High Accuracy Sensor Fault Detection for Energy Management Applications

Vinay Joshi
Mahindra Susten PVT. LTD.
Mumbai, India
Email: vinayjoshi.iitb@gmail.com

Onkar Desai
Intel India PVT. LTD.
Banglore, India
Email: onkardesai30@gmail.com

Anupama Kowli
Department of Electrical Engineering
Indian Institute of Technology Bombay
Mumbai, India
Email: anu@ee.iitb.ac.in

***Abstract*—Wireless sensor networks (WSNs) have found many applications in building environment monitoring and energy management applications. However, WSN data is not completely reliable and hence its use in energy management has to be carefully considered. Experiments conducted on a WSN test bed monitoring a campus classroom highlight how sensor data is prone to errors, underlining the need to detect faulty measurements from the data. This paper describes the experiments showcasing faulty measurements as well as methods to detect these faulty measurements. A key contribution of this paper is highly accurate fault detection methods developed using two machine learning approaches: neural networks and support vector machine. Experimental results showcasing the successful application of the proposed methods for fault detection are discussed. The paper also provides insights on implementation of the proposed methods as well as its integration into an energy management platform.**

I. Introduction

Smart consumers are slated to form a key part of the supply-demand balance equation of future power grids. And sensors are expected to play a critical role in making consumers energy aware and grid responsive. Indeed, with variety of sensors available at affordable costs, they are finding many applications in the energy management domain. A comprehensive survey of how sensors are being used to predict occupancy and hence optimize energy consumption in residential and commercial buildings is available in [1]. Furthermore, as wireless technologies mature and become more economical, wireless sensor networks (WSNs) are expected to play a crucial role in future building energy management systems. It is touted that the information gleaned from the WSNs can be effectively used in improving energy efficiency, lowering electricity bills and enhancing demand responsiveness [2], [3].

Motivated by recent deployment of sensors for energy management applications, a large classroom at the Indian Institute of Technology Bombay (IITB) campus has been instrumented with a WSN to gather the required data regarding the consumer's environment. But processing sensor data without any filtering may lead to poor monitoring and control since WSN data is often prone to noise and error. This paper describes how statistical features of the sensor data can be leveraged to devise fault detection techniques. In particular, two methods based on neural networks (NN) and support vector machine (SVM) are proposed and their capabilities are demonstrated via their deployment on the IITB WSN test bed data.

Deployment of sensors in practical applications such as energy management necessitates use of reliable sensor data and thus underlines the need for good fault detection methods. A survey of outlier detection methods is provided in [4] while [5] contains a more general review of fault detection in WSN for different applications. The reader is referred to these surveys for more details on generic sensor fault detection methods. The following review only focuses on papers that have guided current work.

Feature extraction for NN-based fault detection is discussed extensively in [6] but the accuracy of the filtered data is not reliable for practical applications. Other approaches for sensor fault detection include modeling drift between estimation and measured values of sensor [7] and online model-based fault detection for heterogeneous sensors [8]. Principal component analysis (PCA) has been extensively applied for sensor fault detection as well; see for instance references [9], [10], and[11] where PCA has been used either by itself or in conjunction with expert-based multivariate decoupling or wavelet analysis for sensor fault detection. Wavelet decomposition has also been used for NN-based fault detection in [12]. Likewise, physical properties such as laws of thermodynamics may be exploited for fault diagnosis as shown in [13]. A clear drawback of many of these papers is the need for redundancy in sensors as well as requiring sufficiently large number of non-faulty sensors to provide an effective diagnosis. Proposed research leverages insights from these papers to devise NN and SVM-based fault detection methods. Generalizations of the proposed method to other similar technology sensors are also explored.

The main contribution of this paper are the two fault detection methods. These methods leverage the statistical features of recorded data from a single sensor to identify faulty measurements. Their deployment on the IITB WSN testbed demonstrates their ability to accurately classify faulty and non-faulty measurements. The techniques entail calculation of five statistical features based on previous few samples and are amenable to online implementation. The paper has four more sections: the test bed setup and sensor data analysis is discussed in section II while the fault detection methods are described in section III. The results from actual deployment on the testbed are presented in section IV followed by concluding remarks in the last section.

II. Sensor Data Analysis

This section provides a brief overview of the experimental setup at IITB campus. It also presents key insights from analysis of the sensor data which can be leveraged for sensor fault detection.

A. Test Bed Setup

The WSN test bed at IITB is configured to monitor a classroom environment using temperature, humidity and luminosity sensors while also tracking the energy consumption in the room. A 150-seater classroom located on the topmost floor of the lecture hall complex at IITB is selected for experiments since it presents a worse case scenario in terms of air conditioning load: least shade available and heat influx from the roof. The classroom is cooled using a variable refrigerant flow type air-conditioner consisting of an outdoor unit supplying cool air as well as 8 indoor units circulating the cooled air, as seen in Fig. 1. Other electrical loads that may impact the environment include tubelights, compact fluorescent lamps and fans. Finally, the occupancy in the class is another major factor influencing its environment, which can be tracked via the attendance records.

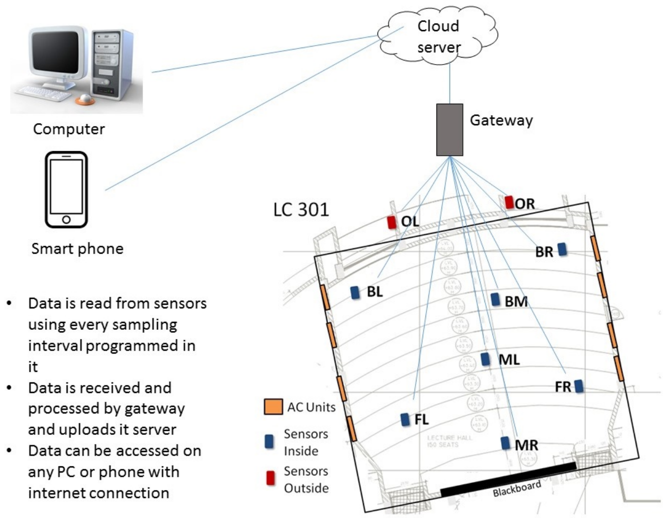

Fig. 1. The experimental WSN setup in the IITB classroom.

The WSN used for monitoring the classroom environment consists of battery-powered nine sensor nodes, each equipped with temperature, humidity and luminosity sensors. Two nodes are placed outside and the rest are strategically spread out across the classroom, shown in Fig.1. All nine sensor nodes communicate to a gateway in star topology. The gateway then communicates the sensor data to a server, wherein it is stored for further processing. Data can be accessed from the server via a personal computer as well as via an android application.

B. Correlated Sensor Readings

Since the spatial spread of the sensors is not large, the sensor readings exhibit high correlation. Sensors with high correlation may be grouped together to exploit the following benefits – data prediction, bad data detection and data correction. In what follows, these benefits are explained in more detail.

A study of the the temperature data from all the sensors emphasizes the high correlation within some sensor readings. Indeed, for such highly correlated data, linear relationships can be established between the sensor readings. For instance, regression analysis on temperature sensors of FL, FR, ML and MR nodes leads to the following relationship:

$$Z_{\mathsf{FR}} = 2.79 + 0.21 Z_{\mathsf{FL}} + 0.65 Z_{\mathsf{MR}} + 0.22 Z_{\mathsf{ML}} \qquad (1)$$

where Z_X is the temperature reading at node X. Such relationships can be leveraged to predict readings of one sensor from another in case of missing/faulty sensor data. Likewise, non-conformity to established sensor relationships may be viewed as indicative of faulty sensor readings.

Sensors having readings with correlations higher than 0.94 are considered to form one group. This value is chosen to limit the errors in data prediction among correlated sensors to under 5%. Groups that are formed are as follows,

- Group 1 : FR, FL, MR, ML
- Group 2 : BL, BR
- Group 3 : OL, OR

The specific relationships between readings from each group are obtained using linear regression similar to (1).

C. Fault Diagnostics

In addition to using correlation for bad data detection, historical data can be used to set up simple checks based on minimum and maximum expected readings which can also be incorporated for bad data detection. Likewise, the maximum rate of change in temperature and humidity observed across subsequent readings is bounded by slow environmental variations and maximum BTU capacity of AC. Since high frequency errors can occur due to inherent sensor noise, a suitable bound may be adopted to identify such erroneous data. Finally, knowledge regarding location of sensors also provides significant insights to guide error detection. For instance, sensors near the indoor AC outlets would be expected to have lower temperatures than those away from the outlets. Such spatial relationships can also be used to detect faulty measurements.

To summarize, a measurement is classified as faulty if it disobeys one of the following:

- Maximum and minimum bounds
- Maximum rate of change
- Spatial relation with other sensors
- Relationship established via regression analysis

The above logic is applied to actual sensor data to label measurements as faults or accurate data in order to generate data sets for training and validating the detection methods devised in the following section.

III. Sensor Fault Detection

While correlation can be leveraged for sensor fault detection, it is not always viable to adopt this approach, particularly when sensor data is being used for energy management application as is the case in this research. The reasons for this are many fold:

- Temperature and humidity patterns change over time so does correlation,
- Implementation requires redundancy in sensor nodes which may not be feasible due to budget concerns,
- Correlation-based methods may not work if more number of sensors in a correlated group are faulty, and,
- Rule-based algorithms will perform poorly when there are sudden climatic changes.

These drawbacks are result of using unprocessed data to form rules and the seasonal impacts on correlated sensors.

Statistics of the data provides richer information than just pure data alone. Statistical parameters vary with the data and depict patterns in the data that can be leveraged to devise reliable fault detection algorithms. In particular, statistics-based fault detection eliminates the dependency on correlation and the need for redundancy while effectively capturing underlying underlying parameters such as location of sensor node and climate changes. This section describes the algorithms adopted for statistics-based fault detection. The following subsections describes the type of faults seen in the test bed data, feature design for identifying these faults and methods used in the identification process.

A. Types of Faults

Faults occur in both time and amplitude domains [14], [15].This research primarily focuses on amplitude domain faults since time domain faults (missing/dropped measurements) are harder to characterize. Based on observations of the WSN data, the following types of faults are considered:

- Offset: Measurements differ from the true values by a constant or time-varying offset.
- Stuck-at-X: Measurements relay the same value for a long time interval.
- Outlier: Measured values abruptly transition towards a large value which is normally not seen by the system.
- Spike: As compared to an outliers, measurements experience a smoother transition to a high value – different from the true value.
- Random noise: Measured values are perturbed by high frequency fluctuations, leading seemingly volatile readings.

The following subsection discusses statistical features that may be employed to characterize the above amplitude domain faults commonly seen in the sensor data from the WSN test bed.

B. Feature Extraction

The nature of the faults expected within the data set plays a vital role in determining which statistical features to use for fault detection. Choosing non-redundant features is desirable to speed up the fault detection process. Since the focus of this research is on amplitude domain faults, the following statistical parameters based on a moving window of T samples are used for fault detection:

- Mean: It is calculated as the average of recent T measurements. If $z(t)$ is the t^{th} measurement, then the corresponding mean $\mu(t)$ is expressed as

$$\mu(t) = \frac{1}{T} * \sum_{\tau=0}^{T-1} z(t-\tau) \,. \tag{2}$$

  Mean helps in classifying an outlier and stuck-at-X faults, as in such instances mean value will be higher than usual.
- Standard deviation: At instance t, it is denoted by $\sigma(t)$ and calculated using the T recent measurements as

$$\sigma(t) = \frac{1}{T} * \sqrt{\sum_{\tau=0}^{T-1} \left(z(t-\tau) - \mu(t)\right)^2} \,. \tag{3}$$

  Standard deviation quantifies the spread of the measurements' distribution and, thus, quantifies the range of possible true measurements.
- Signal to noise ratio: At instant t, it is denoted by $\mathsf{SNR}(t)$ and calculated as the ratio of the corresponding average value and standard deviation:

$$\mathsf{SNR}(t) = \frac{\mu(t)}{\sigma(t)} \,. \tag{4}$$

  In case of faulty measurements, standard deviation is high and SNR value is low but during true measurements SNR is high as standard deviation is very low. Thus, it is a useful characteristic for classifying faults.
- Maximum deviation: It is the maximum deviation observed in the recent T measurements. It is denoted by $\mathsf{MD}(t)$ for the t^{th} measurement and calculated as

$$\mathsf{MD}(t) = \max\left\{|z(t-\tau) - \mu(t)| \; \tau = 0, 1, \ldots, T-1\right\} \tag{5}$$

  This feature will take a high value for small spikes/outliers which may otherwise go undetected.
- Velocity: It is instantaneous rate of change in sensor measurement. If Δt is the sampling period, then velocity $\nu(t)$ at instance t is

$$\nu(t) = \frac{z(t) - z(t-1)}{\Delta t} \tag{6}$$

  Velocity quantifies sudden changes in the measurements and is hence useful quickly classify high frequency fluctuations in the sensor data.
- Measurement value: Finally, the measurement value at each instance $z(t)$ is in itself a useful feature for fault detection.

PCA is performed on these six features to identify potential redundancy, if any. Figure 2 shows component values calculated on training data used in the results section. It is evident from the figure that no component has null value i.e. zero standard deviation and hence feature set has independent feature vectors. Thus, the six features described here may be deemed to be informative about the sensor data.

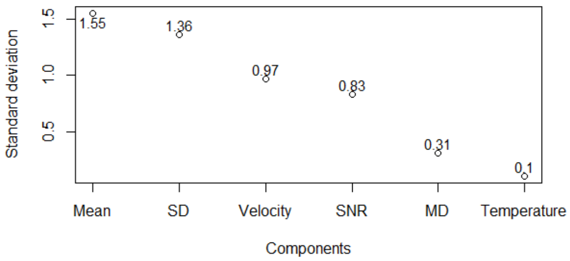

Fig. 2. PCA plot for feature set with window size $T = 5$

C. Fault Detection Methods

The key idea behind fault detection is to use the previously identified features to determine if measurement $z(t)$ at instance t is faulty or not. The six features (compactly represented by vector $X(t)$) calculated at instance t serve as input to the fault detection method while ts output is a categorical variable $y(t)$ identifying whether $z(t)$ is faulty or not. The mapping the feature set $X(t)$ to the response $y(t)$ is accomplished via deployment of NN and SVM.

Neural Network: The inspiration behind this method is the network of neurons: the idea is to use training data to train a representative network for fault detection. The network consists of interconnected cascade multiple layers of neurons. Interconnections between layers are assigned some values know as weights. During training, NN changes its weights so that most of the instances are classified correctly [16]. Here, a feed forward neural network (FFNN) is deployed where all weights are in the forward directions.

Support Vector Machine: SVM is an extension of support vector classifier which expands the feature space using special types of functions known as kernels. Unlike NN, SVM learns classifying plane and provides some margin or slackness along classifying plane. Objective of the SVM is to maximize margin along the classifying plane while minimizing error at the same time [16]; it thus guarantees global optimum for convergence on training data. Just as NN learns any non-linear hyperplane by adding more hidden layers and neurons, SVM learns non-linear hyperplanes using kernels – functions that quantify the similarity between two observations.

IV. Fault Detection in Test Bed Data

The temperature measurements from the WSN test bed are used to generate appropriate data sets for training and validating the proposed fault detection methods. This section summarizes the results. First, an overview of data set generation is provided followed by the use of NN and SVM for fault detection. A comparison of the two methods and their applicability to generic settings is also presented.

A. Data Set Generation

The fault detection are applied to two different data sets: an actual record of data which may contain errors as well as data set deemed to be error free, which is then injected with errors. The feature set is formed with observations from 79292 actual data samples with 70% data used for training and 30% data used for cross-validation. Each measurement in this set is *apriori* labeled as faulty or not by applying rules discussed in section II-C. For instance, faults observed in the raw FR sensor data are labeled as outliers, offset and random noise (RN), as shown in figures 3 and 4.

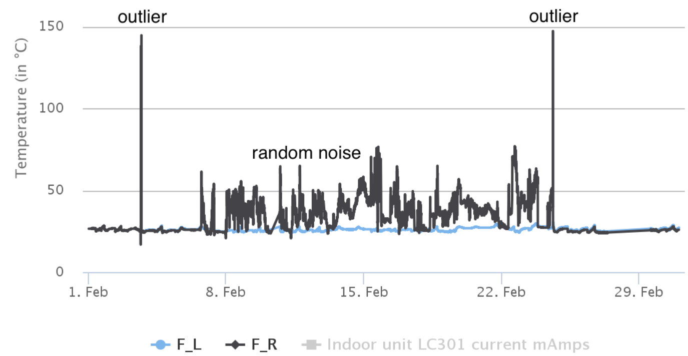

Fig. 3. Outlier and random noise observed in the data

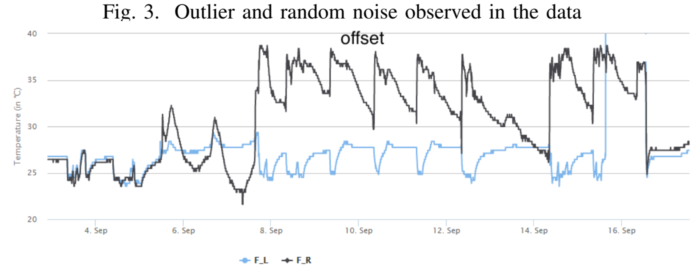

Fig. 4. Offset observed in the data

The methods trained and validated on the raw data set are tested on synthetic test data set wherein errors are injected by design. For the test data set generation, three different months are selected for which no fault was observed in the entire raw data using the established rules in section II.C. The measurement data from these months are injected with faults representative of the faults observed in the actual sensor data. For instance, the FR data indicates outliers of 150°C as well as high frequency noise and offset. Such faults were randomly injected in such a way as to maintain low bias in the test data set. Test data set consists of 23311 measurements, out of which 19519(83.73%) are true measurements (no faults) and 3792(16.27%) are fault injected measurements. The fault detection methods label these measurements as TRUE to indicate no fault and FALSE to indicate fault.

B. NN-based Fault Detection

The FFNN for fault detection is formed with 6 input layers corresponding to the feature set, 4 hidden layers with one extra bias unit and two output layers to classify measurements as TRUE or FALSE. This network was trained with backpropogation algorithm, with each neuron having sigmoid activation function and cross entropy function as an objective function. Separate dataset were used for training and testing a neural network as discussed previously.

Table I shows confusion matrices obtained from the performance of neural network on cross-validation dataset with time window size T of 3, 5 and 10 samples. With change in window size no significant change in performance of the

TABLE I
CONFUSION MATRIX FOR WINDOW SIZE $T = 3$, 5 AND 10 ON THE CROSS-VALIDATION DATASET USING FFNN

Window size	Actual label	Classified TRUE	Classified FALSE
3	TRUE	20926	46
	FALSE	461	2357
5	TRUE	20953	6
	FALSE	550	2280
10	TRUE	20890	16
	FALSE	508	2374

network was observed. This is clearly evident from table II which shows that the true positive rate and F1-score is quite high independent of the window size used for feature set calculation. It also indicates that the false positive rate is also quite consistent and one possible reason could be that model is not able to detect all types of faults equally.

TABLE II
ACCURACY FOR DIFFERENT TIME WINDOW SIZE USING FFNN

Window size	TP rate	FP rate	F1 score
3	0.998	0.164	0.988
5	1.000	0.194	0.987
10	0.999	0.176	0.988

TABLE III
CONFUSION MATRIX OF FFNN-BASED MULTICLASS CLASSIFICATION WITH T AS 3, 5 AND 10 SAMPLES ON CROSS-VALIDATION DATASET

Window size	Actual label	Classified TRUE	Offset	Outlier	RN
3	TRUE	20974	9	2	6
	Offset	309	606	0	27
	Outlier	0	1	728	4
	RN	155	120	3	836
5	TRUE	20992	0	2	4
	Offset	363	534	0	40
	Outlier	0	1	716	1
	RN	156	52	2	926
10	TRUE	20912	8	3	9
	Offset	329	613	0	38
	Outlier	1	0	749	3
	RN	136	70	3	914

A multi-class classification using NN was performed to check if the network is poorly classifying some types of faults. Table III shows confusion matrix of multiclass classification of the data. It is clear from these results that all the outliers are correctly classified with high accuracy but classification is not as good for offset and random noise classes. However, for the observed instances of inaccurate classification, the difference between the actual and faulty measurements is low. Indeed, if the accuracy is tested taking into account an acceptable tolerance margin of 0.5°C (corresponding to the AC control configuration), the classification scheme exhibits high accuracy.

The results obtained on the test data set are represented via the confusion matrix in table IV. Exactly 22900 (98.23%) instances are correctly classified while 411 (1.76%) instances were misclassified. Fig. 5 shows the data plot, with red points signifying misclassified points. Note that 263 misclassified points are close to true data by 0.5°C, thus only 148 misclassified data points lie outside of tolerance margin, bringing the error rate of the model to 0.634%.

TABLE IV
CONFUSION MATRIX OF TEST DATA WITH TIME WINDOW SIZE 5 OF FR SENSOR ON TEST DATASET USING FFNN

Actual	Classified TRUE	Classified FALSE
TRUE	19456	63
FALSE	348	3444

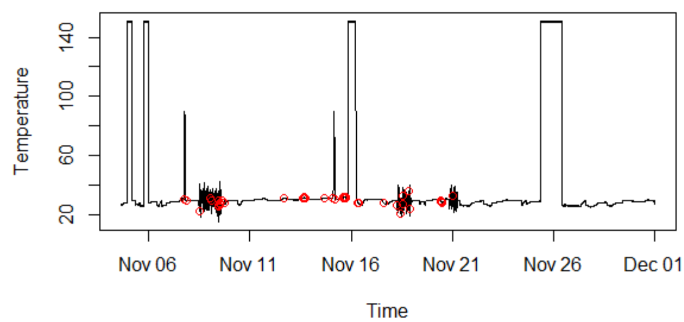

Fig. 5. Fault detection on test data for Nov 2015 using FFNN

C. SVM-based Fault Detection

SVM-based fault detection method is trained with three different kernels – linear function, radial bias function (RBF) and polynomial. The same dataset used for training the FFNN is also used here. Table V lists the accuracy of the three kernel functions. It is evident that RBF performs better than other two kernel function in terms of overall misclassification. Therefore SVM with RBF kernel is used for further performance evaluation. Analysis of the distribution of misclassified points by SVM using RBF kernel indicates that 93% points lie within the tolerance margin, thus bringing the unacceptable error down to 7%. The error rate is even lower 0.2% in the test data.

TABLE V
ACCURACY OF SVM WITH THREE DIFFERENT TYPES OF KERNEL

SVM kernel	TP rate	FP rate	F1 score
Linear	1.00	0.42	0.96
RBF	0.97	0.01	0.98
Degree 3 poly	1.00	0.64	0.76

D. Generalization of model

FFNN and SVM trained on FR data are also tested with data of two different sensor nodes: FL sensor which is highly correlated with FR and BL which is poorly correlated with FR. Table VI shows confusion matrix of testing with FL data. It shows that only 109(0.6% of the total dataset(18261)) points are misclassified. In this case, error rate is better than FR test data itself. Moreover, BL dataset was tested and table VII shows confusion matrix of the same. Accuracy is quite lower than FR in this case, as BL exhibits some patterns that are different than FR.

SVM was also tested with data of two different sensor nodes. Table VI shows confusion matrix of FL data, even though FL is highly correlated with FR sensor SVM has very low accuracy on this dataset. Exactly 2692(15% of the total dataset) points were misclassified by SVM for FL data. Table VII shows confusion matrix for BL data and performance almost same as FFNN on BL data. Exactly 1326(6.3% of the total dataset) points were misclassified by SVM for BL data.

TABLE VI
CONFUSION MATRIX WITH TIME WINDOW SIZE 5 OF FL SENSOR DATA USING FFNN AND SVM

Method	Actual label	Classified	
		TRUE	FALSE
FFNN	TRUE	17466	7
	FALSE	102	686
SVM RBF	TRUE	14883	2590
	FALSE	102	686

TABLE VII
CONFUSION MATRIX WITH TIME WINDOW SIZE 5 OF BL SENSOR DATA USING FFNN AND SVM

Method	Label label	Classified	
		TRUE	FALSE
FFNN	Actual TRUE	17761	918
	Actual FALSE	328	2198
SVM RBF	Actual TRUE	17427	1252
	Actual FALSE	74	2452

E. Comparison of methods

Previous sections discuss the results obtained with two different modeling techniques namely FFNN and SVM. Table VIII shows comparison between two methods on the same training and test dataset. SVM has better error rate compared with FFNN for readings which are within the tolerance margin. However, the overall error rate is lower for FFNN than SVM. Also, the training time of the SVM is about 30 times more than FFNN. The choice between FFNN and SVM for fault detection is governed by speed versus accuracy.

TABLE VIII
COMPARISON BETWEEN PERFORMANCE OF FFNN AND SVM ON THE SAME TRAIN AND TEST DATASET

Parameters	FFNN	SVM (RBF Kernel)
Error rate	1.8%	6.7%
Error rate with difference $\geq 0.5°C$	0.7%	0.2%
Time to train model	98 sec	3000 sec

For the purpose of current work, NN is well suited as computation time is not very significant considering a 5 minute sampling rate for each sensor. But for SVM ,training time and computation time are large and also it does not generalize well to other sensors. Also considering performance on other sensor's data, FFNN has performed better on both FL and BL data, where as SVM has quite lower accuracy on correlated sensor which is a surprise and needs more analysis to find out exact reason.

V. CONCLUSION

This paper presents high accuracy fault detection methods for WSN deployed in energy management applications. The methods leverage statistics of single sensor to accurately classify the readings as faulty or true measurements using NN and SVM. The methods are tested on actual data obtained from a WSN test bed at IITB campus to demonstrate the capabilities of the approaches. Both methods exhibit high accuracy, especially when a tolerance margin of $0.5°C$ is adopted. The proposed fault detection methods show promise and future work entails data correction mechanisms for measurements identified as faulty.

REFERENCES

[1] T. A. Nguyen and M. Aiello, "Energy intelligent buildings based on user activity: A survey," *Energy and buildings*, vol. 56, pp. 244–257, 2013.

[2] M. Kintner-Meyer, "Opportunities of wireless sensors and controls for building operation," *Energy engineering*, vol. 102, no. 5, pp. 27–48, 2005.

[3] E. Arens, C. Federspiel, D. Wang, and C. Huizenga, "How ambient intelligence will improve habitability and energy efficiency in buildings," in *Ambient intelligence*. Springer, 2005, pp. 63–80.

[4] Y. Zhang, N. Meratnia, and P. Havinga, "Outlier detection techniques for wireless sensor networks: A survey," *IEEE Communications Surveys Tutorials*, vol. 12, no. 2, pp. 159–170, Second 2010.

[5] L. Paradis and Q. Han, "A survey of fault management in wireless sensor networks," *Journal of Network and Systems Management*, vol. 15, no. 2, pp. 171–190, 2007. [Online]. Available: http://dx.doi.org/10.1007/s10922-007-9062-0

[6] G. Jager, S. Zug, T. Brade, A. Dietrich, C. Steup, C. Moewes, and A.-M. Cretu, "Assessing neural networks for sensor fault detection," in *Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), 2014 IEEE International Conference on*. IEEE, 2014, pp. 70–75.

[7] X. Xu, J. W. Hines, and R. E. Uhrig, "Sensor validation and fault detection using neural networks," in *Proc. Maintenance and Reliability Conference (MARCON 99)*, 1999, pp. 10–12.

[8] F. Koushanfar, M. Potkonjak, and A. Sangiovanni-Vincentelli, "On-line fault detection of sensor measurements," in *Proceedings of IEEE Sensors 2003 (IEEE Cat. No.03CH37498)*, vol. 2, Oct 2003, pp. 974–979 Vol.2.

[9] S. Wang and J. Cui, "Sensor-fault detection, diagnosis and estimation for centrifugal chiller systems using principal-component analysis method," *Applied Energy*, vol. 82, no. 3, pp. 197–213, 2005.

[10] F. Xiao, S. Wang, X. Xu, and G. Ge, "An isolation enhanced pca method with expert-based multivariate decoupling for sensor fdd in air-conditioning systems," *Applied Thermal Engineering*, vol. 29, no. 4, pp. 712–722, 2009.

[11] X. Xu, F. Xiao, and S. Wang, "Enhanced chiller sensor fault detection, diagnosis and estimation using wavelet analysis and principal component analysis methods," *Applied Thermal Engineering*, vol. 28, no. 2, pp. 226–237, 2008.

[12] Z. Du, X. Jin, and Y. Yang, "Fault diagnosis for temperature, flow rate and pressure sensors in vav systems using wavelet neural network," *Applied energy*, vol. 86, no. 9, pp. 1624–1631, 2009.

[13] S. Wang and J.-B. Wang, "Robust sensor fault diagnosis and validation in hvac systems," *Transactions of the Institute of Measurement and Control*, vol. 24, no. 3, pp. 231–262, 2002.

[14] S. Zug, A. Dietrich, and J. Kaiser, "Fault-handling in networked sensor systems," *Fault Diagnosis in Robotic and Industrial Systems*, 2012.

[15] K. Ni, N. Ramanathan, M. N. H. Chehade, L. Balzano, S. Nair, S. Zahedi, E. Kohler, G. Pottie, M. Hansen, and M. Srivastava, "Sensor network data fault types," *ACM Trans. Sen. Netw.*, vol. 5, no. 3, pp. 25:1–25:29, Jun. 2009. [Online]. Available: http://doi.acm.org/10.1145/1525856.1525863

[16] J. Friedman, T. Hastie, and R. Tibshirani, *The elements of statistical learning*. Springer series in statistics Springer, Berlin, 2001, vol. 1.