**Australian Journal of Basic and Applied Sciences**, 9(2) February 2015, Pages: 40-45

AENSI Journals

**Australian Journal of Basic and Applied Sciences**

ISSN:1991-8178

Journal home page: www.ajbasweb.com

# Vision based Automation for Flame image Analysis in Power Station Boilers

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**ARTICLE INFO**

***Article history:***
*Received 25 October 2014*
*Received in revised form*
*26 November 2014*
*Accepted 29 December 2014*
*Available online 15 January 2015*

***Keywords:***
*Flame image, Temperature monitoring, Monitoring flue gas emissions, Artificial intelligence. Back Propagation Algorithm*

**ABSTRACT**

**Background:** This research work deals with the monitoring the combustion quality of the power station boilers using Artificial Intelligence for improvement in the combustion quality in the power station boiler . Color of the flame tells us whether the combustion taking place is complete, partial or incomplete. When complete combustion takes place the flue gases released are within the permissible limits otherwise its level is high which is out of limit. Analysis is done based on the flame color which was captured using infrared camera and displayed on CCTV. If combustion is partial or incomplete the flue gases released are more which will create air pollution. So this work includes enhancement of quality of combustion, saving of energy as well as check on the pollution level. Characteristics of flame images such as average intensity, area, brightness and orientation are obtained after its pre-processing. Three classes of images corresponding to different burning conditions were taken from continuous video processing. Further training and testing with the data collected have been carried out and performance of the algorithm is presented.



**To Cite This Article:** Dr. K. Sujatha, Dr.M.Kumaresan, Dr. R.S. Ponmagal and P. Vidhushini., Vision based Automation for Flame image Analysis in Power Station Boilers. ***Aust. J. Basic & Appl. Sci.,*** *9(2): 40-45, 2015*

## INTRODUCTION

### *1.1. Role of boilers:*

A boiler is a closed vessel in which water under pressure is transformed into steam by the application of heat. In boiler furnace, the chemical energy in the fuel is converted into heat, and it is the function of the boiler to transfer this heat to the contained water in the most efficient manner. The boiler should also be designed to generate high quality steam for plant use (Sujatha, K., 2010). The typical arrangement of a boiler is presented in Figure 1(a). In water tube boilers the products of combustion pass around the tubes containing water. The tubes are interconnected to common channels or headers and eventually to a steam outlet for distribution to the plant system. A boiler is designed to absorb the maximum amount of heat released in the process of combustion. This heat is transferred to the boiler water through radiation, conduction and convection (Pu Han, 2006). The relative percentage of each is dependent on the type of boiler, the designed heat transfer surface and the fuels. The data relating to the boiler at Neyveli Lignite Corporation (NLC) are given in Table 1(a).

### *1.2. Existing set-up for control of the air/fuel ratio:*

The design of the boiler involves the energy balance between the fire side and the steam side parameters. The combustion takes place in the furnace when fuel and air get mixed up in the proper ratio. The next monitoring point in the flue gas path is the temperature at the exit of the boiler. Flames are generated in the furnace when fuel and air from conduits are mixed up in the proper ratio. The flames generated are turbulent but can look straight and well-defined, which is also the case for flame oscillation. The temperatures of the flame measured using thermocouples are average values and the images of the flame will give instantaneous temperatures. The firing system is shown in

### *1.3. Combustion monitoring using flame images:*

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**Australian Journal of Basic and Applied Sciences,** 9(2) February 2015, Pages: 40-45

Flame monitoring is process which tells us the color of the flame which changes according to its content of the flue gases, the gases for example may be CO, $CO_2$ or $NO_x$. As a result it gives us the indication of quality of combustion whether complete combustion has occurred.

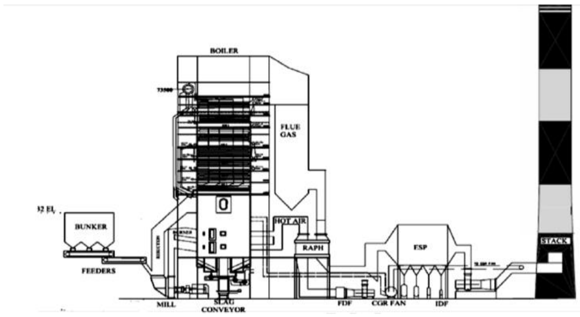



**Fig. 1(a):** General arrangements of a boiler.

So, monitoring the flame gives us the guidance of how to improve the quality of combustion. Hence, it helps in estimating the pollution created by the power plants. So, by improving the quality of combustion pollution level can be checked. The main objective is to design a flame monitoring expert system with progressive cameras, along with artificial intelligence techniques for identifying flame features that can be correlated with the air/fuel ratio, $NO_x$, CO, $CO_2$ emission levels, temperature, etc. The 3D temperature profile is designed to provide control of furnace and flame temperature, which also reduces the flue gas emissions which is the key to achieve high combustion quality. The system is also designed to provide guidance for balancing the air/fuel ratio so as to ensure complete combustion. The goal of 0nline monitoring and controlled combustion is to address the ever-increasing demands for higher furnace thermal efficiency, reduced flue gas emissions and improved combustion quality.

The systems, based on the latest optical sensing and digital image processing techniques, are capable of determining the geometry (size and location), i.e., the geometry of the burner (fixed) luminosity (brightness and uniformity) and the fluid dynamics parameters (temperature) of a flame. In the current set on the basis of oxygen content in the exhaust gas, the air/fuel ratio of the ratio controller is varied manually in a feedback manner. We are proposing a scheme for dynamically varying the air/fuel ratio on the basis of the colour of the flame as images, automatically (feed forward control) (Purushothaman, S. and Y.S. Srinivasa, 1994; Model, IEEE ISIE, 2006). An intelligent feed forward control for adjusting the air/fuel ratio and for minimizing the flue gas emissions for ensuring complete combustion using flame image analysis was implemented. The systems have been evaluated on both laboratory scale and industrial-scale combustion rigs under a variety of operation conditions (Lippmann, R.P., 1987).

## MATERIALS AND METHODS

The schematic diagram in Figure 2 shows the implementation of monitoring of the boiler condition and optimal performance of the boiler for which the video image required is provided from the CCD camera. The images are extracted from the video. The features are extracted from each image. Fisher's linear discriminant function reduces the dimensions of extracted features to two dimensions. The features of each three groups of images are measured according to the content of CO, $CO_2$, and $NO_x$ values, from the flue gas.

In the test phase, the outputs of proposed algorithms are compared with the measured values for the flue gas to decide whether any adjustment in the air/fuel ratio is required for a burner. The extracted features were used for further training and testing by the use of backpropagation algorithm in which we used two methods viz. Quassi Newton algorithm and Resilent back propagation method (Meng Joo Er, 2000; Purushothaman, S. and Y.G. Srinivasa, 1998). Block diagram in Figure 2 shows the methods we used for the execution of the work.

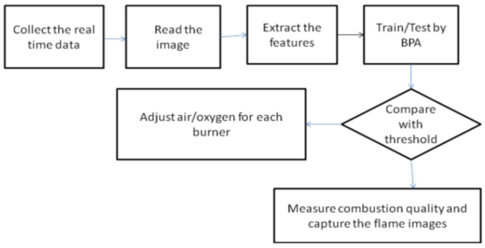



**Fig. 2:** Block diagram of methodology.

## 2. *Experimental Details:*

The flame images are obtained from the control room of the thermal power plant boilers. Table 1 shows samples from the 76 flame images gathered. Of these, 51 images for training and 19 images for testing and 6 images with the proposed algorithm were taken into consideration. Class 1 (flame 1–flame 28), class 2 (flame 29–flame 48) and class 3 (flame 48–flame 76) are of importance, from the control room. Cropping of each image is done to the size of 30×30 pixels but any other size could also be chosen.

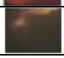
**Table 1(a):** Distribution of number of images for training, testing and validation.

| Class | No. of images for training | No. of images for testing | No. of images for validation |
|---|---|---|---|
| 1 | 18 | 8 | 2 |
| 2 | 20 | 9 | 2 |
| 3 | 13 | 2 | 2 |
| Total | 51 | 19 | 6 |

### *3.1. Preprocessing:*

The video taken from the thermal power station boilers were splitter using video splitter software and the images were resized. The image is preprocessed to make sure that the correct image is used for analyzing and monitoring purposes. To smooth (x, y) is defined as the ratio of the flame centroid measured to the flame centroid in standard conditions.

**Table 1:** Sample flame images.

| Class | Sample flame images | Combustion status | Target |
|---|---|---|---|
| 1 |  | Complete combustion | 1 |
| 2 |  | Partial combustion | 0 |
| 3 |  | Incomplete combustion | -1 |

### *3.2. Feature extraction:*

The Table 2(a) presents sample of the features extracted from each image. The normalized data are given as input data which includes Area, mean, standard deviation, mode, minima, maxima, centroid x and y, internal density, median (Feature Extraction using Fuzzy C., 2006) are tabulated in Table 2(b). These data are used for further training, testing and validation using Matlab and the corresponding graphs and the performances are measured.

**Table 2(a):** Normalized input data.

| S.no | Area | Mean | Standard Deviation | Mode | Min | Max |
|---|---|---|---|---|---|---|
| 1 | 0.9167 | 0.7634 | 0.6808 | 0.7884 | 0.8788 | 0.6679 |
| 2 | 0.9235 | 0.9161 | 0.643 | 0.9206 | 0.9545 | 0.702 |
| 3 | 0.9235 | 0.9176 | 0.7349 | 0.8571 | 0.9242 | 0.7333 |
| 4 | 0.8759 | 0.5529 | 0.7492 | 0.4392 | 0.8333 | 0.5333 |
| 5 | 0.9167 | 0.6912 | 0.6005 | 0.7143 | 0.8939 | 0.5608 |
| 6 | 0.8759 | 0.6088 | 0.6312 | 0.5873 | 0.9091 | 0.5373 |
| 7 | 0.8963 | 0.9298 | 0.7171 | 0.9471 | 0.7424 | 0.7176 |
| 8 | 0.8759 | 0.9147 | 0.596 | 0.9206 | 1 | 0.7098 |
| 9 | 0.9235 | 0.9077 | 0.6625 | 0.9206 | 0.9848 | 0.7059 |

The formula for obtaining the normalized data is $X_i/X_{max}$ where $X_i$ = value corresponding to all data is given by $X_{max}$ = maximum value

**Table 2(b):** Normalized input data.

| S.no | Centroid X | Centroid Y | Internal Density | Median |
|---|---|---|---|---|
| 1 | 0.9167 | 0.9783 | 0.724 | 0.765 |
| 2 | 0.9444 | 0.9565 | 0.8753 | 0.9071 |
| 3 | 0.9444 | 0.9565 | 0.8767 | 0.9071 |
| 4 | 0.9167 | 0.9348 | 0.5011 | 0.5191 |
| 5 | 0.9167 | 0.9783 | 0.6555 | 0.6885 |
| 6 | 0.9167 | 0.9348 | 0.5522 | 0.5956 |
| 7 | 0.9176 | 0.9565 | 0.8622 | 0.929 |
| 8 | 0.9167 | 0.9348 | 0.829 | 0.9071 |
| 9 | 0.9444 | 0.9565 | 0.8673 | 0.9016 |

## RESULTS AND DISCUSSION

The Figure 4(a) to (j) shows the result got by using back propagation algorithm in which Quassi Newton algorithm and resilient back propagation method is used for training, testing and validation. From Figure 4(a) and 4(b) it is inferred that Figure 4(b) gives the better performance because in Figure 4(b) graph is not so closer

**Australian Journal of Basic and Applied Sciences,** 9(2) February 2015, Pages: 40-45

to the performance measure in graph as compared to the graph in Figure 4(a) but error is very less as compared to the error for the graph in Figure 4(a). So, it is recommended that the characteristics in Figure 4(b). Similarly, all the comparisons for the graphs are illustrated below. Also it is recommended that the resilient back propagation algorithm yields optimal results because the data are used for training is not suitable for training using Quassi Newton Algorithm. Resilient back propagation is best suited for the work having smaller number of data. Hence it is clear that the resilient back propagation algorithm for training, testing and validation.

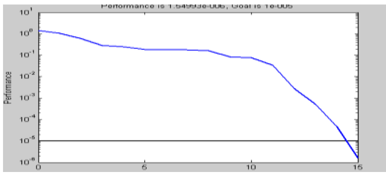


**Fig. 4(a):** Training result with a performance measure of $1.54*10^{-5}$ using Quassi Newton algorithm.

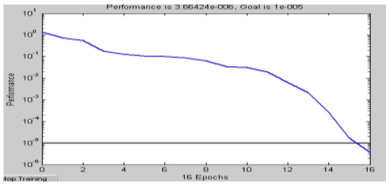


**Fig. 4(b):** Training result with a Performance measure of $1.6*10^{-5}$ using Resilient BPA algorithm.

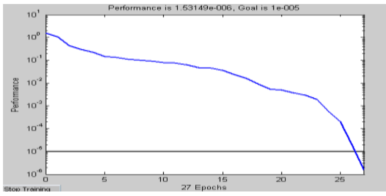


**Fig. 4(d):** Training result with a performance measure of $3.64*10^{-5}$ using Resilient BPA algorithm.

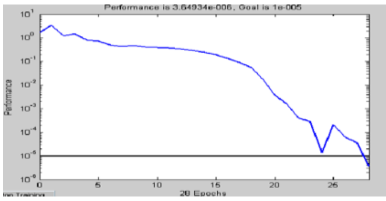


**Fig. 4(c):** Training result with a performance measure of $1.6*10^{-5}$ using Quassi Newton algorithm.

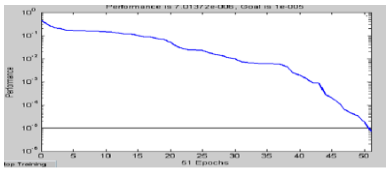


**Fig. 4 (e):** Training result with a Performance Measure is $7.1*10^{-5}$ using Quassi Newton algorithm.

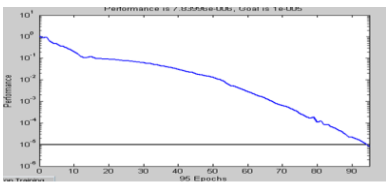


**Fig. 4(f):** Training result with a Performance Measure of` $7.3*10^{-5}$ using Resilient BPA algorithm.

**Australian Journal of Basic and Applied Sciences,** 9(2) February 2015, Pages: 40-45

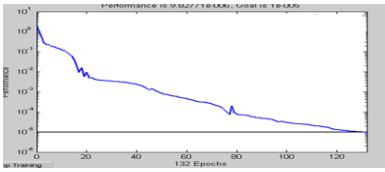



**Fig. 4(g):** Testing using Resilient Back Propagation Performance measure is $9.876{*}10^{-5}$.

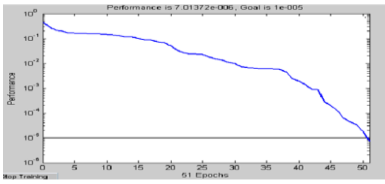



**Fig. 4(h):** Testing using Quassi-Newton Performance measure is $7.013{*}10^{-5}$.

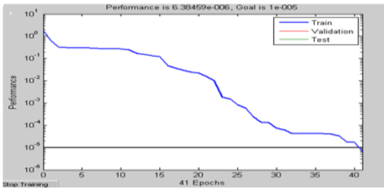



**Fig. 4(j):** Validation results for a performance is $9.8227{*}10^{-5}$ using Resilient BPA algorithm.

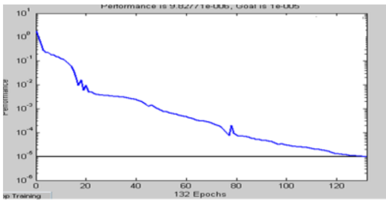



**Fig. 4(i):** Validation result with a performance is $6.38{*}10^{-5}$ using Quassi Newton algorithm.

**Table 3:** ANN parameters.

| S.No | Network parameters | Value |
|---|---|---|
| 1. | No. of nodes in input layer | 10 |
| 2. | No. of nodes in hidden layer | 7 |
| 3. | No. of nodes in the output layer | 1 |
| 4. | Activation function – hidden layer | Sigmoid |
| 5. | Activation function – Output layer | Sigmoid |
| 6. | Mean Squared Error | $7.1\text{x}10^{-5}$ |
| 7. | No. of iterations | 400 |
| 8. | Learning factor | 0.8 |

The Table 3 denotes the ANN parameters for training the neural network. The performance criteria for the proposed ANN architectures are listed out in Table 4. The MSE values obtained during testing and validation of the trained ANN using Quassi Newton and resilient back propagation algorithms are also shown in Table 4.

**Table 4:** Training parameters for various types of BPA.

| Types of BPA | Mean Squared Error (MSE) | | |
|---|---|---|---|
| | For training | For testing | For validation |
| Quassi Newton | $1.54{*}10^{-5}$ | $7.013{*}10^{-5}$ | $6.38{*}10^{-5}$ |
| | $1.6{*}10^{-5}$ | | |
| | $7.1{*}10^{-5}$ | | |
| Resilent BPA | $1.6{*}10^{-5}$ | $9.876{*}10^{-5}$ | $9.8227{*}10^{-5}$ |
| | $3.64{*}10^{-5}$ | | |
| | $7.3{*}10^{-5}$ | | |

### *5. conclusion:*

It is evident that the quality of combustion can be monitored using intelligent techniques like artificial neural networks by analyzing the flame images captured from the furnace. Both the types of the intelligent

**Australian Journal of Basic and Applied Sciences,** 9(2) February 2015, Pages: 40-45

algorithms like resilient back propagation algorithm and Quassi Newton algorithm were used for training, testing and validation. The performance measures were found to be within admissible limits. These results can also be integrated with the Distributed Control System (DCS). Hence we can say that for this work the back propagation algorithm is giving better result as compared to other conventional techniques.

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