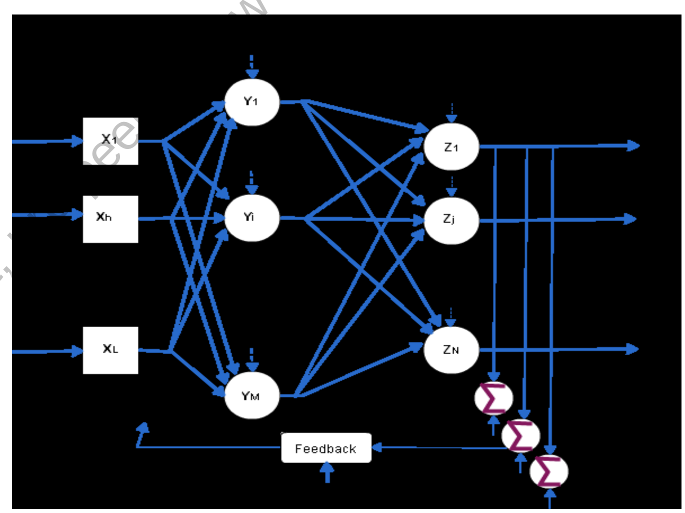

Figure 2: A three-layer ANN model with back propagation

In the three layer ANN shown in Figure 2, variables marked '*y*' denote the desired outputs, the ones marked '*O*' denote the neuron output, '*W*' and '*V*' denote the weights on interconnections, and the ones marked '*F*' denote the threshold values for the layers. Initially, random values between 0 and 1 are assigned to the weights and thresholds levels. On the input data O_{Xh}, the outputs are computed as

$O_{Yi} = f_{sigmoid}\,(\sum_{h=1}^{L} V_{hi}\, O_{Xh} + F_{Yi})$ (4)

$O_{zj} = f_{sigmoid}\,\left(\sum_{i=1}^{M} W_{ij}\, O_{Yi} + F_{Zj}\right)$ (5)

Next, new data is read for the desired outputs and the difference values in weights are calculated.

$\Delta W_{ij} = \alpha\, O_{Yi}\, D_{Zj}$ $\quad 0 < \alpha < 1$ (5)

using, $D_{Zj} = (y_j - O_{Zj})\, O_{Zj}(1 - O_{Zj})$

$\Delta V_{hi} = \beta\, O_{Xh}\, D_{Yi}$ $\quad 0 < \alpha < 1$ (6)

using, $D_{Yi} = \left(\sum_{j=1}^{N} W_{ij}\, D_{Zj}\right)\, O_{Yi}(1 - O_{Yi})$

Thresholds are then adapted as follows.

$\Delta F_{Zj} = \alpha\, D_{Zj}$,

$\Delta F_{Yi} = \beta\, D_{Yi}$,

The iterations are then repeated from the step involving the assignment of weights.

IV. PROPOSED FRAMEWORK

The framework involves post sense processing at the sensor end for predicting the time series using the actual sensed samples. Using the actual sensed values and the predicted values, the sensor performs a comparison between the values and creates two sets of samples, one for transmission and the other for exclusion from transmission using one of the simpler algorithms to reduce the complexity in calculations. The samples that are within allowable error limits are placed in the discarded set. The algorithm at the sensor end is as follows:

1. Read in the set of sensed value samples S_1
2. Using a subset of values from S_1, compute P_1, the set of predicted values
3. If $(S_1 \sim P_1) \leq |\varepsilon|$ (allowable error), generate D_1, the set of discarded values
4. If $(S_1 \sim P_1) \leq$ slope in initial set of samples, add such samples to D_1
5. Transmit $(S_1 - D_1)$

For the sake of simplicity, samples dropped in transmission and the retransmission criteria are omitted in the framework temporarily, so as to have a simple evaluation on savings resulting from the model. The same can be taken up as future work. The algorithm at the coordinating sink station end is as follows:

1. Collect the received data as samples
2. Use the samples to train a neural network for prediction based on non-linear regression
3. Collect the predicted values in a set PR_1
4. Forward the set for analog interpretation and further processing

The use of a neural network for prediction allows for a better accuracy in prediction at the received end, as will be obvious from the results.

V. PERFORMANCE EVALUATION

Although simple, the scheme in [13] for WBSNs using *PID* generates more errors. Some errors could mean that vital details go missing in the predicted time series. A prediction technique with a lesser error would be preferred in healthcare applications. This is where the ANN technique involving non-linear regression (NLR) suggested by us scores over the approach in [13]. The CSS is designed with more resources than the sensor units in terms of computing power, available memory, storage, and energy source. While the sensor units could use a simpler algorithm like *PID* or *Moving Average* for deciding on the samples to be excluded from transmission, the CSS can perform a more accurate prediction using NLR-ANN technique. We prove that the error in case of NLR-ANN is less than in the case of *PID* based prediction.

We have used some data pertaining to some physiological parameters from the *Physionet* database repository [15] for our prediction algorithms. Specifically, the dataset MGH010 for ECG Lead-II, and MGH003 for arterial pressure (ART), central venous pressure CVP) and pulmonary artery pressure (PAP) from the dataset that has been used comprises of 3600 samples of each type of data.

We performed *Linear*, *PID*, *Moving Average* and *PAST* algorithms for generating approximations on the data. For testing these prediction algorithms, we used a more rapidly varying data for putting stringent conditions on the algorithms.

We then trained an ANN based on NLR in prediction for ART, CVP, PAP, ECG and compared the prediction performance with that of PID. The PID algorithm was chosen because of relatively better, more robust and proven performance in the field of control.

MATLAB r2012 was used for training the neural network to predict the time series using non-linear regression involving three different back propagation algorithms. Of these, the Levenberg Marquardt [16] back propagation proved to be a faster algorithm as compared to Bayesian regulation back propagation and Scaled conjugate back propagation for a single training run or for a looped run to find the average performance. Hence, it was the back propagation algorithm of our choice for the various neural networks trained for different physiological data. We generated regression line plots for ECG data to find out the fit of the training algorithm.

Running a smaller subset of data trained the network very fast, in lesser number of iterations with almost the same values for the mean square error or even lesser during some runs. We then compared the errors in prediction for the four physiological parameters for PID and NLR and quantified them. In addition to the saving in the number of samples from the various data compression and fusion schemes, additional techniques involving sample elimination can be implemented in cascade with such schemes on the sensed data, even from transducers. We suggest a linear elimination algorithm on the data that lets the sensor decide whether or not to transmit a particular data sample. The receiving CSS side would reconstruct this data using NLR-ANN prediction. As shown, the predicted values would still be in the acceptable error range without any significant loss in information. Thus the saving would be in the form of samples that were not required to be transmitted.

The linear elimination algorithm is implemented in the sensor and the CSS. The sensor, after sensing compares the slope across successive samples, and if the slope is the same, decides not to transmit successive samples. The CSS can predict the missing samples with a single calculation, having advance knowledge about the interpolation from the algorithm. The algorithm was successfully implemented for the data samples from the four physiological parameters and the savings were recorded.

VI. SIMULATION RESULTS

A. Comparison of control algorithms

We tried to predict a rapidly varying random time series with 128 values varying over time in the range of 1750 and 2100. We used the *PID* algorithm for control and different special cases of *PID* algorithm like *Linear*, *PAST* and *Moving Average* for the prediction The performance of *PID*, *Moving Average* and *PAST* algorithms was better than the *Linear* algorithm, which is the simplest of all, and also more prone to error as can be seen from the graph. The values shown in the graph are for the small subset for data in which *Moving Average* looks to be better than *PID* and *PAST*. However, history of decades of industrial control has proved that *PID* is the algorithm that provides the best compromise for a stable control. It is also generic and simple.

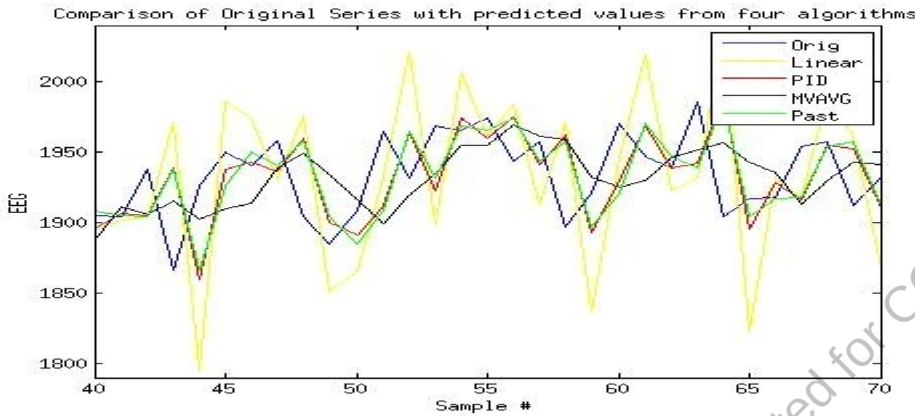

Figure 3: Performance of prediction for the Linear, PID, Moving Average

From Figure 3, it can be seen that the prediction performance of linear algorithm is weaker than the other three, which provide an approximation with better accuracy, and are comparable in overall performance.

TABLE I
COMPARISON OF MSE FOR THE PREDICTION ALGORITHMS

Algorithm	Mean Square Error
LINEAR	81.046
PID	48.572
Moving Average	40.539
PAST	47.673

MSE = Mean Square Error, PID = Proportional, Integral and Derivative

A comparison of mean square error values between the desired values and the values predicted by the *Linear*, *PID, Moving Average* and *PAST* algorithms has been laid out in Table-I. For this small subset of test data, the three latter algorithms seem to perform rather well, and much better than the *Linear* algorithm.

Figure 4 shows the performance of the NLR-ANN predictor as compared to PID based predictor for the four parameters. The parameters behave differently from each other, and have different and characteristic wave-shapes and rates of change. Both the algorithms seem to provide a very good prediction, but the real difference between them that would be clear from the error plots is not very evident in these graphs.

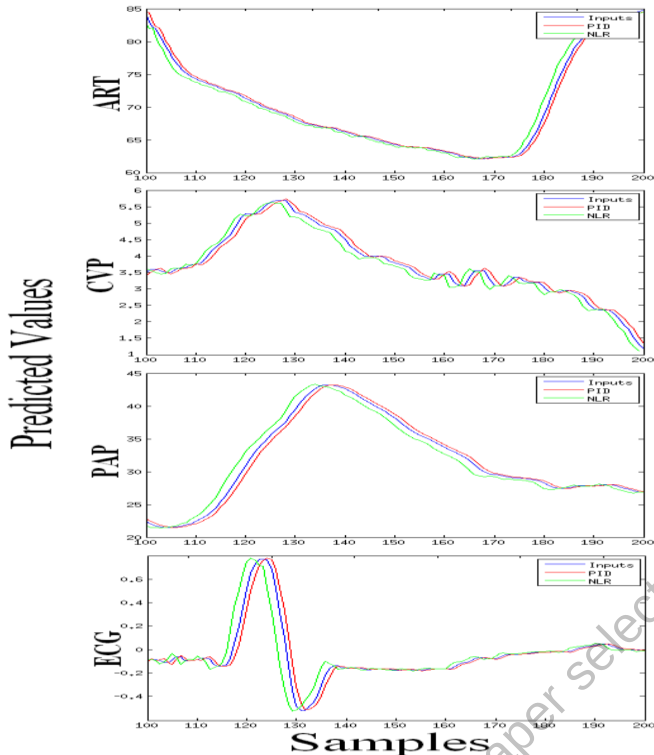

Figure 4: Performance of prediction for Arterial Pressure, Central Venous Pressure, Pulmonary Artery Pressure, and ECG Lead-II using PID and NLR-Neural Network

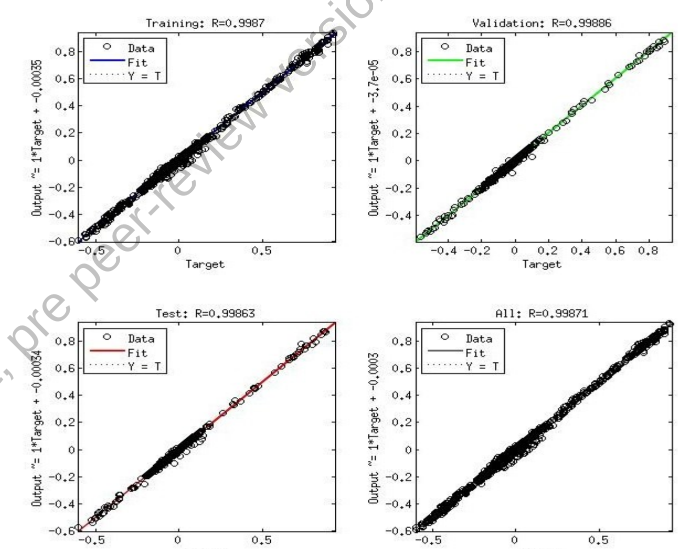

Figure 5: Regression plot for training data, validation data, test data, and the full data set

Regression line plots for training the ANN based on *NLR* algorithm were generated for the data from ECG Lead –II. Figure 5 shows the regression plots. The ECG Lead II waveform was chosen for the check on regression because of its unique wave shape that poses stringent conditions for data prediction. The network trains well and the fit is good for the training, validation as well as test data.

The behavior of error in prediction for NLR-ANN and PID prediction techniques is in Figure 6. Figure 6 shows the observed variations in error for the two techniques for Central Venous Pressure and Pulmonary Artery Pressure. Plots for the other two parameters are similar in nature.

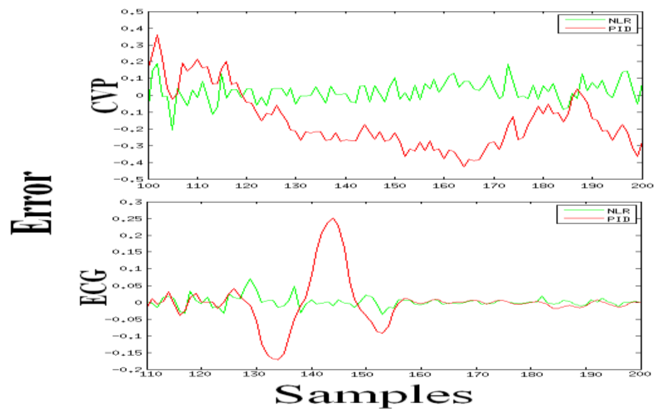

Figure 6: Plot of errors in prediction for the Arterial Pressure, Central Venous Pressure,

TABLE II
COMPARISON OF MSE FOR PID AND NLR-ANN ALGORITHMS

Algorithm	ART	CVP	PAP	ECG-LII
PID	0.5002	0.4672	0.1661	0.0494
NLR-ANN	0.1692	0.0938	0.0124	0.0011

ART-Arterial Pressure, CVP-Central Venous Pressure, PAP-Pulmonary Artery Pressure, ECG-LII-Electro Cardiogram Lead II.

Pulmonary Artery Pressure and ECG Lead-II for PID and NLR

From the error plots in Figure 6, it is evident that NLR-ANN offers better error performance as compared to the PID predictor. We also provide a quantitative basis for supporting this assertion in Table-II.

Table II shows a comparison of mean square errors for PID and NLR for the four physiological parameters over 3600 samples. For the NLR, the error values were calculated over 100 training iterations and the average error reported from those iterations was considered.

Table II and the error plots for the four parameters under test prove the clear supremacy of NLR-ANN technique over the PID technique. This is despite the fact that the nature and shape of the waveforms is very different for the parameters due to different frequency components and ranges of values.

TABLE III
SAVINGS FROM LINEAR ELIMINATION ALGORITHM IN NUMBER OF SAMPLES AND PERCENTAGE

Parameter	ART	CVP	PAP	ECG-LII
No filtering	329	310	281	143
% saving	9.139	8.611	7.806	3.972
With filtering	383	504	383	228
% saving	10.639	14.0	10.639	6.333

ART-Arterial Pressure, CVP-Central Venous Pressure, PAP-Pulmonary Artery Pressure, ECG-LII-Electro Cardiogram Lead II.

The linear elimination algorithm proposed by us was run on the samples from the four physiological parameters with the results shown in Table III. Table III shows the savings recorded in raw sample values in the row labeled as '*No* *filtering*' and the percentage saving in samples obtained. Sample data was then filtered for noise and the algorithm was run on the filtered set. The rows marked '*With filtering*' and the next row containing the percentage saving show the savings observed with filtered data.

VII. Conclusion

We have suggested a modified dual framework using NLR-ANN for prediction at the coordinating and aggregating sink station (CSS) end which provides for more accurate predictions as compared to other algorithms previously tested on WBSNs. We have also suggested a linear elimination algorithm for a reduction on the number of samples to be transmitted from the sensor end. The algorithm can be implemented in the framework on top of other techniques. The savings have been quantified in tabular form. The performance of our trained network for prediction of physiological parameters in a WBSN can also be seen from various graphs.

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