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INTELLIGENT ESTIMATION OF NOX EMISSIONS BY FLAME MONITORING IN POWER STATION USING INTERNET OF THINGS

Nallamilli P. G. Bhavani[1,2] and K. Sujatha[1]
[1]Department of Electrical and Electronics Engineering, Centre for Electronics, Automation and Industrial Research (CEAIR), Dr. MGR Educational and Research Institute, Chennai, Tamil Nadu, India
[2]Department of EEE, Meenakshi College of Engineering, Chennai, Tamil Nadu, India
E-Mail: sbreddy9999@gmail.com

ABSTRACT

The scrutiny of combustion quality and its equivalent NOx emissions from flame images in thermal and gas turbine power plants is of immense significance in the realm of image processing. The principal goal is in detection, recognition and understanding of combustion conditions ensuring low NOx emissions. In this work, soft sensors using feed forward neural network trained with Back Propagation Algorithm (BPA) and Ant Colony Optimisation (ACO) are used for flame image classification. The scheme uses the information from the colour of the flame images as fundamental which is dependent on the combustion quality and NOx emissions. The initial gait is to describe a facet vector for each flame image including 10 feature elements. The distinctive attributes of the captured images is enhanced using curvelet transform. The perception of object (flame feature) recognition and classification of the flame image is conceded out to measure the flame temperature, combustion quality and NOx emissions from the flame colour. The samples including 51 flame images, parts of which are used to train and test the model. Finally, the entire samples are recognized and classified. Experiments prove this method to be effective for classification of flame images. The solution includes the Internet of Things (IoT) where the intelligent sensors are connected to the embedded computing system to monitor the fluctuation of parameters relating to combustion quality. This form is flexible and dispensable for the infrastructural environment that needs continuous monitoring, controlling and behavior analysis in power plants. The working performance of the proposed model is evaluated using prototype implementation, consisting of Arduino UNO board, intelligent sensors and MATLAB with Arduino hardware support package. The implementation is tested for monitoring the combustion quality with respect to the normal operating conditions which provide a feed control for NOx emissions monitoring to make the environment smart.

Keywords: soft sensor, back propagation algorithm, ant colony optimization, combustion quality, NO_x emissions, feature extraction, curvelet transform, fisher's linear discriminant analysis, arduino UNO, internet of things.

1. INTRODUCTION

1.1 Introduction to thermal power plants

The development of thermal power plant and gas turbine power plant in India is an asset to the nation. The capacity of furnaces is constantly increased, which brings about the problems in detection, control and management. Nowadays all kinds of problems are basically focused on the measurement and processing of signals from these furnaces. The most important condition in large-scale power station secure operation is the credible flame detection, which is also the important method and reference for economical operation [1]. The air to fuel ratio must be maintained at appropriate level to ensure complete combustion [16]. The conventional ratio control is being replaced by the soft sensor which uses a feed forward neural network trained with BPA. Apart from BPA, ACO is also used as soft sensor to obtain a precise output. This in turn takes care of the energy balance between the fireside and the steam side parameters. The NOx emissions are monitored only at the exit point in the chimney which leads to wastage of fuel in heating excess air [8]. The images of the flame will give instantaneous temperatures of the flame. Two sequential images would show a greatly different flame shape and location [2].The personnel out of technical experience judges the quality of combustion.

Advanced monitoring of combustion flames plays an important role in the in depth understanding of energy conversion and pollutant formation processes and subsequent combustion optimization [3]. Current practice of flame monitoring is limited to indicate whether the flame is present or absent for safety purpose only. The technical details are given in Table-1 below which also includes the overview of the power plant. The Figure-1 below shows the schematic representation for the firing system. Initially the heavy oil is used to light-up the burner and thereafter lignite is used as the fuel. There are six mills as mentioned in Table-1. These mills provide pulverized coal dust for easy firing. The firing system is called as the tangential firing system. Figure-2 shows the placement of the lignite mills and the firing system. The powdered coal is preheated and only then supplied to the hearth of the furnace. This enables in uniform heat energy distribution [4, 7]. A solution for monitoring the NOx emissions and combustion quality with their levels crossing the threshold value ranges, for example the NOx emissions exceeding the normal levels a wireless embedded computing system is proposed to detect and offer an intelligent control in this paper.

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1.2 Introduction to gas turbine power plants

The gas compressor turbine system handles the fuel into a stream of compressed air, it has an upstream air axial flow compressor mechanically coupled to a downstream turbine and a combustion chamber in between Energy is released when compressed air is mixed with fuel and it is ignited in the combustor [2]. The resulting gases are directed over the turbine's blades, spinning the turbine, and mechanically powering the compressor and rotating the generator. Finally, the gases are passed through a nozzle, generating additional thrust by accelerating the hot exhaust gases by expansion backto atmospheric pressure [14]. A typical single shaft gas turbine is shown in Figure-3.

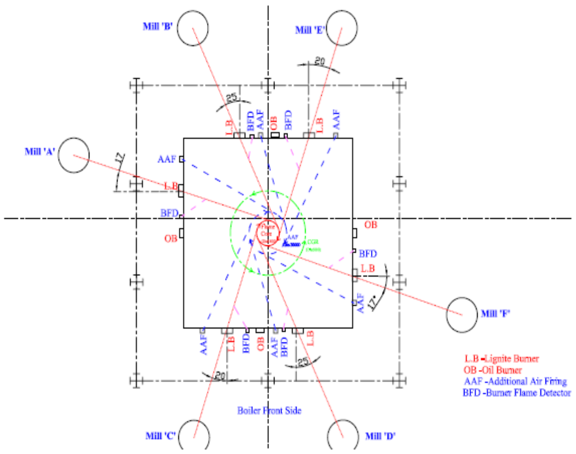

Figure-1. Tangential firing system.

2. LITERATURE SURVEY

In this area of research, only limited literatures are reported. A flame monitoring system was attempted but with a very simple image processing technique to monitor the CO emissions along with combustion quality index in the power plant at South Korea. Hence the research in this area finds a lot of scope which will enable the researchers to develop an indigenous technique for flame monitoring system.

The flame image processing and analysis system has been developed by Woon Bo Baek *et al* (2001) for optimal coal firing of the thermal power plant, especially for low NO_x emissions and safe operation. In this paper, an attempt has been made to gain a relationship between the burner flame image, emissions of NO_x and unburnt carbon in a furnace by utilizing the flame image processing methods, through which the proposed system quantitatively determines the conditions of combustion on the individual burners. The effectiveness of the system was observed by evaluating the combustion conditions monitoring and burner maintenance with a pilot furnace.

A dual silicon carbide photodiode chip was developed by Dale Brown *et al* (2008) to determine the temperature of a natural gas combustion flame. The concept discussed here uses the change in shape of the (260-350nm) OH band with temperature. One half of the chip was covered with a long pass multiple layer dielectric filter with a short wavelength of about 315 nm. After amplification, the two signals produced by the filtered and unfiltered portions of the chip are divided to produce a ratio, which is a very sensitive to the change in the flame temperature. Sensitivity is about 0.35% per 20°Fchange in flame temperature for temperatures between 2700 and 3000°F. The temperature measured is the specific average temperature encompassed by the field of view of the sensor assembly.

The objective is to develop advance sensors to reduce the NO, CO and CO_2 emissions thereby improving the combustion efficiency. In this method proposed by Ronald Hanson et al (2004), a tuneable near infrared diode lasers and absorption spectroscopy are used. Control strategies for active combustion involves robust, rapid response gas temperature sensor, fiber coupled sensor for gas temperature, O_2, CO and novel technique for detection of unburned hydrocarbons. These sensors thus offer a great promise for monitoring and control of combustion and energy and energy conversion technologies of the future.

The design, implementation, and evaluation of a 3 D imaging system for the reconstruction of the luminosity distribution of a combustion flame were proposed by Gilabert *et al* (2005). Three identical red, green and blue charge coupled device cameras together with appropriate optical transmission units are used to capture concurrently six equiangular 2 D images of a flame. A new tomographic approach that combines the logical filtered back projection and the algebraic reconstruction technique is proposed to reconstruct flame sections from the images. A direct comparison between the proposed approach and other tomographic algorithms is performed through computer simulation for different test templates and number of projections. Experimental tests were undertaken using both gas and coal fired flames in order to evaluate the effectiveness of the system. This research initiated has led to the establishment of an effective tool for the reconstruction of the luminosity distribution of flame sections and, ultimately, the quantitative characterization of the inter structures of a combustion flame.

Monitoring and characterization of combustion flames using pattern recognition is one among the techniques for estimation of combustion quality as proposed by Lu *et al* (2009). The features were extracted from the flame images and these features are used for classification of the flame images based on the combustion quality. The feature extraction was done using 2D and 3D techniques based on edge detection to infer combustion quality is the work done in this paper. Edge detection was done to identify the useful portion of the flame images so as to correlate them with the quality combustion. Then segmentation based on 2D and 3D techniques were used for the classification of the flame images based on the quality of the combustion.

In this work done by Sujatha. K. *et al* (2011), flame images collected from the combustion chamber of the boiler in the power station are preprocessed and features are extracted. The extracted features are used as

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ARPN Journal of Engineering and Applied Sciences

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the inputs to the various conventional and intelligent classifiers for combustion quality and NO_x emissions estimation. The intelligent classification techniques include RBF and FLDRBF. Testing results show that FLDRBF gives good classification performance when compared with the conventional classification schemes like EDC and FLD. The classification is also carried out using standalone intelligent schemes like RBF and BPA for combustion quality and NO_x emissions monitoring. But BPA was found to yield low classification performance.

Hence an attempt has been made to increase the classification of BPA classifier by using the coefficients of curvelet transform as an additional input which increase the performance of the classifier. ACO is also used for estimating the NO_x emissions and combustion quality.

3. RESEARCH HIGHLIGHTS

A feed forward method for estimating the NO_x emissions and combustion quality using soft computing techniques like BPA and ACO is implemented. An online monitoring scheme is proposed by integrating these algorithms using IoT. The estimation efficiency of the above mentioned algorithms are increased by using the curvelet coefficients as additional features to the already existing feature set.Hence this research work also indicates the list of the features that are helpful in estimation of NO_x emissions and combustion quality using image processing. A comparative analysis is also done to prove that the inclusion of curvelet coefficients increase the estimation efficiency of the proposed algorithms.

4. FISHER'S LINEAR DISCRIMINANT ANALYSIS (FLD) and BACK PROPAGATION ALGORITHM (BPA)

4.1. Fisher's linear discriminant analysis

The function of the Fisher's linear discriminant (FLD) is dimension reductionality. It helps to map the n-dimensional feature vectors on to a 2 dimensional vector space there by reducing the computational complexity. The process of changing the dimensions of a vector is called transformation. The transformation of a set of n-dimensional real vectors onto a plane is called a mapping operation. The result of this operation is a planar display. The main advantage of the planar display is that the distribution of the original patterns of higher dimensions (more than two dimensions) can be seen on a two dimensional graph [5]. The flowchart is depicted in Figure-4(b).

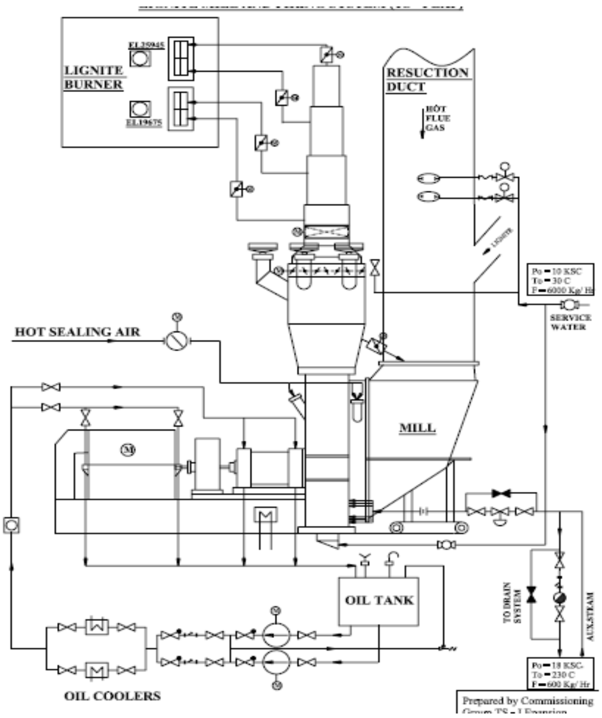

Figure-2. Schematic of lignite mills and firing system.

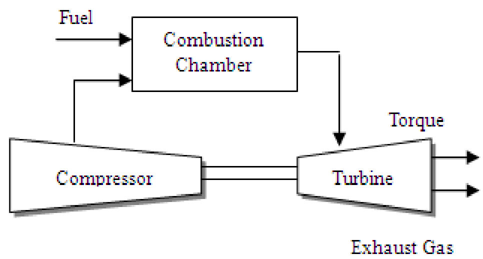

Figure-3. A schematic of a typical single-shaft gas turbine.

4.2 Back propagation algorithm

Artificial Neural Networks (ANN) consists of highly interconnected Processing Elements (PEs) called nodes or neurons which perform simple mathematical operations in a well defined fashion. The architectures for ANN can be classified as single layer and multi-layer topologies. Each layer is made up of the PEs, connection strength and the activation function (used only in the hidden layer and output layer). The various types of activation functions that can be used are unipolar sigmoidal, bipolar sigmoidal, hyperbolic tangent, sine and the basic threshold function. The network models can be static or dynamic. Static networks include single layer perceptrons and multilayer perceptrons. A perceptron or adaptive linear element (ADALINE) refers to a computing unit. This forms the basic building block for neural networks. The input to a perceptron is the summation of input pattern vectors by weight vectors [6].

In the proposed work the information flow is in the feed forward fashion. The flow of signals is from the input layer to the output layer via the hidden layer. No connection exists from the output layer to input layer. The number of nodes in the input layer and output layer is fixed based on the number of inputs and outputs used in the application [4]. In this work, there are seven input variables and one output variable. The number of nodes in a hidden layer is fixed by trial and error. In this application, the network parameters such as the number of nodes in the hidden layers and the number of hidden layers are found by trial and error method. In most of the applications one hidden layer is sufficient. As the name implies Back Propagation Algorithm (BPA) the weight updating takes place in the reverse order i.e. from the output layer to input layer [7]. The architecture for Feed Forward Neural Network (FFNN) trained with BPA is shown in Figure 5.The technical details relating to the boiler at NLC and Gas turbine flame related data at Basin bridge power stations are given below in Tables 1 and 2.

4.3 Ant Colony Optimisation (ACO)

Now consider that there is a colony of ants and they want food. Imagine six ant friends are willing to offer help [10]. These ants are sent to six points in different directions and they send their positions back. Now from their respective positions each of them move towards the food source choosing any random path they feel like and then back towards their initial starting points. At this point, the ants secrete a substance called pheromone on the paths that they take from food to back home. The amount of pheromone secreted on a path is inversely proportional to the distance to the food source using that path. This means that the shortest path to the food source will get maximum pheromone deposited on it. The path which has the maximum pheromone is considered for movement towards the starting point of that path. The second approach would be the identification of the wiser one. The same goes for a number of computational problems as well. This is the basic concept behind ACO. The algorithm is as follows

a) Initialization
b) Randomly place ants
c) Build tours
d) Deposit trail
e) Update trail
f) Loop or exit

4.4. Curvelet transform

The discrete curvelet transform for a 256 × 256 image is performed as is shown in Figure-4(a). The discrete curvelet transform can be performed in three steps:

a) The 256 × 256 image is split up in three subbands

b) The Basis subband consists of 256x256 image

c) Tiling is performed on band pass subbands Δ_1 and Δ_2.

d) Then the discrete Ridgelet transform is performed on each tile.

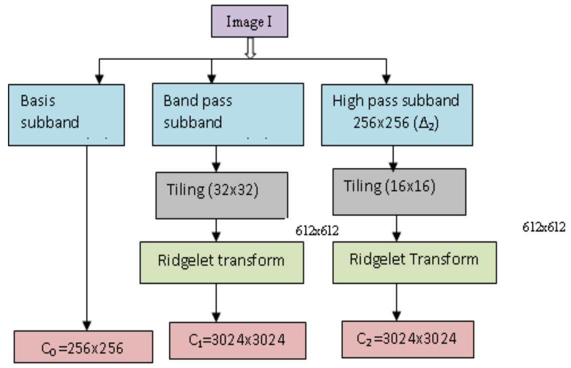

Figure-4(a). Flowchart for curvelet transform.

5. MATERIALS AND METHODS

The mapping operation can be linear or non-linear. Fisher developed a linear classification algorithm (Fisher 1936) and a method for constructing a classifier on the optimal discriminant plane, with minimum distance criterion for multi-class classification with small number of patterns (Hong and Yang 1991) [16]. The method uses the concept of within class mean (the mean value for the flame images within the same combustion category), between class mean (the mean value of the flame images between the categories of combustion) and the global mean. The relations between discriminant analysis and multilayer perceptrons has been addressed earlier [7] by considering the number of patterns and feature size (Foley 1972) [14]. A linear mapping is used to map an n-dimensional vector space onto a two dimensional space. Some of the linear mapping algorithms are principal component mapping, generalized de-clustering mapping, least squared error mapping and projection pursuit mapping. The flow diagram is shown in Figure-5 below.

The flame video is captured from NLC and segregated into frames. The intensity of the flame colour in the captured frame varies with respect to temperature and NO_x emissions. The features are extracted and then reduced using FLD [15]. The reduced feature set is used as an input to the BPN classifier and finally the classification performance is validated with certain performance measures. The Figure-6 shows the schematic representation of the flame monitoring system.

6. EXPERIMENTAL SETUP

The flame images are obtained from the control room of the thermal power plant boiler. Samples of flame images (51 flame images) for various combustion conditions were collected from the control room. Group 1 refers to complete combustion (flame1 to flame 18), group 2 refers to partial combustion (flame 19 to flame 38) and group 3 refers to incomplete combustion (flame 39 to flame 51). A square image extraction is done by cropping each image to a size of 30 x 30 pixels is done. The combustion quality and Nitrogen Oxide (NO_x) emissions were measured with simultaneous recording of the flame video [11]. The existing set-up at NLC is shown in Figure-7.

In order to modify the set-up so as to automate the process as shown in Figure-8(a), the flame video should be

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ARPN Journal of Engineering and Applied Sciences

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transferred to the PC where different image processing and artificial intelligent algorithms can be used. Tables 3 (a) and (b) below shows the three categories refer to the complete combustion, partial combustion and incomplete combustion conditions [12]. The partial and incomplete combustion conditions are not advisable as it results in wastage of coal as well as affects the power generation. Similar is the case with gas turbine power plants and leads to wastage of naphtha.

The proposed embedded device is for monitoring NO_x emissions to make the environment intelligent or interactive with the objects through wireless communication. The proposed model is shown in Figure 8(b) which is more malleable and dispensable in natural world to monitor the NO_x emissions from power plants. The proposed architecture discussed is a 4 layered model with the task of each individual module to monitor NO_x emissions and offer an intelligent feed forward control [13]. The layer 1 is the power plant environment where the flame temperature, combustion quality, SO_2 and NO_x emissions are to be monitored, intelligent sensors and gas analyzer in layer 2, sensor data acquisition and feed forward NN trained with BPA in layer 3 and the integration of the intelligent environment in layer 4 with the cloud technology using IoT.

Here, the layer 1 provides information about the NO_x emissions to be monitored from power plants. Layer 2 deals with the intelligent sensors with suitable characteristics, features and each of these sensors are operated and controlled based on their sensitivity as well as their range of sensing [9]. In between layer 2 and layer 3 necessary sensing and controlling actions will be taken depending upon the conditions, like fixing the threshold value, periodicity of sensing, messages (alarm or buzzer or LED) etc. Based on the data analysis performed in between layer 2 and layer 3 and by trial and error the threshold values during complete, partial and incomplete combustion conditions are determined.

Layer 3 depicts the data acquisition from sensor devices and also includes the decision making. In the proposed model layer 4 denotes the intelligent environment which identifies the variations in the sensor data and fix the threshold value depending on the identified level of NO_x emissions from power plants. In this layer the sensed data will be processed, stored in the cloud which is made available in Google spread sheets for analyzing the sensed parameters with respect to the reference values. The end users can browse the data using mobile phones, PCs etc.

6.1 Pre-processing

The image is pre-processed to make sure that correct image is used for analysis and monitoring purposes [7]. Median filtering is applied to eliminate the noise present in the images during the capture of the flame video. The smoothening will remove the speckles of dust captured in the image which is shown in Figure-9. After this the yellowish white region of the flame corresponding to complete combustion is alone extracted as in Figure-10. Plane 1, plane 2 and plane 3 of the images are analyzed for all 51 images to find which plane contains more information about the flame.

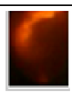
Table-1. Technical details for coal fired boiler specifications.

Type	Radiant tower
Circulation	Natural
Rh Design Pressure	42.5 kg/cm^2(a)
Fuel	Lignite
Start-Up Fuel	Light Diesel Oil – Heavy Fuel oil
Burners Type	Tangential Firing
Number Of Burners	12, Lignite and 8 Fuel oil
Number Of Mills	6
Mills Type	Ventilation Mill MB 3400/900/490
Manufacture	AnsaldoEnergia

Table-2. Technical details for gas turbine power plant specifications.

Process parameters	Related data
Capacity	120 MW (4 units * 30)
Liquid Fuel	Naptha
Naphtha used for combustion process	10,150 Calorific value/Kg
Fluid usage per day	13Klt/hr(for 30MW)
Colour of the flame	yellow
Exhaust temperature	5400 C on base load (30 MW)
Flame Temperature	11100 C
Air/fuel ratio	43/1
Mode of Operation	Open Cycle
Temperature measurement device	JK Thermocouple

Table-3. Combustion quality and NOx emissions for various combustion categories.

Group	Image	Combustion quality index (no units)	NO_x emissions in mg/Nm^3
1		In the range of 0.9 to 1	In the range of 20 to 25
2		Greater than 0.5 and less than 0.8	Greater than 25 and less than 40
3		Less than 0.5 and greater than 0.1	Greater 40 and less than 60

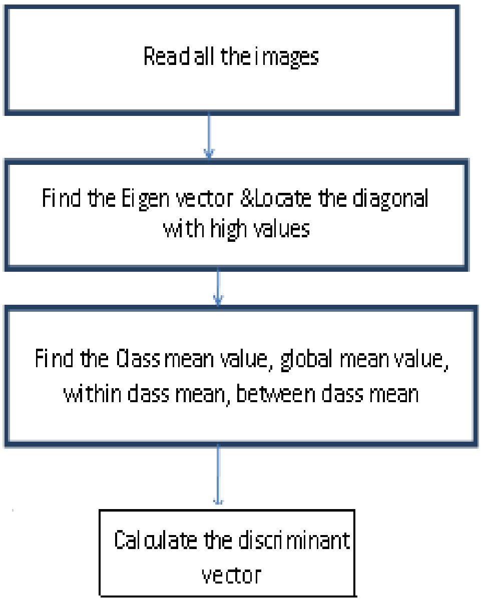


Figure-4(b). Sequence diagram for FLDA.

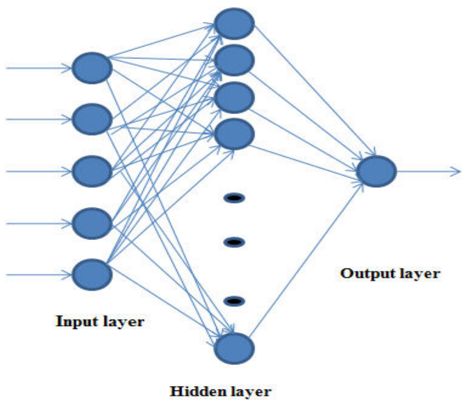


Figure-5. Architecture for feed forward neural network trained with BPA.

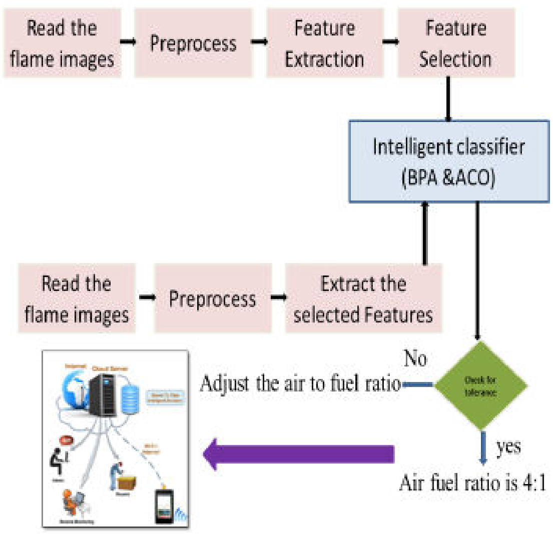


Figure 6. Block diagram for intelligent flame monitoring system using IoT

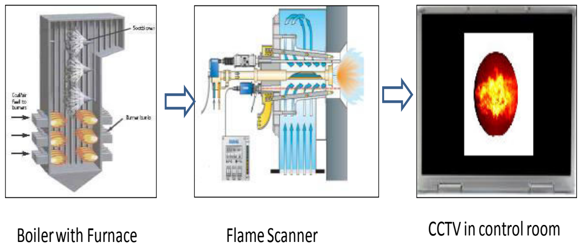


Figure-7. Monitoring of the furnace flame at NLC.

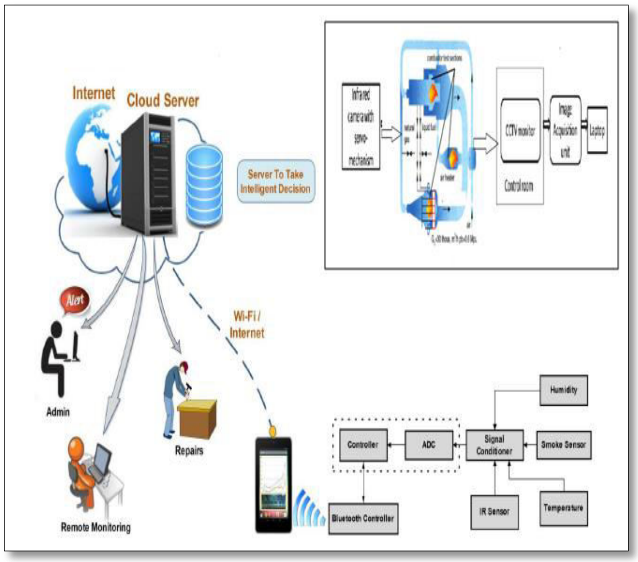


Figure-8(a). Arrangement for intelligent flame monitoring.

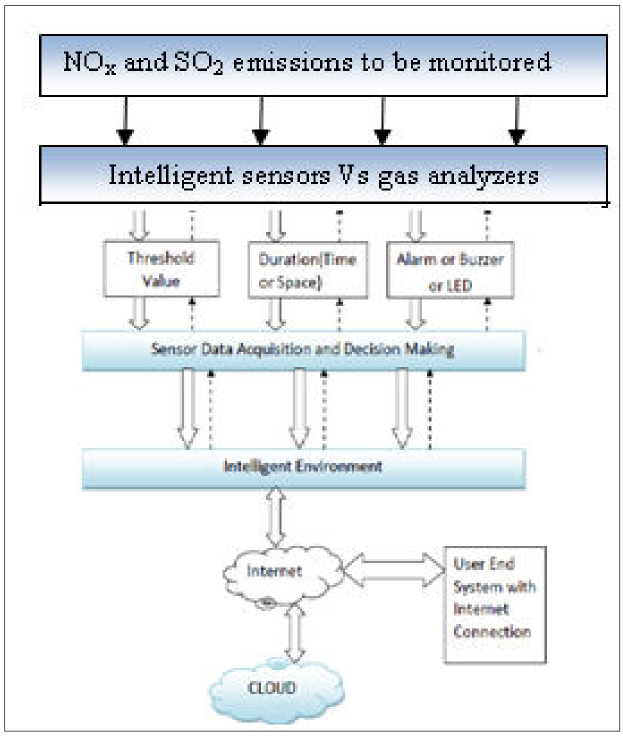


Figure-8(b). IoT based intelligent flame monitoring system.

The features extracted from each image which are displayed in Figure-11. The features are basic identity patterns present in the image and gets repeated in all directions in the image [10]. The inputs are φ_1,φ_2 vectors obtained from FLD, centroid x and centroid y of the flame in the image, number of pixels in the flame portion of the image, orientation of the flame as it gives indication of the speed of air blown, average intensity of the flame in each image, and the rate of area of high temperature flame, area of the flame using mathematical equation and curvelet coefficients [8]. The outputs are the combustion quality for set of images along with the NO_x (milligram per nomial cubic meter-mg/Nm^3). The features are extracted and used for training and testing process is shown in Table 4. As a part of this investigation it is also concluded that the feature set mentioned in Table 4 can be used as an optimal set of attributes for flame image analysis.

7. RESULT AND DISCUSSIONS

The images captured are colour images, hence hierarchical colour correction is done using curvelet transform which helps to maintain the white balance in order to make white portion appear white which indicates the region of complete combustion and the auto contrast adjustment enhances the perceptual quality of an image. The results for hierarchical colour correction using Iterated TMR filter are depicted in Figures 12 and 13 respectively. Almost equivalent results are achieved to ensure combustion quality when naphtha is used as fuel for gas turbine power plants. The following steps were followed to implement BPA and ACO for flame image analysis. It includes four major steps which are indicated below.

- Selection of Training data set
- Selection of ANN and ACO parameters (Input neurons, hidden layers, hidden neurons, initial weights, bias, learning rate, momentum factor, iterations, tolerance, learning algorithm, Attractiveness, heuristic strength, pheromone decay rate, number of ants, etc)
- Selection of appropriate architecture and parameters
- Validation of the ANN and ACO estimator

The ANN parameters like mean squared error, no. of iterations, no. of nodes in various layers and the type of the activation function used are shown in the Table 5 indicates that the FFNN is trained to estimate the flame temperature, combustion quality and NO_x emissions for thermal as well as gas turbine power plants. The ACO parameters are tabulated in Table 6. Figures 14(a) to (d) and Figures 15(a) to (d) indicate the estimation by ANN and ACO respectively.

The number of images classified by the proposed classifier is indicated in Table-7. Figure-16 denotes the performance of the BPA and ACO classifier for recognizing the flame images and their related parameters. The performance metric used for this purpose are recall and precision. Both the values of recall and precision are closer to 1. Hence the ACO and BPA are able to provide an optimal measurement of values. The usual reference method for the measurement of NO_x emissions is based on the absorption of infrared radiation by the gas in a non-dispersive photometer. This method is suitable for stable installations at fixed site monitoring stations. More recently, gas analyzers [9] with automated data logging are used for personal exposure monitoring. These measurements are based on the electrochemical reactions which are detected by especially dedicated sensors. Nowadays the resolution, stability and sensitivity of these analyzers are within the specifications of the reference method and; together with the datalogging systems, they become handy and portable.

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ARPN Journal of Engineering and Applied Sciences

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Table-4. Features used for training the classifier.

S. No.	Phy 1	Phy 2	Centroid x	Centroid y	Area	Orientation	Average intensity	Area through equation	Rate of area of hightemp flame	Entropy from curvelet transform
1	1.15	1.17	1.12	1.17	1.11	1.14	1.11	1.14	1.16	6.3223
2	1.13	0.95	0.95	1	0.95	1	0.97	1.01	0.97	6.3222
3	0.96	0.99	16.1	17.44	17.34	17.42	18.62	17.36	17.44	6.3321
4	17.38	17.98	17.91	24.63	22.7	22.07	23.25	23.19	23.18	6.342
5	22.56	22.13	22.73	22.52	1148	1409	1387	1442	1511	6.3311
6	1449	1409	1383	1448	1456	111.51	87.7	88.94	87.36	6.382
7	87.51	88	89.21	88.27	87.06	89.65	125.34	162.64	173.57	6.413
8	169.51	152.81	181.22	187.24	174.43	171.95	170.58	562	877	6.4243
9	750	785	841	797	795	777	820	783	0.5	6.4252
10	0.62	0.54	0.54	0.56	0.55	0.56	0.56	0.57	0.54	6.4223
11	1.15	1.17	1.12	1.17	1.11	1.14	1.11	1.14	1.16	6.471
12	1.18	1.08	1.08	1.17	1.12	1.16	1.10	1.13	1.06	6.476
13	1.06	1.02	1.05	1.04	1	1.03	1	1.09	1.05	6.523
14	1.07	1.04	1.05	1.09	1.05	1.07	1.04	1.05	1.03	6.531
15	1	0.88	0.88	0.91	0.88	0.91	0.9	0.89	0.9	6.5223
16	0.89	0.87	0.86	0.9	0.89	0.93	1.04	1.04	0.94	6.618
17	1	0.95	1.02	0.99	1.09	1.08	1.1	1.09	1.08	6.623
18	1.09	1.09	1.13	1.04	1.08	1.02	1.1	1.07	1.04	6.672
19	1.08	1.02	1.1	1.07	1.09	1.13	1.19	1.19	1.18	5.8723
20	1.19	1.17	1.18	1.19	1.18	1.19	1.22	1.22	1.19	5.9723
21	1.19	18.04	17.39	17.39	18.9	17.33	16.25	17.48	17.79	5.9723
22	11.21	11.13	0	9.67	6.96	0	16.0	13.16	17.23	5.9723
23	14.37	0	11.91	9	17.23	14.37	0	11.91	9	5.9723
24	16	13.12	20.52	17.06	14.58	20.52	19.95	21.44	14.14	5.9723
25	16.47	15.22	16.02	15.43	14.92	15.23	22.72	21.94	21.94	5.9723
26	23.13	23.17	24.34	23.06	22.51	15.75	16.04	0	12.89	5.9723
27	13.82	0	15	9.42	20.76	15.61	0	14.96	25	5.9723
28	20.76	15.61	0	14.96	25	15	9.42	3.18	5.77	5.9723
29	8	3.48	2.73	3.43	7.68	7.36	8.3	7.78	7.63	5.9723
30	7.98	7.68	1442	1381	1381	1580	1452	1119	1436	5.9723
31	1366	486	494	0	18	136	0	1	52	5.9723
32	599	141	0	504	1	599	141	0	504	5.9723
33	1	1	52	95	136	166	106	66	95	5.9723
34	174	152	211	197	197	167	149	87.08	90.63	5.9723
35	90.63	88.05	88.14	111.33	89.27	89.65	62.26	70.75	0	5.9723
36	92.12	61.56	0	0	0.71	84.78	59.99	0	70.32	5.9723
37	0	84.78	59.99	0	70.32	0	0	0.71	3.5	5.9723
38	32.1	44.87	3.45	1	7.47	36.74	38.42	38.79	38.51	5.9723
39	39.08	42.29	41.06	175.12	153.83	153.83	191.37	219.46	124.58	4.243
40	153.08	133.5	114.54	116.34	0	100.25	102.2	0	100.08	4.238
41	101.29	106.9	101.87	0	116.47	102.34	106.9	101.9	0	4.221
42	116.47	102.36	100.08	101.29	121.98	120.07	116.97	120.28	120.16	4.326
43	121.36	119.74	120.91	120.31	123.95	123.75	119.62	120.66	751	4.361
44	756	756	740	957	563	770	760	228	228	4.375
45	0	5	61	0	1	19	246	73	0	4.443
46	235	59	246	73	0	235	59	1	19	4.323
47	66	57	65	60	74	63	83	65	92	4. 412
48	114	90	73	59	0.52	0.55	0.55	0.47	0.66	4. 424
49	0.51	0.54	0.56	0.48	0.48	0	1	0.56	0	4. 452
50	1	0.53	0.45	0.68	0	0.49	0.52	0.45	0.68	4.53
51	0	0.49	0.52	1	0.53	0.51	0.45	0.41	0.41	4.571

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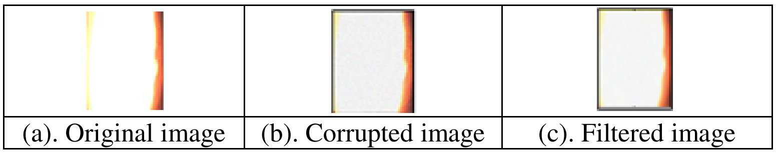

Figure-9. Effect of median filtering on the corrupted flame image.

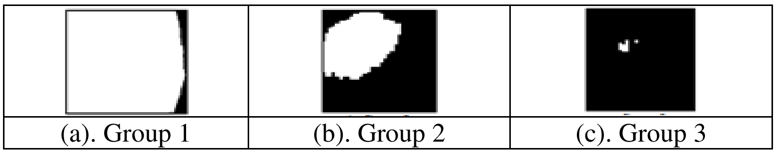

Figure-10. Results after thresholding and edge detection.

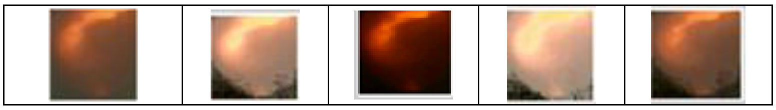

Figure-11. Feature extraction.

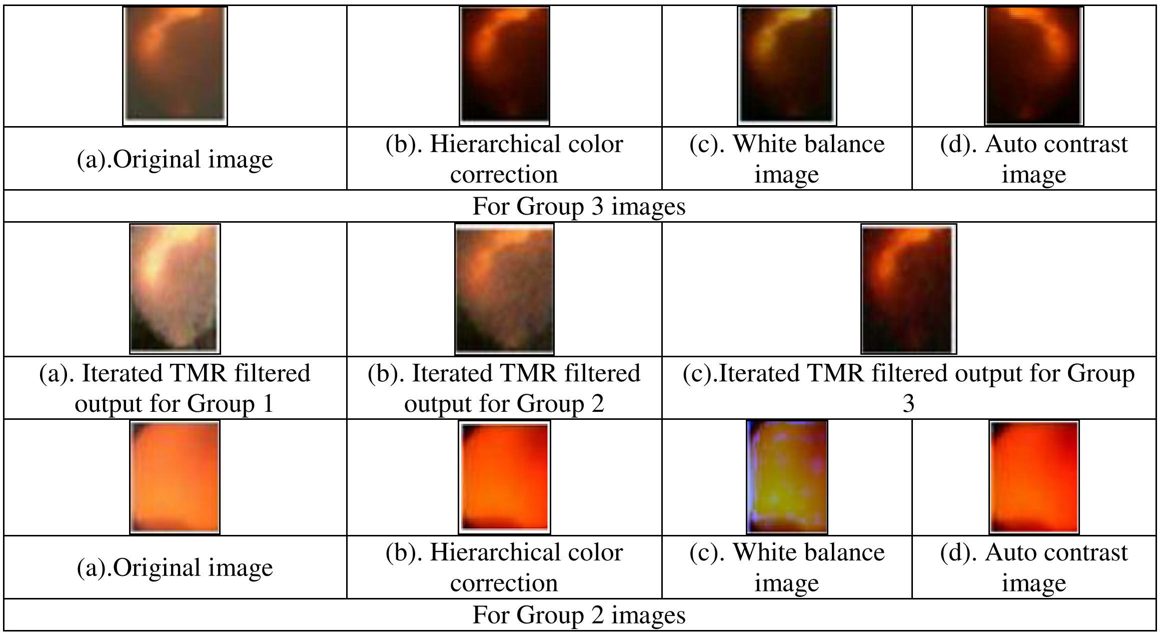

Figure-12. Outputs in different conditions.

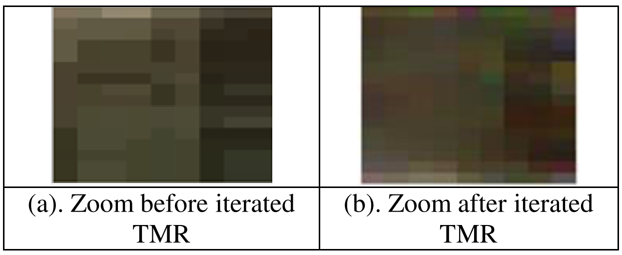

Figure-13. Iterated TMR images.

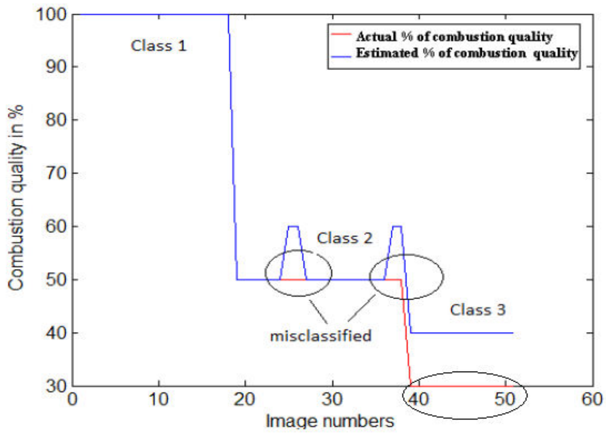

Figure-14(a). Estimation of combustion quality

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using BPA.

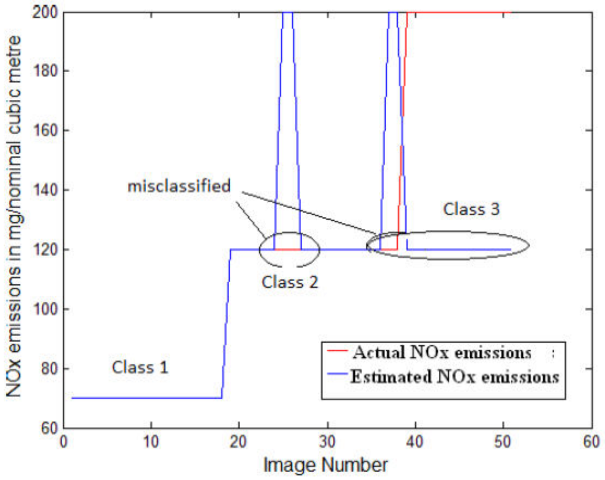


Figure-14 (b). Estimation of NO_x emissions using BPA.

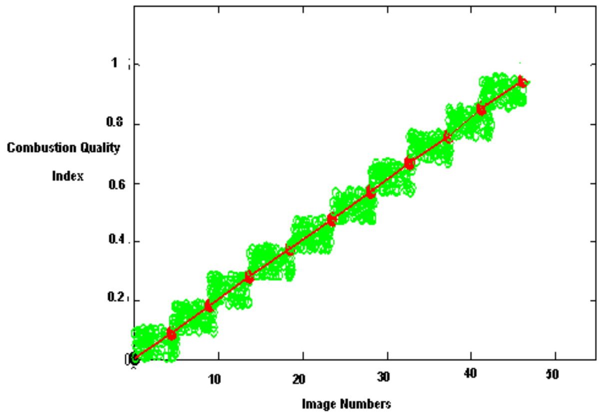


Figure-15(a). ACO results for combustion quality estimation.

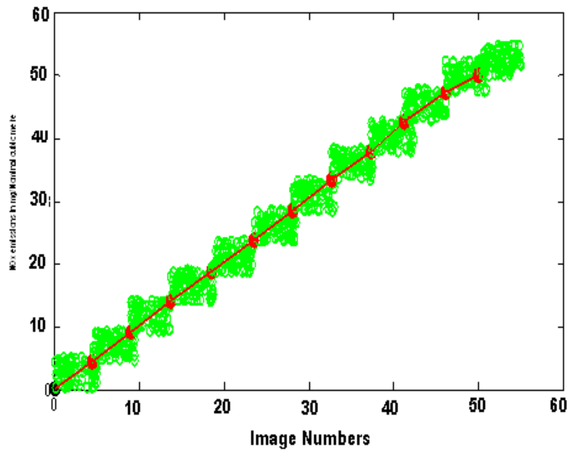


Figure-15(b). ACO results for NO_x emissions.

Table-5. ANN parameters for Estimation by ANN.

S. No.	Network parameters	Values for network with curvelet coefficients
1.	No. of nodes in input layer	10
2.	No. of nodes in hidden layer	6
3.	No. of nodes in the output layer	4
4.	Activation function - hidden layer	Sigmoid
5.	Activation function - Output layer	Sigmoid
6.	Mean Squared Error	0.0198
7.	No. of iterations	400
8.	Learning factor	0.8

Table-6. ACO parameters for estimation.

S. No.	Parameters	Value
1	Attractiveness (α)	0.1
2	Heuristic strength (β)	2
3	Pheromone decay rate (ρ)	0.1
4	Number of ants (m)	50

Table-7. Variation between target and actual values for all the three category of flame images.

S. No.	Name of the parameter to be estimated	Images classified by FFNN using BPA with curvelet coefficients			Images classified by ACO		
		Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Number of images used		18	20	13	18	20	13
1	combustion quality	18	20	8	18	20	13
2	NOx emissions	18	20	13	18	20	13

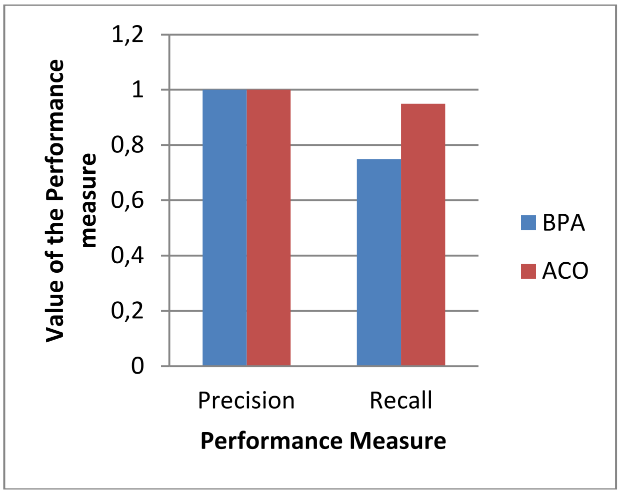


Figure-16. Performance metrics for BPA and ACO.

The embedded device is placed in particular area for testing purpose. The combustion quality sensor detects the intensity levels in the flame and will record them based on the threshold limit which when crossed, the corresponding controlling action will be offered (like issuing message alarm or buzzer or LED blink).All the sensor devices are connected to internet through Wi-Fi module and sent as messages to the mobile. Based on the framework a suitable implementation model is identified such that it consists of combustion quality sensor and other modules, in this implementation Arduino UNO board is used with Wi-Fi module as an embedded device for sensing and storing the data in cloud.

Arduino UNO board consist of analog input pins (A_0-A_5), digital output pins (D_0-D_{13}), inbuilt ADC and Wi-Fi module connects the embedded device to internet. Sensors are connected to Arduino UNO board for monitoring, ADC will convert the corresponding sensor reading to its digital value and from that value the corresponding environmental parameter will be evaluated. The Wi-Fi connection has to be established to transfer sensors data to end user and also send it to the cloud storage for future usage. Before sending the sensed data to cloud, the data will be processed in

MATLAB for analyze and visualize data to end user. The data analysis in MATLAB makes easier to us to set threshold level and to perform necessary controlling actions. Figures 17and 18 shows the excel spread sheet to store the combustion quality index, flame temperature and NO_x emissions in the cloud. After successful completion of sensing, the data will be processed and stored in database for future reference. After completing the analysis on data the threshold values will be set for controlling purpose. An SMS alert can also be incorporated as shown in Figure-19.

8. CONCLUSIONS

A different approach to develop an intelligent classifier to monitor and control the combustion quality, flame temperature and NO_x emissions in thermal and gas power plants was successfully implemented. This BPA and ACO classifiers are robust when compared to other conventional classifiers. The performance metrics well establishes that the proposed classifier was able to recall all the flame images with slightly reduced precision.

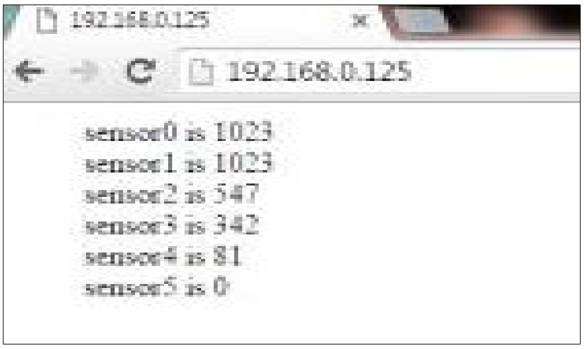
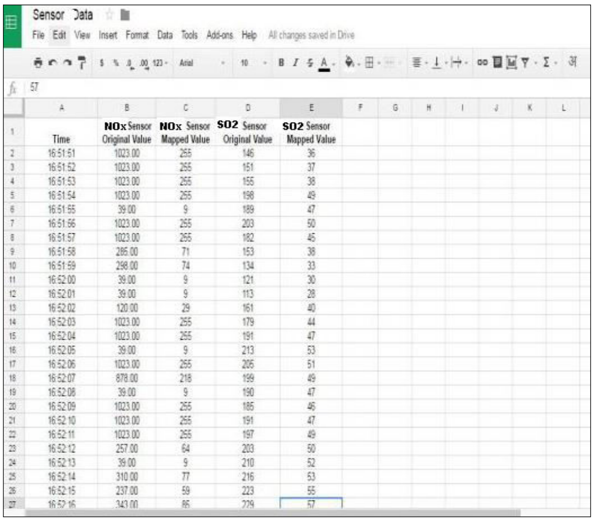


Figure-17. Web server page for measurement by sensor.



	Time	NOx Sensor Original Value	NOx Sensor Mapped Value	SO2 Sensor Original Value	SO2 Sensor Mapped Value
2	16:51:51	1023.00	255	146	36
3	16:51:52	1023.00	255	151	37
4	16:51:53	1023.00	255	155	38
5	16:51:54	1023.00	255	198	49
6	16:51:55	39.00	9	189	47
7	16:51:56	1023.00	255	203	50
8	16:51:57	1023.00	255	182	45
9	16:51:58	285.00	71	153	38
10	16:51:59	298.00	74	134	33
11	16:52:00	39.00	9	121	30
12	16:52:01	39.00	9	113	28
13	16:52:02	120.00	29	161	40
14	16:52:03	1023.00	255	179	44
15	16:52:04	1023.00	255	191	47
16	16:52:05	39.00	9	213	53
17	16:52:06	1023.00	255	205	51
18	16:52:07	878.00	218	199	49
19	16:52:08	39.00	9	190	47
20	16:52:09	1023.00	255	185	46
21	16:52:10	1023.00	255	191	47
22	16:52:11	1023.00	255	197	49
23	16:52:12	257.00	64	203	50
24	16:52:13	39.00	9	210	52
25	16:52:14	310.00	77	216	53
26	16:52:15	237.00	59	223	55
27	16:52:16	343.00	85	229	57

Figure-18. Cloud storage for NOx emissions sensors.

Figure-19. Sample output - NO_x emission sensor client.

Therefore an intelligent sensor for measurement of flame temperature, combustion quality and NO_x emissions estimation using IoT can be made possible from flame image analysis for online monitoring. Moreover the load generation is consistent at maximum intensities. Hence a correlation can be arrived based on the flame colour and the quality of combustion to ensure complete combustion. As a result an intelligent system can be developed to monitor and control the air fuel ratio. The NO_x emissions are also minimized there by reducing air pollution. The major idea behind this research is to identify the adverse combustion conditions, to provide a number of quantifiable parameters to evaluate flame stability and combustion quality along with NO_x emissions and to develop a PC based system for flame monitoring in thermal and gas turbine power plants.

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