# Smart Sensing System for Built Environment

Abhishek Singh, Anuj Kumar, Heisik Kim and Anshul Gaur

***Abstract*— In this paper, a fully functional smart sensing system for measurement of air quality gases and environmental parameter is presented. The system has been developed in compliance with IEEE1451.2 standard. The sensor array is implemented using electrochemical sensors. The smart transducer interface module (STIM) is implemented using the PIC18F4550 microcontroller. Network Capable Application Processor (NCAP) implemented in LabVIEW 9.0 is based on the IEEE 1451.1 standard. The NCAP is connected to the STIM through a USB 2.0 Transducer Independent Interface. The level of indoor environment parameters and information regarding the STIM can be seen on the graphical user interface (GUI) of NCAP and also be presented the adaptive estimation for missing environmental parameters for short duration. The Radial Basis Function based Artificial Neural Network technique has been discussed and used this technique the estimation of the missing environmental parameters. This work assumes that data are missing completely at random. This implies that we expect the missing values or input vector to be deducible in some complex manner from the remaining data. Two cases of missing parameters have been considered, in first case one parameter is missing, and in second case two parameters are missing. The SSS is low cost, energy efficient, and portable.**

***Index Terms*—IEEE 1451, network capable application processor, transducer independent interface, artificial neural network, missing data.**

## I. Introduction

Energy and efficiency have now become an important concern for sustained growth and overall development [1]. For a developing country like India, the situation is further grieved because major part of energy, to drive the economy, is imported [2]. Today it is widely accepted that human activities are responsible for high level of pollution and climate change. United Nation Environment Program (UNEP) report states that buildings are using the lion's share (40%) of the available global energy and are responsible for one third of global greenhouse gas emissions, both in developed and developing countries [3].

Manuscript received

Abhishek Singh, at School of Engineering & Technology Radha Govind Group of Institutions, Meerut (UP). (e-mail: abhishek1028@gmail.com)

Anuj Kumar, Post Doctoral Fellow, at Electrical and Computers Engineering Department, University of Seoul, South Korea. (e-mail: anujkumariitd@gmail.com).

Hiesik Kim, Professor, at Electrical & computer engineering Department, Universty of Seoul, South Korea. (Tel: +82-2-2210-2427, e-mail: drhskim@uos.ac.kr)

Anshul Gaur, at School of Engineering & Technology Radha Govind Group of Institutions, Meerut (UP).

The main source of greenhouse gas emissions from buildings and exponential increases the industry. Major greenhouse pollutant include $CO_2$, CO, $SO_X$, $NO_X$, suspended particulate matter (SPM), Lead aerosol, volatile organic compounds and other toxicants [4].

Several different studies reveal that when human beings come in contact these chemicals/pollutants, they have adverse effect on human health. These chemicals are responsible for diseases like lung-cancer, pneumonia, asthma, chronic bronchitis, coronary artery disease and chronic pulmonary diseases [5,6].

In view of ever increasing pollution sources with toxic chemicals, these systems should have the facilities to detect and quantify the sources of pollution rapidly. This paper is organized as follows. Section II presents selection of sensor suitable for built environment. Developments of smart sensing system are described in section III, IV, V and VI. Analysis of missing environmental parameters in case of one or more than one sensor malfunction is discussed in Section VII. Section VIII presents the basic of ANN. Section IX describes the methodology of the prediction of missing data and Section X and XI conclude the results and discussion of the paper.

## II. Sensors

A gas sensor is a transducer that detects gas molecules and produces an electrical signal with a magnitude proportional to the concentration of the gas [7]. There are five commonly used technologies for monitoring of gas and these are; electrochemical, solid state, infrared, catalytic bead, and photo ionization [8,9]. More details of these sensor including their usage, life time, advantages and disadvantages are given elsewhere [9,10]. The electrochemical gas sensors are capable of detecting different gases with high accuracy. These sensors have many advantageous aspects such as minimum power consumptions as compared to catalytic bead and semiconductor sensors, cost effectiveness and miniature size. These sensors are being extensively used in various applications like: automotive, consumer, commercial, industrial and indoor environment monitoring [10,11].

## III. Developed Smart Sensing System

The developed air quality and environmental parameter monitoring system (SSS) is a complete real time monitoring and data recording system. It automatically measures and records the air quality and environmental parameter. The developed SSS is based on IEEE 1451 standards [12,13]. The developed SSS can measure and analyze the concentration of major air pollutant gases such as $O_2$, CO, $CO_2$, $SO_2$, and $NO_2$. The STIM is linked to a Network

Capable Application Processor (NCAP) PC through transducer independent interface (TII). The detailed block diagram of developed SS system is shown in Figure 1.

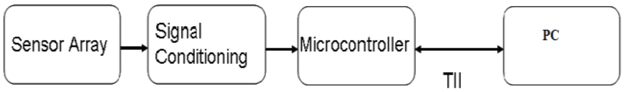


Fig. 1. Block diagram of SSS.

## IV. IMPLEMENTATION OF SENSOR ARRAY AND STIM

### A. *Sensor Array*

The selected sensor has several advantages such as low power consumption, low cost, high accuracy, and capable of detecting different gases. The detailed explanation of the selected electrochemical sensors including their usage, advantages and disadvantages are given in [8-11].

The CO-CF sensor module is made of a control circuit, a current measuring circuit, and an amplification circuit. In this module the amplifier OP90 is used for the controlling and measuring circuits, where as, other amplifier OP07 is used for the amplification circuit. The operating voltage range of the developed module is from ±7.0V to ±9.0V and it is being operated at fixed voltage of ±9.0V. The range and sensitivity of the sensor is given in [7]. The load resistance, $R_{Load}$, is fixed at 33.0Ω for the measuring circuit and the output of the measuring circuit is applied to the input of a non-inverting amplifier with a fixed gain of 48. The response time and power consumption of the developed sensor module were observed to be 60 sec and 9.0936mW, respectively. The gas sensing range of the developed module is set from 0.5ppm to 20ppm. A schematic diagram and photograph of the developed module are shown in Figure 2 and Figure 3, respectively. The relationship of the sensor output voltage and the concentration of gas in ppm can be expressed by the equation 1. The CO sensor module accuracy after calibration is ±2% (Standard Instrument - TSI Inc.: 8552 and 8554 Q –Track Plus)

$$C_{CO}(PPM) = 4.1 \times V_{OUT-CO} \qquad (1)$$

Where: $C_{CO}$ – Concentration of CO gas in ppm, $V_{OUT\text{-}CO}$ – Output voltage of CO-CF sensor module in volts.

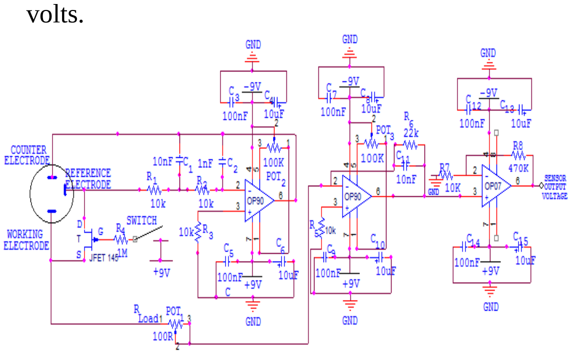

Fig. 2. CO sensor signal conditioning circuit

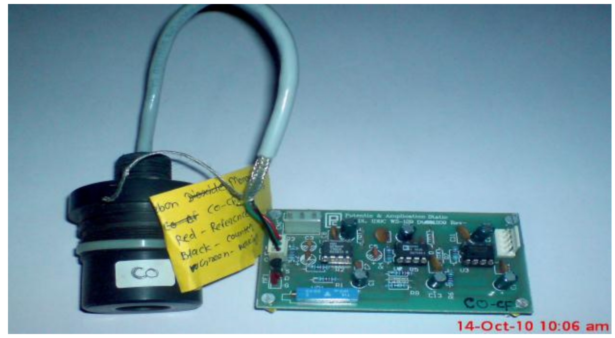


Fig. 3 Photograph of CO-CF Sensor Module.

### B. *Smart transducer interface module (STIM)*

The development of a smart transducer interface module with electrochemical gas sensors has to be designed according to IEEE 1451.2 standard. The STIM must be capable of handling the actuator interface, supporting TEDS, communicating with NCAP and supporting TII interface. A microcontroller is selected to support all above functions. PIC 18F4550 has been chosen to develop the STIM [14]. The developed STIM includes all the above mentioned facilities.

#### 1) *MMC Interface Module*

The PIC 18F4550 and MMC interface module has been developed. The MMC is a flash memory storage device designed to provide high capacity, non-volatile, and rewritable storage in a small size. The capacity of the MMC can be increased at any time for further use. Presently, the available capacities of these memories lie in the range of 128MB to 32GB.

The MMC can be interfaced to microcontroller using two different protocols: the SPI (Serial Peripheral Interface) protocol and SD (serial digital) protocol. As the SPI protocol is being widely used, it is preferred over SD protocol in this module. The standard MMC has nine pins and these pins have different function depending on the interface protocol. The function of each pin in both the SD and SPI modes of operation are given in [14,15].

## V. IMPLEMENTATION OF THE TRANSDUCER INDEPENDENT INTERFACE (TII)

A parallel port interface between STIM and NCAP based on the IEEE 1451.2 standard has been developed and discussed in detail using SPI data transfer protocols [7] and [16, 17].

In this investigation, the USB 2.0 based TII (transducer independent interface) between the STIM and NCAP PC has been used. The TII and data transfer protocols used are based on the IEEE 1394 standard. One side of TII is connected with the STIM and the other side is interfaced with NCAP PC (USB port). The USB is a four wire interface with two data lines and two power lines. Here the STIM receives power from USB, hence no external power supply is required and the data transfer rate supported by USB 2.0 may be up to 480Mb/sec.

## VI. General Protocols

The data transfer functions have been implemented using the protocols described in the IEEE 1451.2 [12]. The active control of the developed system is handled by the NCAP. A data transport frame begins by the NCAP sending an address to the STIM. The complete address specifies whether the data should be written or to be read in the MMC from the STIM and which channel with corresponding function is involved. Then the data is transferred from the NCAP to the STIM via D+ and D-. Thus the whole system is controlled through the NCAP and provides the power to the STIM. The NCAP Program.

The developed NCAP is in accordance with IEEE 1451.1 standard [13]. Its logical componets are included in two groups: support and application. The components of support are; the transducer interface, the network interface, and the operating system. The transducer interface block encapsulates the details of the transducer hardware implementation with a programming model when the NCAP is connected to a STIM. The network interface block encapsulates the details of the different networks protocols implementations behind a set of communication methods. Whereas the operating system provides an interface with applications. The use of NCAP includes; a PC with USB connection as the hardware component and a software component fully developed in LabVIEW 9.0 [18-20].

The NCAP program has two main sub programs: controlling of the STIM and providing the Graphical User Interface (GUI). The STIM controlling program excutes data transport and interrupt request functions. In addition, it also supports the TII through the USB 2.0. The GUI displays; the STIM information, the output of the sensor module in digital and graphical waveforms and the status of the MMC. The real time data are saved on the basis of set value of sample/sec. Hence NCAP GUI can be used for the samples in the range of 1 s to 100 s. Moreover, it also provides the facility to add the user interaction to trigger the STIM and send fuctional address to the required channel. The front panel of air quality monitoring system handels function, input and outputs, while the flow chart performs the work of NCAP.

All coding in LabVIEW is done as given in the block diagram from Fig. 4. In block diagram the outer ractangular structure represents a while loop and inner ractangular structure is represented by the conditional structure and controlling structure of the VI. The controlling structure which is accessible from the structure palette is shown in Figure 4.

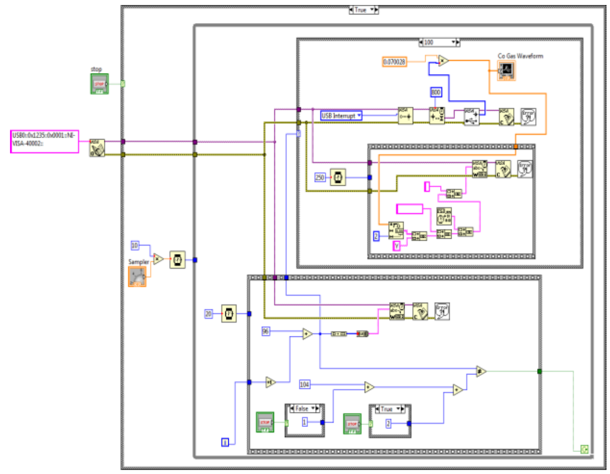

Fig. 4. Block diagram of CO module.

## VII. Analysis of Missing Environmental Parametr in Case One or More Than One Sensor Malfunction

Real time processing applications are highly dependent on data acquisition and therefore quite often suffer from the problem of missing input variables. Databases such as those which store measurement or environmental data may be subjected to missing value or variable either in data acquisition or data storage process [21]. There are several reasons, why the data may be missing. They may be missing because one or more than one sensor may have temporarily malfunctioned, or the data may not have been entered correctly or a break in the data transmission line [22]. Missing data has difficulty in the analysis and decision making processes which depend on these data; no matter how accurate and efficient are the methods of estimation. To overcome this issue, various techniques have been proposed to find the missing data, can be reported as [23-31]. However, some statistical methods, like mean substitution, and hot deck imputation have a high likelihood of producing biased estimates or make assumptions about the data that may not be true, affecting the quality of decisions made based on the data. To predict the exact values of the missing variables, a proper estimation method needs to be selected.

In this paper, the RBF based ANN technique has been proposed as a solution to the problem of missing data for short duration. Radial basis function (exact fit) approach has been used for ANN training and test. Further the radial basis neural networks can be designed directly by fitting special response inputs where they will do the most good. The applicability of the Graphical User Interface (GUI) of Neural Network tool box under MATLAB environment has been explored.

## VIII. Artificial Neural Network Techniques

### A. *Basics of Artificial Neural Networks (ANN) and Radial Basis Function (RBF)*

An ANN is a computational model of the brain. The $\text{ANN}_\text{S}$ assume that computation is distributed over several simple units called neurons, which are interconnected and operate in parallel, thus known as parallel distributed processing systems or connectionist systems. Implicit knowledge is built into the ANN by training it. The ANN captures the domain knowledge from the examples. ANN can handle continuous as well as discrete data and has good generalization capability. Several types of ANN structures and training algorithms have been proposed in [32, 33]. The transfer function for a radial basis neuron is:

$$radbas(n) = e^{n^2} \quad (2)$$

Here *n* is the net input to the *radbas* transfer function and it is defined as the vector distance between its weight vector and the input vector, multiplied by the bias. This *radbas* function calculates a layer's output from its net input.

### B. Radial Basis Function (RBF) Based ANN

In radial basis function (RBF) based ANN; the learning is equivalent to finding a surface in a multi dimensional space that provides a best fit to the training data, with the criterion for best fit being measured in some statistical sense. Radial basis networks may require more neurons than standard feed-forward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available. The basic form of RBF architecture involves entirely three different layers. The input layers is made up of source nodes while the second layer is hidden layer of high enough dimension which serves a different purpose from that in a multilayer perceptron. Finally the output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input layer to hidden is nonlinear whereas the transformation from the hidden unit to the output layer is linear [33-36].

### C. MATLAB Based Neural Network Toolbox Graphical User Interface

Neural network toolbox provides tools for designing, implementing, visualizing, and simulating neural networks. Neural networks are invaluable for applications where formal analysis would be difficult or impossible, such as pattern recognition, and nonlinear system identification and control. Neural network toolbox software provides comprehensive support for many proven network paradigms, as well as graphical user interface that enable to design and manage given networks. The modular, open, and extensible design of the toolbox simplifies the creation of customized functions and networks.

The graphical user interface is designed to be simple and user friendly, but we will go through a simple example to get started.

The GUI allows creating networks, entering data into the GUI, initialize, train, and simulating networks, exporting the training results from the GUI to the command line workspace, import data from the command line workspace to the GUI, for the opening of the Network/Data Manager Window, the command is 'nntool'.

## IX. Methodology of Prediction of Missing Environmental Parameter for Short Duration

The selections of the method are dependent on the nature of the missing data and the accuracy required.

### A. The Nature of Missing Data

If there are data sets with variables $X = \{X_1, X_2, \ldots, X_N\}$, where $X_1, \ldots, X_N$ are some input variables and if $X_1$ or $X_2$ or $X_N$ or $X_1X_2$ or $X_1X_2, \ldots, {}_N$ are missing input variables. The nature of the missing data can be characterized in three categories as follows [37-39]:

#### 1) Missing Completely at Random (MCAR)

There are several reasons why the data may be missing. They may be missing because one or more than one sensor malfunctioned, the data were not entered correctly, a break in data transmission line, etc. Here the data are missing completely at random (MCAR). When we say that data are missing completely at random, we mean that the probability that an observation ($X_{1or\ldots\ldots,\ or\ N}$) is missing is unrelated to the value of any other variables.

#### 2) Missing at Random (MAR)

This occurs if the missing value for the input vector depends on other variables in the dataset, such that the pattern in which the data becomes missing is traceable. That is the probability of the missing data is dependent only on any input vector, the existing values in the database and not on any missing data.

#### 3) Missing not at Random (MNAR)

This occurs when the missing value for the input vector depends on the other missing values, such that the existing data in the database can not be used to approximate the missing values. This is also known as the non-ignorable case. The probability that $X_{1\ or\ldots\ or\ N}$ is missing is dependent on the missing data.

This work assumes that data are missing completely at random (MCAR). This implies that we expect the missing values or input vector to be deducible in some complex manner from the remaining data.

Initially the real time data of seven parameters for 30 days is collected and the collected data are applied to the above mentioned methods.

### B. RBF based ANN Architecture for Missing One Parameter

The inputs and outputs of ANN, structure of the its network using appropriate data should be done with utmost care for effective incipient missing parameter of the smart sensing system. The inputs are real time measuring environmental parameters by the EM system and there is one output of the missing parameter. For simulation, a case of a real time measured six parameters and one missing parameter is taken up by the EM system. The instantaneous values are used in the training and testing/validation process. A total of 1,16,387 data sets are used in the training. Therefore, six input neurons and one output neurons in the proposed scheme. The architecture of the network is shown in Figure 5.

*1) Simulation Results/Performance of Proposed RBF ANN*

The network is trained using the radial basis function (exact fit) ANN under MATLAB Neural Network tool box (GUI). The spread constant is taken as 1.0 in the present work. The trained network is tested with data sets consisting of trained data of 15 data sets (24 hours averaging). The tested results are shown in Table I. These test data sets show the expected output. It is clear from the Table 1 that the ANN has successfully identified the missing parameter. The output of the ANN for a particular missing parameter is exactly the same as expected.

### *C. RBF based ANN Architecture for Missing Two Parameters*

Here again the inputs and outputs of ANN, structure of its network using appropriate data should be done with utmost care for effective incipient missing parameter of the SS system. The inputs are real time measuring environmental parameters by the SS system and there are two outputs of the missing parameters. For simulation, a case of a real time measured five parameters with two missing parameters are taken up by the SS system. The instantaneous values are used in the training and testing/validation process. A total of 1,16,387 data sets are used in the training. Therefore, there are five input neurons and two output neurons in the proposed scheme. The architecture of the network is shown in Figure 6.

*1) Simulation Results/Performance of Proposed RBF ANN*

The network is trained using the radial basis function (exact fit) ANN under MATLAB Neural Network tool box. The spread constant is taken as 1.0 in the present work. The trained network is tested with data sets consisting of trained data of 15 data sets (24 hours averaging). The tested results are shown in Table II. These test data sets show the expected output. It is clear from the Table II that the ANN has successfully identified the missing parameter. The output of the ANN for a particular two missing parameter are exactly the same as expected.

## X. Results

The main aim of this paper is to develop a smart sensing system which is proficient in the measuring common indoor air pollutant concentrations by a sensor array of electrochemical sensors. The system is based on the IEEE 1451 standards. Having developed the electrochemical sensor array system, the standard transducer interface module (STIM), the transducer independent interface (TII), and the network capable application processor (NCAP) program have also been successfully developed. These STIM, TII, and NCAP modules were developed using the guidelines provided by the IEEE 1451.2, IEEE 1451.7, and IEEE 1451.1 standards.

The total power consumption of the developed STIM module is 28.467mW.

The sensors were recalibrated through the 'field calibration' by comparing the results of the developed SS system with the available standard instruments from known manufactures. This was achieved to verify the accuracy of the developed system. CO_CF Sensor module accuracy represents are ±2% after calibration. The current indoor air pollutant levels can be directly read from the NCAP Graphical User Interface. Online data is saved on a memory card (MMC) to be used for further processing.

A set of real time field measurements of the indoor gases, namely, CO, $CO_2$, $O_2$, and $SO_2$ sensor were recorded in a normal laboratory environment. Table III shows the minimum, maximum levels and one hour mean of the indoor air quality with thermal parameter data in-situ.

In the $1^{st}$ part of this paper an effort has been made to describe the best estimation techniques for the missing data of completely random nature. The technique has been proposed as the solution to estimate these missing data. This technique is based on radial basis function neural network. This technique is successfully demonstrated in previous sections to predict the indoor environmental parameters.

Table I and Table II show the results of implemented scheme for missing one parameter and missing two parameters.

We found, the RBFNN simulated error varies from 0.249E (-3) % - 0.768E (-3) % for missing one parameter and 0.969E (-3) % – 0.35E (-2) % for missing two parameters.

Further analysis of the models proves that the result obtained by $RBFNN_S$ model is more accurate and suitable for estimating the missing parameters for short duration.

Table III
Indoor Air Quality with Thermal Parameter Measurement Data In-Situ

| **Indoor air Quality with Thermal parameter** | **Minimum Level** | **Maximum Level** | **Exposure based on an hourly mean** |
|---|---|---|---|
| CO | 7.7ppm | 9.02ppm | 8.60125ppm |
| $CO_2$ | 411ppm | 434ppm | 428.68ppm |
| $SO_2$-BF | 0.07ppm | 0.15ppm | 0.11ppm |
| $NO_2$ | 0.01ppm | 0.03ppm | 0.02125ppm |
| $O_2$ | 19.68% | 20.57% | 20.12% |
| $SO_2$-$D_4$ | 0.07ppm | 0.15ppm | 0.11ppm |
| Temperature | 26ºC | 28.5ºC | 27.3ºC |
| Humidity | 56% | 67% | 58% |

## XI. Conclusions

The indoor smart sensing system has been successfully developed in compliance with the IEEE 1451standards with the main functional blocks: the STIM, the TII, and the NCAP. Therefore, the aim of the IEEE 1451 standard to provide an industry standard interface to efficiently connect transducer to microcontrollers and to connect microcontrollers to network is achieved.

The STIM driver (which is part of the NCAP Model) uses the network communication capabilities of the LabVIEW 9.0. The ten “smart” transducers have plug and play capability: the STIM can be moved from one NCAP to another. The developed STIM module is low power consumption in the range of 28.467mW.

The electrochemical sensors can be successfully used to real time monitoring target gas concentration and environmental parameters. The usage of these sensors adds several advantages to a system such as; low power consumption, low cost, fast response, ability to produce online measurement, etc. The calibration of the sensor with the appropriate accuracy is beneficial for the energy efficiency in the building automation.

This paper has been discuses RBF based ANN technique for the solution of the problem related to missing data for short duration.

Radial basis function (exact fit) approach has been used for ANN training and testing. Further the radial basis neural networks can be designed directly by fitting special response inputs where they carry out the most good. The applicability of the GUI of Neural Network tool box under MATLAB environment has been explored. The technique as described here is successfully used in estimating the missing parameters in both the cases with fairly good accuracy.

Findings also showed that the RBFNN based ANN seem to perform better in cases where the missing data is completely random.

## REFERENCES


[1] UNEP, "Sustainable Buildings and Climate Initiative (SBCI)," Tech. rep., United Nations Environmental Programme report, 2009.

[2] AWO, "Asia and World Outlook," Tech. rep., Institute of Energy Economics, Japan, Tokyo, 2007.

[3] IEO, "International Energy Outlook," Tech. rep., Energy Information Administration, Washington, DC, 2009.

[4] ASHRAE, "Indoor Environment Monitoring," ASHRAE Hand Book, ch. 9, pp.9.1-9.20, 2001, Chapter.

[5] C. K. Chau, W. K. Hui, and M. S. Tse, "Evaluation of health benefits for improving indoor air quality in work place," *Environment International*, vol. 33, no. 2, pp. 186 – 198, 2007.

[6] W. S. Cain, J. M. Samet, and M. J. Hodgson, "The quest for negligible health risks from indoor air," *ASHRAE Journal*, vol. 37, no.7, pp. 38, 1995.

[7] A. Kumar, I. P. Singh, and S. K. Sud, "Energy efficient and low cost indoor environment monitoring system based on IEEE 1451 standards," *IEEE Sensors J.*, vol. 11, no. 10, pp. 2598 – 2610, October 2011.

[8] D. D. Lee and D. S. Lee, "Environment gas sensors*," IEEE Sensors J.*, vol. 1, no. 3, pp. 214-215, Oct. 2001. [15] F. Sarry and M. Lumbreras, "Gas discrimination in air-conditioned system," *IEEE Trans. on Instrumentation and Measurement*, vol. 49, no. 4, pp. 809-812, 2000.

[9] U. S. EPA, "Electrochemical sensors for environment monitoring: a review of recent technology," U. S. Environment Protection Agency, Mar. 2005. [Online]. Available: www.epa.gov.

[10] IST, Chapter 2- "Electrochemical Sensors," International Sensor Technology, CA, pp. 27-35. [online]. Available: http://www.intlsensor.com/

[11] J. W. Gardner, P. K. Guha, F. Udrea, and J. A. Covington, "CMOS interfacing for integrated gas sensors: A Review," *IEEE Sensors J.*, vol. 10, no.12, pp. 1833-1848, Dec. 2010.

[12] *IEEE Standard for a Smart Transducer Interface for Sensors and Actuators - Transducer to Microprocessor Communication Protocols and Transducer Electronic Data Sheet (TEDS) Formats*, IEEE standard 1451.2-1997, IEEE, The institutes of Electrical and Electronics Engineers, Inc., NY, 1997.

[13] *IEEE Standard for a Smart Transducer Interface for Sensors and Actuators—Network Capable Application Processor (NCAP) Information Model*, IEEE standard 1451.1-1999, IEEE, The institutes of Electrical and Electronics Engineers, Inc., NY, 1999.

[14] *Microchip Devices Data Sheet*, *The PIC18F4550 Microcontroller*, Microchip Technology Inc., Arizona, USA, 2009.

[15] D. Ibrahim, *Advanced PIC Microcontroller Projects in C*, I$^{ST}$ ed., Elsevier ltd., USA, Ch.-8, pp. 409-464, 2008.

[16] H.M.G. Ramos, J. M. D. Pereria, V. Viegas, O. Postolache, and P. M. B. S. Girao, "A virtual instrument to test smart transducer interface modules (STIM$_S$)," *IEEE Trans. on Instrumentation and Measurement*, vol. 53, no. 4, pp. 1232-1239, 2004.

[17] S. R. Rossi, A. A. Carvalho, A. C. R. Silva, E. A. Batista, C Kitano, T. A. S. Filho, and T. A. Prado, "Open and standardized resources for smart transducer networking," *IEEE Tran. on Instrumentation and Measurements*, vol. 58, no. 10, pp. 3754-3761, oct. 2009.

[18] *NIC LabVIEW Manual*, National Instruments Corporate, Austin, USA, Aug. 2007.

[19] NI Plug & Play Sensors Program, IEE Computing and Control Engineering, February/March 2005. [Online]. Available: http://digital.ni.com/worldwide/portugal.nsf/webproduct.

[20] Y.S. Chan, A. Tantram, S. Desmond, and B. Hobbs, *US Patent: 41 32 616*, 1996.

[21] V. Tremp, R. Neuneier, S. Ahmad, "Efficients methods of dealing with missing data in supervisedlearning, Advances in Neural Information Processing Systems," vol.7, MIT Press, Cambridge MA, 1995.

[22] J. L. Schafer, J. W. Graham, "Missing data: our view of the state of the art," *Psychological Methods*, vol. 7, no. 2, pp. 147-177, 2002.

[23] F. V. Nelwamondo, S. Mohamed, and T. Marwala, "Missing data: a comparision of neural network and expectation maximization techniques," *Current Science*, vol. 93, no. 11, pp. 1514 - 1521, 10 December 2007.

[24] P. K. Sharpe and R. J. Solly, "Dealing with missing values in neural network based diagnostic systems," *Neural Computing and Applications*, vol. 3, pp. 73-77, 1995.

[25] B. M. Boshkoska and M. Stankovski, "Prediction of missing data for Ozone concentration using support vector machine and radial basis neural networks," *Informatica*, vol. 31, pp. 425-430, 2007.

[26] M. Kolehmainen, H. Martikainen, and J. Ruuskanen, "Neural networks and periodic components used in air quality forecasting," *Atmospheric Environment*, vol. 35, pp. 815-825, 2001.

[27] M. Kolehmainen, H. Martikainen, T. Hiltunen, and J. Ruuskanen, "Forecasting air quality parameters using hybrid neural network modeling," *Environmental Monitoring and Assessment*, vol. 65, pp. 277-286, 2000.

[28] G. Calori, M. Clemente, R. D. Maria, S. Finardi, F. Lollobrigida, and G. Tinarelli, "Air quality integrated modeling in turn urban area," *Environment Modelling & Software*, vol. 21, pp. 468-476, 2006.

[29] C. M. Ennett, M. Frize, and C. R. Walker, "Influence of missing values on artificial neural network performance," *Proceeding of Medinfo 2001*, London, UK, Sep. 2-5, 2001 pp. 449-453.

[30] A. Pelliccioni and T. Tirabassi, "Air dispersion model and neural network: a new perspective for integrated models in the simulation of complex situations," *Environment Modelling & Software*, vol. 21, pp. 539-546, 2006.

[31] E. A. Basurko, G. I. Berastegi, and I. Madariaga, "Regression and multilayer perceptron-based models to forecast hourly $O_3$ and $NO_2$ levels in the Bilbao area," *Environment Modelling & Software*, vol. 21, pp. 430-446, 2006.

[32] M. Benghenem and A. Mellit, "Radial basis function network-based prediction of global solar radiation data: application for sizing of a stand-alone photovoltaic system at Al-Madinah, Saudi Arabia," *Energy*, vol. 35, pp. 3751-3762, 2010.

[33] L. Gao, M. X. Liu, G. X. Sheng, Y. Y. Sui, and Y. K. Zhuang, "Fuzzy discrimination analysis method based on RBFNN and its application in soft measurement," *Proceedings of the IEEE International Conference on Automation and Logistics*, Qinadao, china, Sep. 2008, pp. 2603-2607.

[34] J. Hertz, R. G. Palmer, and A. S. Krogh, "Introduction to the theory of neural computation," Perseus Books, 1990, ISBN 0-201-51560-1.

[35] J. Lawrence, "Introduction to neural networks," California Scientific Software Press., 1994, ISBN 1-883157-00-5.

[36] M. Timothy, "Signal and image processing with neural networks," John Wiley & Sons, Inc., 1994, ISBN 0-471-04963-8.

[37] R. J. A. Little and D. B. Rubin, "Statistical analysis with missing data," 2$^{nd}$ Edition, New York: John Wiley, 2000.

[38] J. L. Schafer, "Analysis of incomplete multivariate data," New York: Chapman & Hall, 1997.

[39] S. F. Burk, "Amethod of estimation of missing values in multivariable data suitable for use with an electronic computer," *J. royal Statistic Soc*, pp. 302-306, 1990.

TABLE I
RESULTS OF IMPLEMENTED METHOD FOR MISSING ONE PARAMETER

| **Input Parameters (24 Hours Averaging)** | | | | | | **Simulated Results** |
|---|---|---|---|---|---|---|
| CO (ppm) | $CO_2$ (ppm) | $SO_2$ (ppm) | $NO_2$ (ppm) | $O_2$ (%) | RH (%) | Temp. ($^oC$) |
| 8.15875 | 421.6541 | 0.130 | 0.025 | 20.45000 | 69.40 | 31.97 |
| 8.45250 | 421.7654 | 0.130 | 0.020 | 19.29375 | 71.00 | 32.34 |
| 8.46125 | 427.2375 | 0.110 | 0.150 | 19.02250 | 77.00 | 30.17 |
| 8.39125 | 423.8738 | 0.105 | 0.026 | 19.32000 | 79.90 | 29.46 |
| 8.25125 | 424.3525 | 0.110 | 0.025 | 20.16125 | 81.90 | 28.87 |
| 8.44375 | 423.3925 | 0.116 | 0.020 | 19.22875 | 81.10 | 29.35 |
| 8.13750 | 423.3938 | 0.115 | 0.025 | 19.39500 | 82.40 | 28.96 |
| 8.09375 | 423.3925 | 0.130 | 0.029 | 19.25875 | 85.20 | 28.44 |
| 8.06750 | 428.6788 | 0.120 | 0.025 | 19.05500 | 84.40 | 29.09 |
| 8.39125 | 423.8738 | 0.105 | 0.026 | 18.64500 | 81.10 | 29.77 |
| 8.10250 | 428.6788 | 0.110 | 0.025 | 19.05500 | 81.40 | 30.05 |
| 8.10250 | 428.6788 | 0.110 | 0.025 | 19.05500 | 84.30 | 28.83 |
| 8.10250 | 428.6788 | 0.120 | 0.025 | 20.01000 | 85.90 | 28.21 |
| 8.24250 | 425.7963 | 0.100 | 0.021 | 19.25000 | 86.70 | 27.68 |
| 8.46125 | 427.2375 | 0.110 | 0.140 | 19.00200 | 89.10 | 27.40 |

TABLE II
RESULTS OF IMPLEMENTED METHOD FOR MISSING TWO PARAMETERS

| Input Parameters (24 Hours Averaging) | | | | | Simulated Results of RBFNN | |
|---|---|---|---|---|---|---|
| $CO_2$ (ppm) | $SO_2$ (ppm) | $NO_2$ (ppm) | $O_2$ (%) | RH (%) | CO (ppm) | T ($^oC$) |
| 421.6541 | 0.130 | 0.025 | 20.45000 | 69.40 | 8.16 | 31.97 |
| 421.7654 | 0.130 | 0.020 | 19.29375 | 71.00 | 8.45 | 32.34 |
| 427.2375 | 0.110 | 0.150 | 19.02250 | 77.00 | 8.46 | 30.17 |
| 423.8738 | 0.105 | 0.026 | 19.32000 | 79.90 | 8.39 | 29.46 |
| 424.3525 | 0.110 | 0.025 | 20.16125 | 81.90 | 8.25 | 28.87 |
| 423.3925 | 0.116 | 0.020 | 19.22875 | 81.10 | 8.45 | 29.35 |
| 423.3938 | 0.115 | 0.025 | 19.39500 | 82.40 | 8.14 | 28.96 |
| 423.3925 | 0.130 | 0.029 | 19.25875 | 85.20 | 8.10 | 28.44 |
| 428.6788 | 0.120 | 0.025 | 19.05500 | 84.40 | 8.10 | 29.09 |
| 423.8738 | 0.105 | 0.026 | 18.64500 | 81.10 | 8.40 | 29.77 |
| 428.6788 | 0.110 | 0.025 | 19.05500 | 81.40 | 8.10 | 30.05 |
| 428.6788 | 0.110 | 0.025 | 19.05500 | 84.30 | 8.10 | 28.83 |
| 428.6788 | 0.120 | 0.025 | 20.01000 | 85.90 | 8.10 | 28.21 |
| 425.7963 | 0.100 | 0.021 | 19.25000 | 86.70 | 8.24 | 27.68 |
| 427.2375 | 0.110 | 0.140 | 19.00200 | 89.10 | 8.46 | 27.40 |

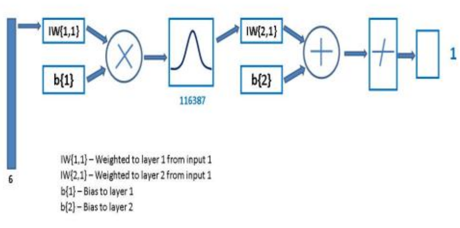


Fig. 5. Architecture of the 6:1Network.

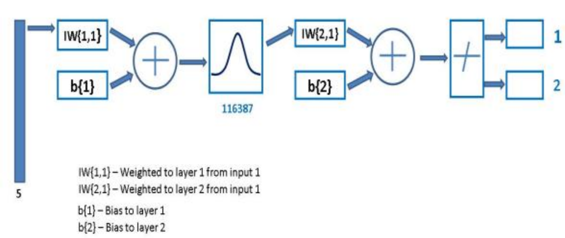


Fig. 6. Architecture of the 5:2 Network.