Furnace Flame Tracking for Combustion Quality Estimation in Coal Fired Boilers

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Abstract. This research work focuses on optimization of the combustion quality as the combustion quality plays a vital role in minimizing NOx and CO emissions in the flue gas. Power generated is also another important factor under consideration so as to meet the demand. Flame monitoring in boilers using digital imaging provides replacement for the conventional technique of temperature measurement. The indigenous method can be replaced by incorporating an online PC based system by analyzing the flame images.

Keywords: Combustion quality, Image J, Image Processing, K-mean algorithm, Farthest First algorithm, Weka.

1. INTRODUCTION

Boiler efficiency can be optimized by reducing the operating cost and it is one of challenging task in the power stations. The improvement in combustion quality leads to consistency in power generation and reduction in cost [1-6]. Presently, the ON-OFF conditions of the flame inside the furnace alone are determined. Explosion of the boiler can be prevented at the time of start-up conditions. Unmonitored dumping of coal in the furnace is very dangerous. So a boiler flame surveillance system is incorporated [7]. Conveyors are used to transport coal from the coal yard to the grinding mills. It is then crushed in mills and the unwanted materials associated are removed in the ESP which attracts all the fine iron particles. The advantage of using pulverized coal is that the finely preheated coal is uniformly spread on the hearth of the furnace [8,9]. The tangential firing system consists of 12 lignite and 8 oil burners. Oil burners are used for initial firing at 21m. The coal firing takes place at 23m. Hence the entire firing process is over within 23m and the total height of the boiler is about 91m.

2. PROCEDURE FOR FLAME ACQUISITION

The flame video is recorded along with the readings relating to the parameters as indicated in Table 1. The flowchart for flame acquisition is illustrated in Figure 1.

| S.No. | % O2 (Left) | % O2 (Right) | % O2 (Average) | Load (MW) | Temperature of the flame (°C) |
|-------|------------|-------------|----------------|-----------|-----------------------------|
| 1     | 4          | 3.8         | 3.9            | 210       | 897                         |
| 2     | 3.6        | 4           | 3.8            | 210.6     | 912                         |
| 3     | 3.4        | 3.9         | 3.65           | 210.8     | 913                         |
| 4     | 3.2        | 3.4         | 3.3            | 212.21    | 933                         |

Table 1: Experimental Data from NLC
3. IMAGE PROCESSING SYSTEM FOR FLAME MONITORING

Figure 1 shows the block diagram for flame image analysis. Noise removal, which is a pre-processing technique to remove noise from Flame images, is done using median filters. The attributes included maximum intensity, minimum intensity, area of the flame, standard deviation; Kurtosis and Internal Density were extracted using Image J. Table 2 shows the feature elimination using the mean threshold. Similarly, the Table 3 shows the second level of threshold in which the 1st feature was eliminated using the above said criteria. As a result out of nine features only seven features were selected and used for classification. The main aim of clustering was to identify the combustion condition [5, 6]. The classification was done with Weka, a user-friendly tool. The procedure for implementing any clustering algorithm to find the combustion quality is shown in Figure 1.
Table.2 Features selected after first level of threshold

| S. No | Mean   | Features selected |
|-------|--------|-------------------|
|       | Mean Threshold is 1999878 |        |
| 1     | 76576.9 | 1                 |
| 2     | 233.5838 | 2                 |
| 3     | 45.17203 | 3                 |
| 4     | 254.4443 | 4                 |
| 5     | 18.99749 | 5                 |
| 6     | 254.7211 | 6                 |
| 7     | 151.3636 | 7                 |
| 8     | 119.8586 | 8                 |
| 9     | 17921246 | 0                 |

Table.3 Features selected after second level of threshold

| S. No | Mean   | Features selected |
|-------|--------|-------------------|
|       | Mean Threshold is 9735.008 |        |
| 1     | 76576.9 | 0                 |
| 2     | 233.5838 | 2                 |
| 3     | 45.17203 | 3                 |
| 4     | 254.4443 | 4                 |
| 5     | 18.99749 | 5                 |
| 6     | 254.7211 | 6                 |
| 7     | 151.3636 | 7                 |
| 8     | 119.8586 | 8                 |

4. RESULTS AND DISCUSSION

It is evident from Figure 2 that the Load generation can be tracked from the colour changes taking place in the flame during combustion and the intensity ranges from 230 to 240 nearly. In addition to it Table 4 and Figure 3 indicate the tracking of oxygen content. It is indicated that if the air fuel ratio is maintained closer to 4:1 then the mean intensity of the flame is increased which indicates that the flame colour approaches to yellowish white indicating the complete combustions. From Table 4 and Figure 3 it is identified that, the load generated is uniform at higher intensities.

Table.4 Tabulation for mean intensity Vs % Average O$_2$

| S.No | Average Intensity | % O$_2$ (Left) | % O$_2$ (right) | Supply of Oxygen (%) |
|------|-------------------|----------------|-----------------|---------------------|
| 1    | 239.052           | 4              | 3.8             | 3.9                 |
| 2    | 235.6469          | 3.6            | 4               | 3.8                 |
| 3    | 234.751           | 3.4            | 3.9             | 3.65                |
| 4    | 233.8803          | 3.2            | 3.4             | 3.3                 |
Additionally, it is obvious that high temperature of the flame is related to colour mapping table, which is used to identify the temperature in various portions of the flame images [7]. The difficulty involved is that the colour associated with each portion of the flame need to be identified using segmentation algorithms with appropriate threshold [8]. The clustering results (Table 5 and 6) are represented graphically as shown in Figure 4. In Figure 4 shown above the farthest first algorithm applied for reduced feature set by the proposed technique also yields cent percent results to identify the combustion conditions.

Fig. 2 Scatter plot for % Air Supply

Fig. 3 Tracking of Intensity-load change
Table 5. Comparison of various clustering algorithms

| S.No | Parameters for comparison | K-means clustering with all features | K-means clustering with reduced feature set | Farthest First clustering with all features | Farthest First clustering with reduced feature set |
|------|---------------------------|------------------------------------|------------------------------------------|------------------------------------------|-----------------------------------------------|
| 1    | Number of Attributes      | 10                                 | 09                                       | 10                                       | 09                                            |
| 2    | Number of iterations      | 24                                 | 21                                       | 24                                       | 20                                            |
| 3    | Squared error in %        | 87.2% misclassified                | 86.3% misclassified                      | No misclassification                     | No misclassification                          |

Table 6. Comparison of Performance of different clustering algorithms

| S.No | Algorithm Type                  | % Performance classification |
|------|---------------------------------|------------------------------|
| A1.  | K-means with all features       | 13                           |
| A2.  | K-means with reduced features   | 14                           |
| A3.  | Farthest First with all features| 100                          |
| A4.  | Farthest First with reduced features | 100                      |

Fig. 4. Comparison Chart for Clustering Performance

5. CONCLUSION

The clustering of images was done to identify the combustion quality. The performances of the various clustering algorithms were shown in Figure 4. Therefore the automation of combustion quality and power generation can be made possible by flame image analysis. The work can be extended to develop an intellectual system to monitor and control the air fuel ratio. It is also possible to reduce flue gas emissions such as to minimize the air pollution.

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