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FLAME MONITORING IN POWER STATION BOILERS USING IMAGE PROCESSING

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Abstract

Combustion quality in power station boilers plays an important role in minimizing the flue gas emissions. In the present work various intelligent schemes to infer the flue gas emissions by monitoring the flame colour at the furnace of the boiler are proposed here. Flame image monitoring involves capturing the flame video over a period of time with the measurement of various parameters like Carbon dioxide (CO_2), excess oxygen (O_2), Nitrogen dioxide (NO_x), Sulphur dioxide (SO_x) and Carbon monoxide (CO) emissions plus the flame temperature at the core of the fire ball, air/fuel ratio and the combustion quality. Higher the quality of combustion less will be the flue gases at the exhaust. The flame video was captured using an infrared camera. The flame video is then split up into the frames for further analysis. The video splitter is used for progressive extraction of the flame images from the video. The images of the flame are then pre-processed to reduce noise. The conventional classification and clustering techniques include the Euclidean distance classifier (L_2 norm classifier). The intelligent classifier includes the Radial Basis Function Network (RBF), Back Propagation Algorithm (BPA) and parallel architecture with RBF and BPA (PRBFBPA). The results of the validation are supported with the above mentioned performance measures whose values are in the optimal range. The values of the temperatures, combustion quality, SO_x, NO_x, CO, CO_2 concentrations, air and fuel supplied corresponding to the images were obtained thereby indicating the necessary control action taken to increase or decrease the air supply so as to ensure complete combustion. In this work, by continuously monitoring the flame images, combustion quality was inferred (complete/partial/incomplete combustion) and the air/fuel ratio can be automatically varied. Moreover in the existing set-up, measurements like NO_x, CO and CO_2 are inferred from the samples that are collected periodically or by using gas analyzers (expensive). The proposed algorithm can be integrated with the distributed control system (DCS) that is used for automation of the power plant. The inferred parameters can be displayed in the centralized control room a (cost-effective solution). The major contribution of this research work is to develop an indigenous online intelligent scheme for inferring the process parameters and gas emissions in the centralized control room directly from the combustion chamber of a boiler.

Keywords:

Flame Monitoring, Radial Basis Function Network, Fisher's Linear Discriminant Analysis, Parallel Architecture of Radial Basis Function and Back Propagation Algorithm

1. INTRODUCTION

The boiler converts the chemical energy available in the fuel (coal) into internal energy of steam, the working fluid. The boiler feed water pumps deliver feed water to the boiler drum from where water is directed into the down comers and the circulating pumps located at the bottom of the boiler. The circulating pumps deliver the feed water to the distribution headers beneath the furnace sections. The water rises in the circuits, which are the vertical enclosing walls of the furnace. During combustion, the water walls absorb radiant heat in the furnace, boiling take place and a water-steam mixture (saturated steam) enters the drum, while the saturated water leaves the drum and enters the down comers.

Combustion takes place when fuel, most commonly a fossil fuel, reacts with the oxygen in the air to produce heat. The heat created by burning the fossil fuel is used in the operation of boilers, furnaces, kilns, and engines. Along with the heat, CO_2 (carbon dioxide) and H_2O (water) are created as by-products of the exothermic reaction.

By monitoring and regulating some of the gases in the stack or exhaust, it is easy to improve the combustion efficiency, which conserves fuel and lowers operation cost. Combustion efficiency deals with the calculation of how effectively the combustion process takes place. To achieve the highest levels of combustion efficiency, complete combustion should take place. Complete combustion occurs when all the energy in the fuel being burnt is extracted and none of the carbon and hydrogen compounds are left unburnt. Complete combustion will occur when proper amounts of fuel and air (fuel/air ratio) are mixed in correct proportion under the appropriate conditions of turbulence and temperature. Although theoretically stoichiometric combustion provides the perfect air to fuel ratio, which in turn lowers the losses and extracts all the energy from the fuel. In reality, stoichiometric combustion is unattainable due to many factors that are varying with respect to time. Heat losses are inevitable thus making cent percent efficiency impossible. In practice, to achieve complete combustion, it is necessary to increase the amount of air so as to ensure the complete burning of all the fuel. The amount of air that must be added to make the combustion complete is known as excess air. In most of the combustion processes, some additional chemicals are formed during the combustion reactions. Some of the products as a result of combustion process are CO (carbon monoxide), NO (nitric oxide), NO_2 (nitrogen dioxide), SO_2 (sulphur dioxide), soot, and ash. These flue gas emissions should be minimized and accurately measured. The EPA has set specific standards and regulations for emissions of these products, as they are harmful to the environment. Combustion analysis is a vital step to properly operate and control any combustion process in order to obtain the highest combustion efficiency accompanied by low flue gas emissions.

2. MOTIVATION OF THE RESEARCH

The colour of the combustion flames depends on the calorific value of the lignite (fuel) used for firing. The colour of the flame images in turn indicates the amount of air to be supplied so as to ensure complete combustion. When combustion process is incomplete the colour of the furnace flame is blackish due to the presence of unburnt carbon content. Offline analysis of the flame images with its corresponding flue gas emissions and combustion quality using indigenous image processing and intelligent algorithms has motivated this research work so that the information obtained from the colour of the flame images can be used for online monitoring which can be achieved by integrating these results with the Distributed Control Systems (DCS) for optimization of flue gas emissions at the furnace level.

3. OBJECTIVE OF THE WORK

The primary objective of this work is to develop an intelligent combustion quality monitoring system using flame image analysis by colour image processing at the furnace level. Conventional combustion control systems for multi-burner furnaces rely on simplified temperature measurement schemes away from the flame and monitoring of excess O_2, CO, CO_2, NO_x and SO_x emissions. According to the brightness value of flame image pixels, the combustion characteristic parameters are picked up from the flame image. The online monitoring of combustion quality and flue gas emissions using intelligent image processing technique thereby automatic adjustment of air/ fuel ratio can be achieved so as to ensure complete combustion.

4. LITERATURE REVIEW

A novel instrumentation system for deducing the two-dimensional (2-D) distribution of temperature across a cross section of a furnace fired with pulverized coal is proposed by Chun Lou et al [1]. Four coloured images were captured by the four detectors, which were mounted in the four corners of a tangentially fired furnace. Results obtained over a range of combustion conditions demonstrated that the average temperature of the cross section changed in direct proportion to the load of the furnace.

A dual silicon carbide photodiode chip was developed to determine the temperature of a natural gas combustion flame is discussed by Brown D.M et al [2]. Half portion of the chip was covered with a long pass multiple layer dielectric filters with a short wavelength cut off at about 315 nm. This is a feasible way of implementation and the sensor used for this type is a closed loop control system for gas turbines so as to maintain the emissions of NO_x within the admissible limits.

In this technique as proposed by Dale M. Brown et al [3], the measurements are done by observing the ultraviolet emission spectrum emitted from a natural gas flame taken over a range of flame temperatures using a fibre-optic/CCD spectrometer. This method is well suited for determining the CO and NO_x emissions in the exhaust hence qualified to monitor the temperature of premixed natural gas flames. Studies are required to determine how well this concept can be adapted for multiple nozzle combustors.

The neural network model has strong adaptability and learning capability, and is suitable for pattern classification. This concept is introduced for flame monitoring by Hyeon Bae et al [4]. Hence the recorded images were sorted according to operating conditions and were converted to gray scale images. The reconstructed data corresponding to the burner-on/off conditions showed definite differences, the neural network model offered superior recognition performance in using the projection data for the inputs to the model.

The three dimensional (3D) visualization and luminosity reconstruction of a combustion flame is proposed by G Gilabert et al [5]. A combination of image processing techniques and filtered-back projection algorithms is employed to reconstruct grey-scale sections of the flame from three 2D images taken by three identical CCD monochromatic cameras placed around the flame. The 3D visualization and reconstruction of the luminosity distribution of a combustion flame was used to identify the combustion quality.

An intelligent image processing technique for determination of complete combustion is proposed by M. Shakil et al [6]. The features are extracted and reduced using Principal Component Analysis (PCA) and the classification was with an intelligent classifier like dynamic neural networks so as to determine NO_x and O_2 emissions were determined from the flame status.

A combination of neural network with genetic algorithm was introduced to monitor the flame images. Time delay in the dynamic neural network was reduced using Genetic Algorithm (GA). A pattern recognition technique is proposed by R. Hernandez et al [7] to estimate the NO_x emissions.

The features extracted are filtered (median filter, average filter and self adaptive filters) to enhance the flame images that are used for testing the performance of the Self-Organizing feature Maps (SOM) which classifies the flame images as proposed by Fan Jiang et al [8]. Advanced flame and temperature measurement techniques include Laser Raman (LR)/Laser Rayleigh Scattering (RS), Fourier Transform Infrared (FTIR) Spectroscopy and interferometry along with the traces of smoke, small particles, gas streams and bubbles were used to visualize combustion phenomenon.

5. METHODOLOGY

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 separate conduits are mixed up in the proper ratio. The flame temperatures are measured using thermocouples. This gives the instantaneous values of the corresponding flame temperatures. Similarly the flue gases are measured using the gas analyzers which are very expensive.

The flame colour varies with respect to the carbon content in the coal. Moisture content of the coal is also very important as the calorific value of the coal directly depends on the moisture content [13]. The flame video was captured using an infrared camera. The flame video is then split up into the frames for further analysis. The Cannon video splitter is used for progressive extraction of the flame images from the video.

The images of the flame [15] are then pre-processed to reduce noise. Filtering is done using median filtering. The effects of various other filters for noise removal are also discussed. The flame image is a colour image; hence the intensity variation was studied by histogram technique corresponding to all the three planes (R-plane, G-plane and B-plane) [12]. Analysis proves that the median filtering eliminates noise to a greater extent when compared to the other type of the filters. Once the noise is removed edge detection was done to extract the features from the useful portion of the flame images.

The various features like average intensity, orientation, area of the high temperature flame, centroid, standard deviation, median, mode etc., were extracted. The tools used for feature extraction are MATLAB and Image J. The within class mean and the between class mean obtained from the Fisher's Linear Discriminant analysis (FLD) are also used as the inputs to the intelligent classifier.

The extracted features are then used for training the various conventional and intelligent classifiers. The features are reduced using Support Vector Machine (SVM) as well as Principal Component Analysis (PCA). Reduced feature set reduces the computational complexity of the classifiers. The feature reduction is done using WEKA [14] so as to obtain the ranking of the various features. The feature set or the number of features for testing is chosen based on the performance of the clustering and classification.

The conventional classification and clustering techniques include the Euclidean distance classifier (L2 norm classifier). The intelligent classifier includes the Radial Basis Function Network (RBF), Back Propagation Algorithm (BPA) and parallel architecture with RBF and BPA. The RBF uses Gaussian function as the activation function in the hidden layer nodes and linear activation function in the nodes of the output layer. The BPA uses sigmoid activation function in the nodes of the hidden layer and output layer. Similarly in the case of clustering various techniques like Meta clustering via classification and Bayes classifier are used for inferring the combustion quality from the colour of the flame images. MATLAB is used to implement the intelligent classifiers like RBF, BPA and parallel architecture with RBF and BPA MATLAB is used. Whereas for implementing the clustering algorithms a database management tool called WEKA was used. WEKA is a collection of machine learning algorithms for data mining. Choice of the intelligent techniques is substantiated with the index like, Mean Squared Error (MSE).

WEKA is a collection of machine learning algorithms for data mining. The modules of WEKA like explorer and knowledge base were used for inferring the flue gas emissions, flame temperature, air/fuel ratio and combustion quality. The similar set of output was also measured and MATLAB was used as the programming language. Totally hundred and two flame images were collected out of which fifty one flame images are used for training and remaining fifty one for testing respectively.

The testing of the various algorithms (RBF, BPA and parallel architecture of RBF and BPA) were done using MATLAB. Similarly testing the K-means clustering algorithm, Bayes classifier, RBF and MLP was also done using WEKA. The performance of the various algorithms are evaluated in terms of the number of instances correctly classified (% classification accuracy), number of instances incorrectly classified (%misclassification), confusion matrix, True Positive (TP), False Positive (FP), Precision, Recall, Region of Operating Characteristic (ROC) and F-measure. The values of the performance measures are found to be in the optimal range for the various intelligent techniques as compared with the conventional techniques. Finally validation of all the algorithms were done with the help of the flame images collected in a similar fashion as discussed earlier during some other period (different month and year). The results of the validation are supported with the above mentioned performance measures whose values are in the optimal range. The scope of the current research is shown in Fig.1.

The conventional methods discussed in various literatures have used the BPA for identifying the flame status inside the furnace. In another paper the Hidden Markov Model (HMM) was used to infer the quality of combustion. There is no information regarding the flue gas emissions. But in this work using various intelligent schemes the combustion quality and the flue gas emissions were inferred. Algorithms like linear regression, linear multi-nominal expression and constructed inference algorithms were used to find the amount of NO_x and CO emissions. The intelligent techniques include RBF, parallel architecture of BPA and RBF (with MATLAB) and SVM based feature reduction with MLP and RBF classifiers.

RBF classifier along with the discriminant vectors (Φ_1 and Φ_2), area, centroid X, centroid Y, area through equation, orientation, average intensity and rate area change for high temperature flame as the feature set proved to be beneficial for inferring the combustion quality and flue gas emissions corresponding to different class of furnace flame. Similarly the parallel architecture of RBF and BPA with seven features namely the area, centroid X, centroid Y, area through equation, orientation, average intensity and rate area change for high temperature proved to be efficient in inferring the combustion quality and flue gas emissions based on the colour flame images. Hence this method offers an economical intelligent feed forward control to minimize the flue gas emissions based on the colour of the furnace flame. The techniques are similar to pattern recognition of the flame images [9].

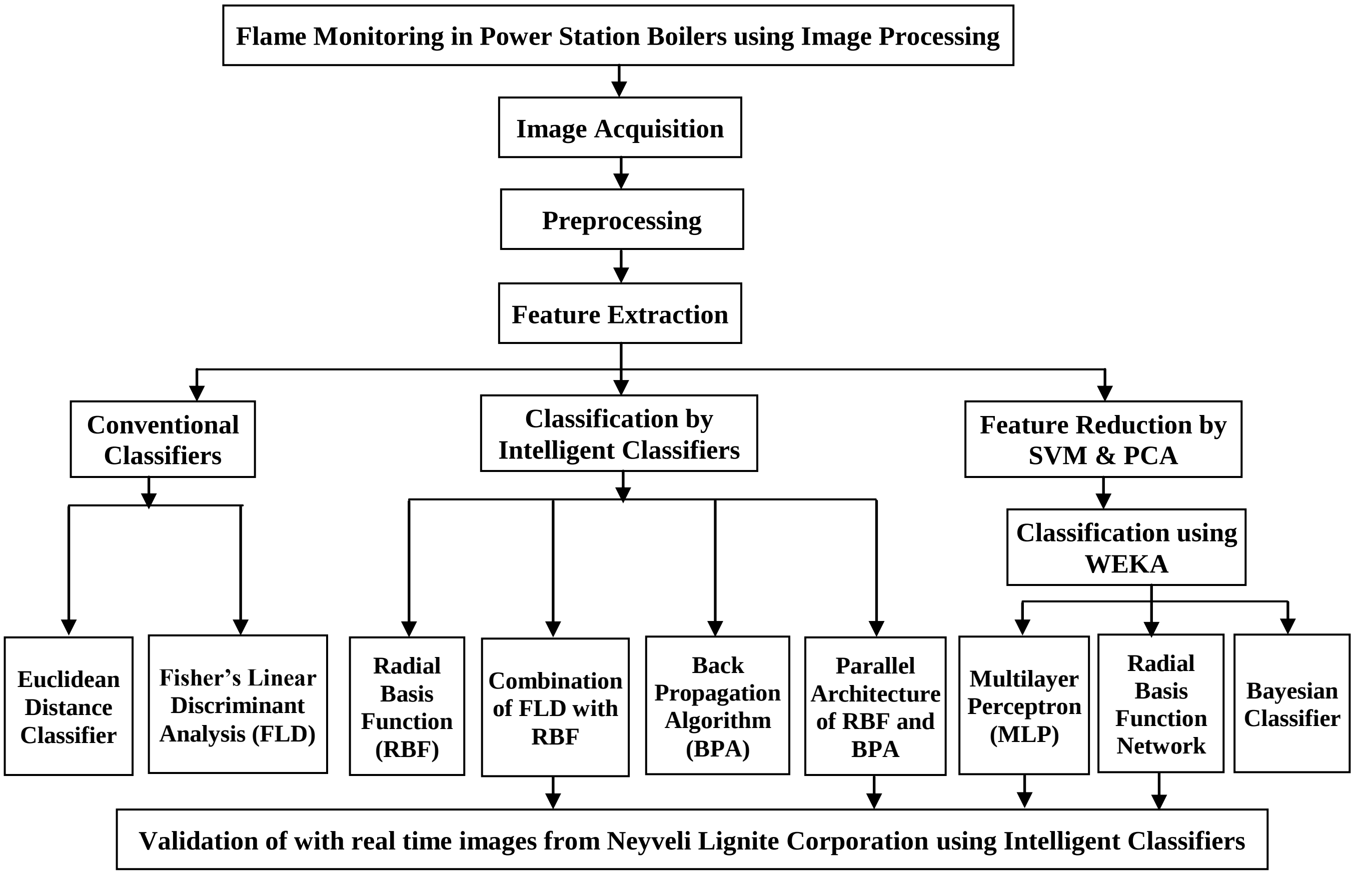

Fig.1. Scope of the work

6. EXISTING SETUP FOR CONTROL OF AIR TO FUEL RATIO AT NLC

The design of the boiler involves the energy balance between the fireside and the steam side parameters. The combustion takes place in the furnace when fuel and air get mixed up in proper ratio. The next monitoring point in the flue gas path is the temperature at the exit of the boiler. Flame is generated in the furnace when fuel and air from separated conduits are mixed up in a proper ratio. The flame generated is turbulent and can be looked straight and well-defined, which also refers to the flame oscillation. The temperatures of flame measured by thermocouples are the average values and the images of the flame will give instantaneous temperatures. The firing system at NLC is known as tangential firing system. Similarly the details of the boiler and the number of burners at NLC are given in Table.1.

Also, combustion monitoring involves boiler performance and optimization. The necessity to condition monitor the flame is to control emissions of nitrogen oxide (NO_x), carbon monoxide (CO), carbon dioxide (CO_2), increased fuel efficiency and improved burner reliability to maintain required furnace temperature. When the air to fuel ratio is incorrect, NO_x, CO_2 and CO emissions will increase at the outlet which in turn influences the flame temperature. For efficient combustion of different fuels the quality of the flame must be maintained in order to reduce air pollution and fuel consumption. Burner imbalances in coal, oil and air which results in low combustion efficiency, elevated emissions of nitrogen oxides (NO_x), carbon monoxide (CO), localized reducing conditions and promotion of slag formation. Differences from one burner to the next in combustion conditions are due to factors such as imbalances in air/fuel ratio and maintenance problems at individual burners. The existing set-up as shown in Fig.2 at NLC indicates only the presence or absence of the flame in the furnace.

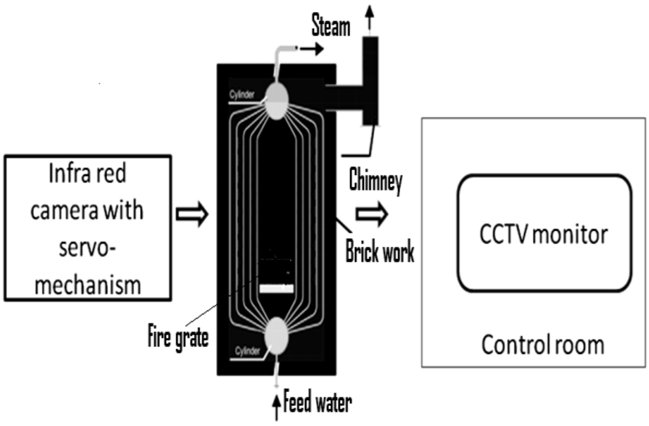

Fig.2. Existing set up for flame monitoring in boilers at NLC

Table.1. Boiler data at Neyveli Lignite Corporation (NLC)

Sl. No	Parameters	Specifications
1.	Type	Radiant tower
2.	Circulation	Natural
3.	Manufacture	Ansaldo Energia
4.	Boiler Design Pressure	182 kg/cm^2(a)
5.	Fuel	Lignite
6.	Start-up fuel	Light Diesel Oil – Heavy Fuel oil
7.	Burners type	Tangential Firing
8.	Number of burners	12 Lignite and 8 Fuel oil burners
9.	Mills type	Ventilation Mill MB 3400/900/490
10.	Number of Mills	6 numbers
11.	SH Flow at outlet	540 t/hr
12.	Temperature SH at outlet	540 degree Celsius
13.	Lignite fired-Best	189 t/hr
14.	Lignite fired-Average	213 t/hr
15.	Lignite fired-worst	230t/hr

Table.2. Measurement data for different combustion categories

Combustion Category	SO_x Emission mg/Nm^3	Temperature of superheated steam in (degree Celsius)	Combustion Quality (%)
Class 1 Complete combustion	400	530	100
Class 2 Partial combustion	600	240	50
Class 3 Incomplete combustion	900	170	30

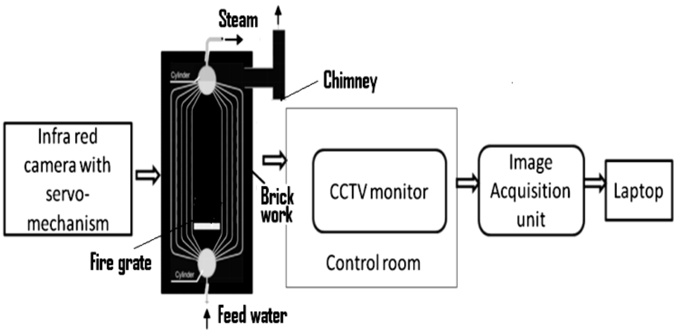

Fig.3. Proposed arrangement for intelligent flame monitoring system

Table.3. Measurement data for different combustion categories

NO_x mg/Nm^3	CO ppm	CO_2 Nm^3/hr	Flame Temperature in (degree Celsius)
70	100	400	1250
120	200	700	900
200	300	1000	300

Table.4. Sample Flame images

Class 1 Complete Combustion				
Class 2 Partial Combustion				
Class 3 Incomplete Combustion				

7. COMBUSTION MONITORING FROM FLAME IMAGES

The Maximum Posterior Marginal method (MPM) based on Hidden Markov Model (HMM) for recognition and classification of flame images are used to identify the complete combustion conditions. Another method based on edge detection and pattern recognition to identify the combustion conditions is also available. Even though it is possible to infer the flame temperature these techniques do not give information regarding the CO_2 and NO_x emissions in flue gases thereby providing a control of air/fuel ratio. The main objective is to design a flame monitoring expert system with progressive cameras, along with artificial intelligence techniques to identify flame features that can be correlated with air/fuel ratio, NO_x, CO, CO_2 emission levels, temperature, etc as shown in Fig.3. The 3D temperature profiler is designed to provide control of furnace and flame temperature which also reduces the flue gas emissions which is the key in achieving high combustion quality. The system is also designed to provide guidance for balancing air/fuel ratio so as to ensure complete combustion. The goal of on-line monitoring and controlled combustion is to address 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 geometry (size and location), i.e., the geometry of the burner (fixed), luminous (brightness and uniformity) and fluid-dynamics parameters (temperature) of a flame. Thus various intelligent inferential schemes to minimize the flue gas emissions for ensuring complete combustion using flame image analysis are proposed. These schemes have been validated on an industrial combustion chamber a variety of operation conditions. Table.2, Table.3 and Table.4 denotes the corresponding data with the flame images captured from the gas analyzers (offline).

8. COMBUSTION QUALITY AND FLUE GAS MONITORING IN POWER STATION BOILERS BY FLAME IMAGE ANALYSIS USING fld AND RBF

This section of the research work includes a combination of Fisher's linear discriminant (FLD) analysis and a radial basis network (RBN) for monitoring the combustion conditions for a coal fired boiler so as to allow control of the air/fuel ratio. For this, two dimensional flame images are required, which were captured with an infra-red camera; the features of the images - average intensity, area, brightness and orientation etc., of the flames are extracted after pre-processing the images. The FLD is applied to reduce the *n*-dimensional feature size to a two-dimensional feature size for faster learning of the RBF. Also, three classes of images corresponding to different burning conditions of the flames have been extracted from continuous video processing. In this, the corresponding temperatures, and the carbon monoxide (CO) emissions and those of other flue gases have been obtained through measurement. Further, the training and testing of Fisher's Linear Discriminant Radial Basis network (FLDRBF), with the data collected, have been carried out and the performance of the algorithms is presented. The classification performance is given in Table.5 below.

Table.5. Comparison of performance for FLD, RBF and FLDRBF Algorithms

Images	Number of images used for testing	Number of images classified		
		FLD	RBF	FLDRBF
Class 1	18	17	17	18
Class 2	20	18	18	20
Class 3	13	13	1	11
Total classified	51	48	36	49

9. COMBUSTION QUALITY AND FLUE GAS MONITORING USING PARALLEL ARCHITECTURE OF INTELLIGENT CLASSIFIERS

This part of the research work includes a combination of Fisher's Linear Discriminant (FLD) analysis by combining Radial Basis Function Network (RBF) [11] and Back Propagation Algorithm (BPA) [10] for monitoring the combustion conditions of a coal fired boiler so as to control the air/fuel ratio. For this two dimensional flame images are required which was captured with infra red camera whose features of the images, average intensity, area, brightness and orientation etc., of the flame are extracted after pre-processing the images. The FLD is applied to reduce the *n*-dimensional feature size to 2 dimensional feature size for faster learning of the RBF. Also three classes of images corresponding to different burning conditions of the flames have been extracted from a continuous video processing. In this the corresponding temperatures, the Carbon monoxide (CO) emissions and other flue gases have been obtained through measurement. Further the training and testing of Parallel architecture of Radial Basis Function and Back Propagation Algorithm (PRBFBPA) with the data collected have been done and the performance of the algorithm is presented.

Table.6. Performance metrics for classification by single and parallel multiple RBF Classifiers

Flue gas emissions	Category	Single RBF		Multiple RBF	
		Precision	Recall	Precision	Recall
CO, CO_2, SO_x and NO_x emissions	Class1	0.039	1	0.0789	1
	Class2	0.0196	1	0.196	1
	Class3	0	1	0.0392	1

The images are preprocessed and features are extracted. The extracted features are the input to Fisher's linear discriminant function to transform the *n*-dimensional feature size into 2D vector. Training of RBF and BPA was done with 51 images taken from class 1; class 2 and class 3 images and finally the outputs from these networks are combined and given as the input to another RBF so as to obtain the final output. Testing and validation results shown in Table.6 and Table.7 indicate that PRBFBPA gives maximum classification performance when compared to FLD, RBF and various other combinations of parallel architectures of the neural networks. Classification performance can be improved by further pre-processing of the acquired images. By continuously monitoring the flame images, combustion quality was inferred (complete/partial/incomplete combustion). From the combustion quality the air/fuel ratio can be automatically varied. Moreover in the existing set-up measurements like SO_x, NO_x, CO and CO_2 are inferred from the samples that are collected periodically or by using gas analyzers (expensive). The inferred parameters can be displayed in the centralized control room (cost effective solution). To conclude with there is a further scope to extend the work by considering the spectrum of the flame images.

Table.7. Performance metrics for classification by Parallel Intelligent classifiers

Flue gas emissions	Category	Multiple BPA		RBF+BPA	
		Precision	Recall	Precision	Recall
CO, CO_2, SO_x and NO_x emissions	Class1	0.039	1	1	1
	Class2	0.1176	1	0.894	1
	Class 3	0.0196	1	0.85	1

10. INTELLIGENT FLUE GAS MONITORING IN POWER STATION BOILERS

The last part of the research work which deals with monitoring of flue gas emissions is an intelligent technique for flue gas monitoring based on the colour of the flame images acquired from the furnace will be discussed here. A combination of image processing algorithms with Bayesian and intelligent classifiers are used to identify the flue gas emissions in order to ensure complete combustion. The features are extracted with Image J. The number of features is reduced using Support Vector Machine (SVM). The classification of the flame images was achieved from the selected features using both the intelligent and Bayesian classifiers. The intelligent classifiers were found to be beneficial compared to the Bayesian classifier to monitor the flue gas emissions at the furnace level.

The flame images are collected from the control room of a boiler in the power station where forty eight correct images are identified. The images are preprocessed, features are extracted which are reduced using SVM so as to reduce the computational complexity. Training the Bayesian, RBF and MLP classifiers was done with 39 images taken from class 1, class 2 and class 3. For testing the classifier's performance, 9 images are considered. Comparison of various algorithms during testing, indicate that the intelligent classifier gives maximum classification performance as compared to Bayesian classifier. The SVM feature reduction with intelligent classifier yields optimal values for true positive, false positive, recall and precision as shown in Table.8 and Table.9. Classification performance is also validated by cross validation. The proposed algorithm is used to provide an intelligent combustion quality monitoring technique in a feed forward manner thereby preventing excess emission of flue gases.

Table.8. Analysis for performance evaluation after testing the various classifiers

Name of Classifier	Specificity	Sensitivity	F-measure	ROC
MLP	1	1	1	1
RBF	1	1	1	1
Naives Bayes	0.76	0.76	0.8	0.861
Bayes net	0.76	0.76	0.8	0.861

Table.9. Analysis for performance evaluation after testing the various classifiers

Name of Classifier	Type I error	Type II error	Accuracy (%)
MLP	0	0	100
RBF	0	0	100
Naives Bayes	33.3%	33.3%	66.6
Bayes net	33.3%	33.3%	66.6

11. MAJOR FINDINGS FROM THIS RESEARCH WORK

The research highlights are as follows

- The combustion quality in power station boilers can be determined from the intensity of the flame images. The core of the fire ball is yellowish white during complete combustion.
- The colour of the furnace flame denotes whether the combustion is complete or incomplete
- The colour of the furnace flame also denotes the flue gases at the exhaust. Under complete combustion conditions the amount of flue gases like NO_x, SO_x, CO and CO_2 emissions are within the tolerance limit.
- The gas analyzers (Offline) used for measurement of various flue gases can be replaced by intelligent algorithms (Online).
- This image processing based flame monitoring system minimizes flue gas emissions at the furnace level thereby ensuring complete combustion.

12. CONCLUSION

Thus in this work, 102 flame images collected (51 for training and 51 for testing) from the control room for a boiler in the power station and forty nine images out of them were identified to be correct when FLDRBF. The images are pre-processed and features are extracted. The extracted features are the input to Fisher's linear discriminant function to transform the n-dimensional feature size into 2D vector. Training of RBF was done with 51 images taken from class 1, class 2 and class 3 images. Testing results indicate that FLDRBF gives maximum classification performance when compared to FLD and RBF. Classification performance can be improved by further pre-processing of the acquired images. The values of the temperature, NO_x, CO, CO_2 and air/fuel ratio were inferred corresponding to the flame images thereby indicating the necessary control action to increase or decrease the air supply so as to ensure complete combustion.

The extracted features used as the input to Fisher's linear discriminant function to transform the n-dimensional feature size into 2D vectors are also used for training the RBF and BPA with the same set of 51 images taken from class 1, class 2 and class 3 and finally the outputs from these networks are combined to form the parallel architecture and given as the inputs to another RBF so as to obtain the final output. Testing and validation results shown indicate that PRBFBPA gives maximum classification performance when compared to FLD, RBF and PRBFBPA. Classification performance can be improved by further pre-processing of the acquired images. Depending on the quality of combustion corresponding to the colour of the flame images necessary action is taken to increase or decrease the air supply so as to ensure complete combustion. In this work by continuously monitoring the flame images, combustion quality was inferred (complete/partial/incomplete combustion). From the combustion quality the air/fuel ratio can be automatically varied.

The features extracted are reduced using SVM so as to reduce the computational complexity. Training the RBF and MLP was done with 39 images taken from class 1, class 2 and class 3. For testing the classifier's performance, 9 images are considered. Comparison of various algorithms during testing, indicate that the intelligent classifier gives maximum classification performance as compared to Bayes classifier. The SVM feature reduction with intelligent classifier yields optimal values for true positive, false positive, recall and precision. Classification performance after training is also validated by cross validation. The proposed method can provide an inferential scheme for intelligent combustion quality monitoring thereby preventing excess emission of flue gases. Moreover in the existing setup measurements like SO_x, NO_x, CO and CO_2 are inferred from the samples that are collected periodically or by using gas analyzers (expensive). The proposed algorithms can be integrated with the Distributed Control System (DCS) that is used for automation of the power plant. The inferred parameters can be displayed in the centralized control room (cost effective solution). To conclude with there is a further scope to extend the work by considering the spectrum of the flame images.

13. SCOPE OF THE FUTURE WORK

There is further scope to extend this work by considering the spectrum of the flame images in the set of extracted features. This work has been carried out by only by collecting the flame images pertaining to three different combustion conditions like complete, partial and incomplete combustion conditions. The intermediate combustion conditions (like less partial, highly partial, less incomplete and highly incomplete) apart from complete condition can also be added to the source data so as to make the combustion condition and flue gas emission analysis more efficient. The integration of these simulation results with the DCS in real time for online monitoring of the flue gas emissions and combustion quality can also be carried out. Then the proposed intelligent algorithms can be used for the automation of the power plant. The inferred parameters are displayed in the centralized control room (cost effective solution).

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