A Review on Efficient Combustion with Multifarious Approaches for the O_2 Analysis in Boiler Section

K Ganpati Shrinivas Sharma[1,*], Dr.Surekha Bhusnur[2]

[1, 2] Department of Electronics & Telecommunication, Bhilai Institute of Technology, Durg,India
([*]Corresponding author's e-mail: ganpatishrinivas01@gmail.com)

Abstract - Efficient combustion is the essential part of a boiler section in a power plant. Various methods are identified for analysis of CO, NOx, and O_2 measurement in a coal-fired boiler. One of the approaches is Zr-O_2 sensor based method commonly used in an industrial furnace system. After extensive literature review, it has been concluded with the speculation in advanced modular furnace that it could not be operated below 0.8% excess in the critical modern furnace and did not depict improved efficiency. However, Various approaches have been used previously namely, Multilayer Deep Belief Network (DBN) flame image characterization, hybrid prediction model for oxygen content, CFD modeling for placement of measurement components, to define the furnace structure and position of the burner establishment, specific gravity analyzer, oxygen demand analyzer,TDL-O_2 Analyzer, Thermo Matrix Algorithm, etc. This paper presents a review of comprehensive technologies delineating the latest developments and trends especially in the Real-time Machine learning algorithms for Gas-Fired or **bagasse-based cogeneration power plant.**

Keywords: Thermo-gas Analyzer, Tunable diode laser (TDL), Thermal Furnace, Thermo Matrix Algorithm, Deep Belief Network

I. INTRODUCTION

In modern technology, many processes involve combustion wherein oxygen concentration is one of the critical issues in controlling the optimal performance of the process. Improving the efficiency of combustion and reducing pollutant formation is of paramount importance[1]. The combustion process is the main and essential part of the boiler section in industries, and it is possible to have an efficient process only with the exact air-fuel ratio[2]. Monitoring of oxygen concentration is crucial for executing proper air- fuel ratio[3][4]. Therefore it is essential to measure the exact value of oxygen with proper placement of an oxygen analyzer probe and an appropriate sensor to optimize boiler performance by using quintessential analysis in the field[5]. The problem encountered is to place the probe in the correct location, where accurate measurement of oxygen concentration is achieved. The recent research interest in this area is to upgrade the technology for designing the fuel cell for optimizing the boiler performance with the aid of analysis done by various software tools and soft computing techniques[6], namely, Computational fluid dynamics (CFD), MATLAB, Lab-Vie, Fuzzy, Neural techniques[7]–[10], etc. Modeling, image acquisition, and analysis can be conveniently made using these tools. Deep learning is applied to the furnace combustion process by obtaining color flame images through the charge-coupled device .Flame images are characterized by two DBN-based regression models that are simply constructed to obtain the nonlinear relationship between the flame images and the outlet oxygen content[11]. A novel deep belief network algorithm-based hybrid prediction model for boiler flue gases oxygen content is proposed[11]–[16]. First, the algorithm is used to build a model based on the historical data collected from the distribution control system. The variables are divided into control variables and state variables to meet the needs of advanced control requirements. Then, a lasso algorithm is used to select variables highly related to the oxygen content as the inputs of the prediction model[17]. Two basic models based on the deep belief network are established, using control variables and state variables. Finally, the two basic models are combined with a least square support vector machine to improve the prediction accuracy of the oxygen content of boiler flue gas[18].In most of the boiler applications, Zirconia analyzer has been used whose voltage output is higher for a lower oxygen content[19].

Also, there are some other sensors like TDL, paramagnetic sensors, etc. The main objective is to analyze the boiler conditions for different loading conditions, obtain the image set of oxygen concentration that leads to appropriate designing of the fuel cell/ sensor and its positioning for correct measurement of oxygen content[19], [20]. Improving the technique adds to several advantages like less fuel consumption, reducing greenhouse gas effects, increased boiler efficiency, etc., thereby contributing to the safety of the environment and society. In a steam boiler heating of fuels for generation of high-pressure steam to rotate blades of turbine is one of the most prominent

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sources of greenhouse gases emissions. To keep fuel ratio appropriate and to maintain apt O_2, NOx and CO levels is very crucial as it adversely affects the combustion process and efficiency of the furnace. In the previous research methods, various approaches are used to control and maintain the combustion process fuel and air ratio, measured by oxygen available in combustion. The efficiency of a furnace depends on the formation of emissions. In accordance with various particle sizes of fuel, variation occurs in Oxygen contents. The main aim of Flue gas O_2 content measurement and control is to be close to optimum levels. Temperature in a gas field boiler will be identifying with acquiring images in infrared region and calculate the collected data. By combining both images and their temperature values design a matrix algorithm by the method of thermo-gas imaging system and it can also be used to implement for NOx, and O2 level measurement below the previously identified [12], [21], [22].

II. COMBUSTION SYSTEM PREDICTION OF OXYGEN BY ACQUIRING FLAME IMAGES USING DBN

For obtaining multilevel abstraction, A Multilayer Architecture of a Deep Belief Network for multiple data is constructed[21]. Online flame image monitoring is less expensive with the help of digital image processing[22], by using CCD (charge-coupled device) cameras and flame-images, flame images can be directly obtained. That is, the flame images are received by a color CCD camera and digitized using the frame grabber[23]. The temperature distribution visualization of the flame in a gasifier was proposed by Yan et al. [24]. Draper et al. proposed an image-based method to obtain the total emissivity and the coal flame temperature. Gonzalez-Cencerrado et al. utilized the flame visualization[25].

In Figure 1 is a simple combustion process diagram, where Air and Fuel ratio are populated inside the furnace and high dimensional data corresponding to images of burning process required in Deep Learning-Based Modeling Framework are obtained. Deep learning methods have been applied to explore and analyze intricate structures in high-dimensional data (e.g., image and natural language). Interestingly, unlike traditional machine learning methods, unsupervised and supervised learning are properly integrated into a framework, yielding a semi-supervised model [26]

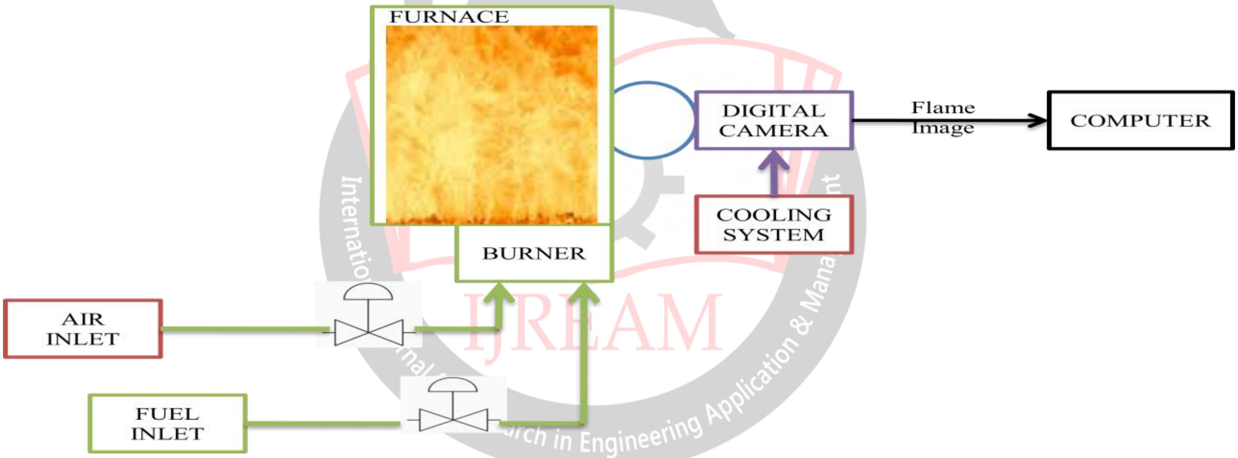

Figure 1 A Schematic Presentation of Field Boiler

.When deep learning is applied to regression problems, using the extracted features in the unsupervised learning stage, a regression model is established in the supervised learning stage[14][24].In illustrated cases, Four flame images of the combustion with different oxygen contents are shown in Figure 2.

			
Oxygen:- 3.3	Oxygen:-6.24	Oxygen:-7.9	Oxygen:-8.65
Temperature:- 768	Temperature:- 725	Temperature:-700	Temperature:- 685
Gas feed:- 19.44m^3	Gas feed:- 17.88m^3	Gas feed:- 14.47m^3	Gas feed:- 19.44m^3
Time:- 12:25PM	Time:- 12:37PM	Time:- 12:47PM	Time:- 12:54PM

Figure 2 Flame Images Along with their oxygen values

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In figure 2 images are acquired from a Gas fired boiler in jayaswals NECO Ltd. Siltara, Raipur in constant time at different temperature and also measured the level of Oxygen. As well as rate of gas feeding during the period.

In Fig.3 Flame images are captured in a furnace through CCD device and output flame images have some inherent relationships with oxygen contents in main modeling framework there are two learning model which is involved in the process known as Supervised and Unsupervised Learning both compared with extracted frame of images with oxygen content and calculate the prediction values.

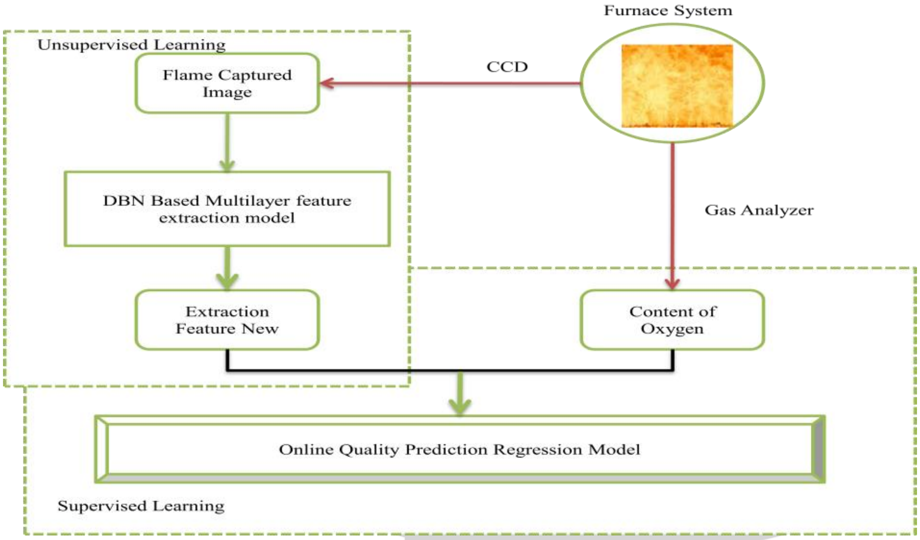

Figure 3 Online Prediction of Oxygen Content based on Deep Learning for flame image-based combustion

For example, a general trend can be obtained by manually observing the flame images. Additionally, several areas in the flame images contain only useless information or noise, such as the black background of the furnace and the gas pipeline. However, just through human experience, getting the quantitative relationship between the oxygen contents and the observed flame images is difficult. In practice, important features are more attractive to be learned from images automatically, rather than being designed by engineers in a cumbersome manner. Therefore, for the online prediction of the oxygen content, the deep learning method is used to construct a soft sensor system upon the flame images directly[27].

2.1 Frame Work of Deep Learning Based Model

In practice, crucial features are better learned from images automatically rather than being anticipated by design in a obscure manner. Predictions of Oxygen content are measured using soft sensor in deep learning method and analyzed through flame images[14][24].

Restricted Boltzmann Machine (RBM) method can be viewed as a nonlinear feature extraction method that can be used to curtail the data dimensions. The main modeling procedures of a DBN entails hierarchically constructed RBMs layers of flame images by successively stacking a series of RBMs as shown in Figure 4[28]. The outputs of previous RBM are used to train the next RBM in order. Vector 'v' and 'h' respectively represent the visible and hidden layers of RBM. In the training stage the hidden layer parameters are estimated using optimization of the probability model of the input. This is an unsupervised phenomenon as no target is involved. Every layer the flame images are mapped to various dimensions to obtain multilevel representation of images with an outcome of useful feature extraction.

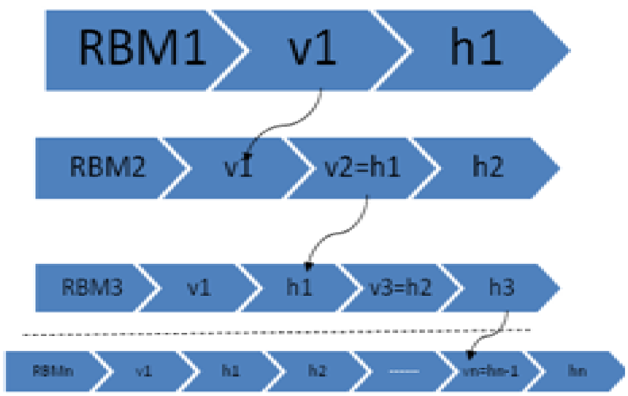

Figure 4 Simplified representation of RBM layers of a DBN

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To get features out of RGB color images of flame, rather than using a combined RGB big vector in DBN, it is beneficial to have three different channels for R, G and B of known size of the image with a sub-DBN structure separate for each and then stacking on top the complete DBN structure for feature representation.

In the subsequent step, after training the extracted features are correlated to the oxygen content using supervised techniques by constructing two regression models based on DBN with the aid of Back propagation and support vector machine algorithms[24].

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III. Boiler Flue Gas Oxygen Content Measurement by Deep Learning Model

In this technique, data are collected from the distributed control system, a hybrid model is developed which requires bifurcation of variables as state variables and control variables. To select the input variables of the prediction model, that are more relevant to the oxygen content, a LASSO algorithm is used. DBN based models are developed one each for state and control variables[29]. Least square support vector machine is used to enhance accuracy in oxygen content prediction with the aid of combination of the two models [31].

3.1 Process Analysis of Boiler

A Process is represented by two different set of variables namely, state variables and control variables.

Process Variable analysis is characterized by two quantities control variable and state variable, by the method of changing fuel quantity in the furnace for control of various control variables control valve opening by which fuel quantities are controlled 2nd one is state variable it automatically controls when control variable changes both variables are essential for the safety of workers during the combustion process[29][30].

The Following figure shows the production process of gas fired boiler

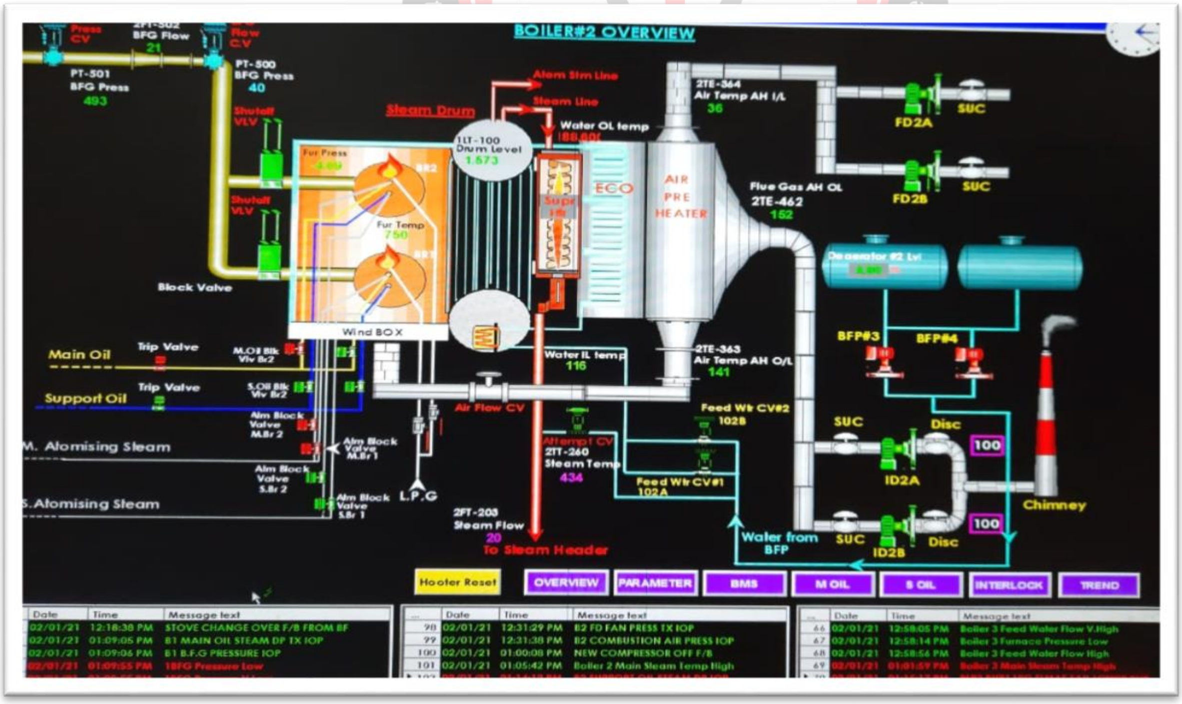

Figure 5 Image of Boiler Section reference from JNL Power Plant

With reference to jayaswals NECO Ltd. figure 5 represent the functional diagram of gas fired boiler section where Blast Furnace Gas used to be as a fuel in Power plant boiler , In boiler wind box, gases are supplied through pipeline and ignited through a burner section , two drums are connected in upper and lower chamber known as Mud Drum and Steam drum outlet

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of flue gas is fed to economizer and air pre-heater section through Air Flow Control Valve and this will be sucked by Force draft Fan and fed to Chimney section, various locking and interlocking system are available to maintain the pressure inside the boiler As well as required temperature, level and flow will also be maintain for proper functioning.

3.2 Selection of Input Variable: -For the Acquisition of input variable need **to** increase Computational time and decrease the prediction in this they used lasso algorithm to increase accuracy

3.3 Deep Belief Network Process Model: - it is a neural network based on brain neurons in which multiple restricted Boltzmann machines (RBMs) are stacked one by one to realize a back propagation (BP) neural network. The training method of the DBN firstly adopts unsupervised pre-training to initialize the parameters of the DBN model layer by layer. The data are inputted into the bottom layer of the DBN, which is the first visible RBM layer. Then, supervised fine-tuning is used to optimize the network structure[31]. The steps of DBN algorithm modeling are as follows:

Step 1: Divide the processed data into training and testing sets, and input the training sets at the bottom of the DBN.

Step 2: The DBN performs unsupervised pre-training. Randomly initialize the parameters of the network and set the layer node number of the DBN network

3.4 DBN Based Non-Linear Combined Prediction Model

During the operation of the coal-fired boiler, the oxygen content of the flue gas can be influenced by adjusting the total airflow, blower baffle opening, and so on. State variables, such as exhaust temperature and furnace temperature, also affect or reflect the oxygen content of the flue gas. The inputs of the control prediction model are fuel quantity, primary air flow, secondary airflow, blower flow, water supply flow, induced draft valve opening, and blower baffle opening, and the inputs of the state prediction model are negative furnace pressure, reheat steam temperature, furnace temperature, main steam flow, main steam temperature, unit load, exhaust temperature. The control prediction model and the state prediction model output the oxygen content of flue gas[32].

The DBN algorithm is applied to establish the control prediction model and state prediction model. The nonlinear combination of the control and state prediction models can provide the final combined prediction model, which reflects the influence of different operation parameters on the flue gasses, oxygen content of the flue gas, and allows us to obtain a more accurate prediction model. In this study, the Least Square Support Vector Machine is implemented to construct the final Non Linear Combined Deep Belief Network prediction model. First, the original process datasets are divided into training datasets and testing datasets. The training datasets are utilized for training the control and state prediction models. The control prediction model and the state prediction model are trained separately by using the training datasets[33].

Two predicted sub-models (Nonlinear combined prediction model and Control prediction model based on DBN) content of oxygen in flue gas combining into two dataset and LSSVM is applied to construct forecasting model used to verify accuracy of prediction and store the model parameter

Lasso-based feature selection can accurately select input variables with strong correlation, and also has the stability of variable selection. Therefore, lasso has significance for variable selection. The control variables and state variables are selected according to a lasso-based feature selection algorithm, respectively. 7 control variables and 7 state variables were chosen as input variables for establishing the control prediction model and the state prediction model[34].

Step 1: This step involves data pre-processing. Standardize the original process data using the Z-score method.

Step 2: Divide the input variables into the control variables and state variables. The features selection of the control variables and the state variables using the lasso

Step 3: Train the DBN model using the training datasets of the control variables and state variables, and obtain the control prediction model and the state prediction model, respectively.

Step 4: Obtain the NCDBN model by a nonlinear combination of the control and state prediction models. For the nonlinear combination method the relevance can be found in these references[33][35].

IV. OXYGEN MEASUREMENT USING POTENTIOMETER ZIRCONIA SENSOR

All Industries use Zirconia based Oxygen Sensor, and it is electrochemical cell which has solid electrolyte and two platinum-based electrodes, sintered on the opposite sides of the zirconia ceramic exposed to the process and reference gases[36][37][38][39][40][41].

Potential difference is generated across the reference electrodes according to the nernst equations[42]

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$E = \frac{RT}{UF} \ln \frac{p(O2)process}{p(O2)ref}$…………. (1)

R= Universal Gas Constant

F= Faraday Constant

T= Process Temperature

Oxygen reduction, as well as oxidation process, will take place.

Oxygen balance will depend on thermal Condition, and Oxygen Sensor operates at elevated temperatures

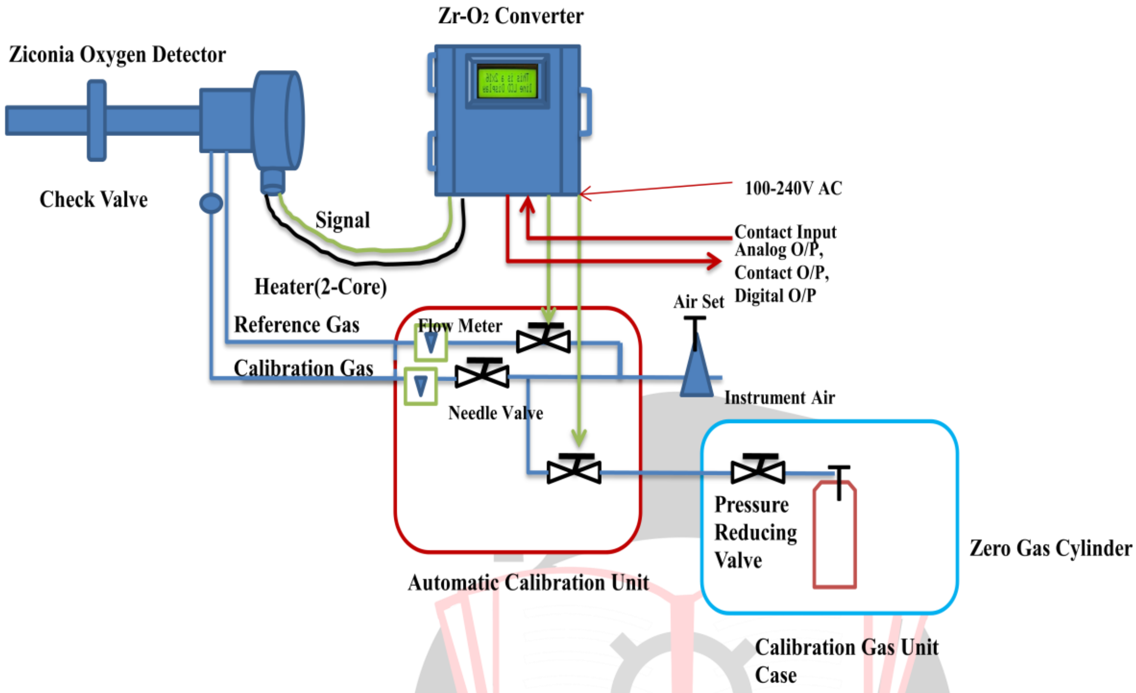

Figure 6 Functional Diagram of Zirconia- Oxygen Analyzer[43]

Zirconia element electrolyte process will perform at temperatures more than 300˚C.

In fig. 6 It consist one Analyzer and one detector where externally reference gas and calibrated gases are introduce through external calibration gas unit ,In a high degree of temperature in Zirconia element gases are oxidized and attracted of O_2 molecules present in flue gases. Along with this Oxidized value will display in Indicator. The Zirconia analyzer is a ceramic based sensor with two electrodes fastened at the two ends of an electrolyte tube. It is aptly placed inside the furnace. At controlled operating temperature, electricity is conducted using difference in oxygen partial pressures at the electrodes. This results in an EMF which can be measured, thus as depicted by Nernst equation, as the partial pressure of reference gas is known, the oxygen partial pressure of sample can be calculated and hence oxygen concentration. It can measure 100 ppm to 1 ppm of O_2.By this method, Process reliability and efficiency is improved. This design is placed in Economizer and pre-heater section where the flue waste gas temperature is about to 250˚ - 300˚C.This sensor befits a wide range of oxygen concentration measurements except that it may give inaccurate reading if the gases it is subjected to consists of halogens and sulfur compounds

Various other methods are reported in this reference[36].

V. TDLS (TUNABLE DIODE LASER SPECTROSCOPY TECHNIQUE)

It is based on optical Measurement techniques by use of Semiconductor lasers to detect various gases in the chamber, including oxygen near the infrared range. A Longer Optical path provide higher absorption, high resolution and high performance and it doesn't need any calibration to provide higher performance and efficient performance [44].
In this method of TDL Analyzer, wavelength modulation spectroscopy is applied for measurement, it will scan a very narrow band absorption spectrum by injecting current through laser using a non-intrusive measurement of gases in the environment[45].Laser diodes are designed to measure a selective range of wavelength between 0.70 to 1.70µm. Molecular absorption level is weaker near IR wavelength in higher absorption are archived only by Using Special type of fibres photonic Core band gap.

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As light passes through the beam tube where gases are interact with glass-gas surface where micro-spheres Q factors in glass is very high and it will increase absorption sensitivity of gas molecules.

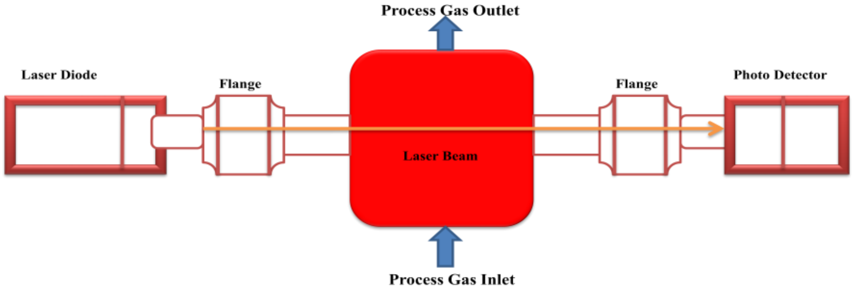

Figure 7 Process Flow Diagram of TDLS Technique[20]

TDL O_2 Analyzer provides real time data of concerned gas without contact of any media. Gas analysis is performed in the duct, variation of oxygen measured within 0-5% Concentration range. Fibre optic path used in TDL analyzer to limit their sensitivity to 500 ppm[45].

TDL O_2 Analyzer performs at temperatures more than 100˚ temperature.

VI. OXYGEN GAS SENSING BY PARAMAGNETIC TECHNOLOGY

In this paramagnetic sensing technology a strong magnetic field is produced in the chamber, where paramagnetic gas is attracted to paramagnetic gas (two unpaired electrons with Oxygen). Measurement technology is applied in 3 different methods.

1) Non Contact Quinke Method
2) Thermo Magnetic Method
3) Magnetic Dynamic Method

Magneto dynamic method works on magnetic pressure. This device consists of 2 nitrogen filled glass spheres mounted on rotating suspension. When oxygen enters in strong magnetic field oxygen molecules will push the pressure a side and cause the suspending wire to be twisted.

This twist is detected as the movement of light from reflective mirror that is secured at centre of suspended wire, the output from photo sensor is fed back to a coil around suspension assembly restoring the torque to original zero position. Oxygen partial pressure in magnetic field is directly proportional to current that gives accurate value of oxygen[46].

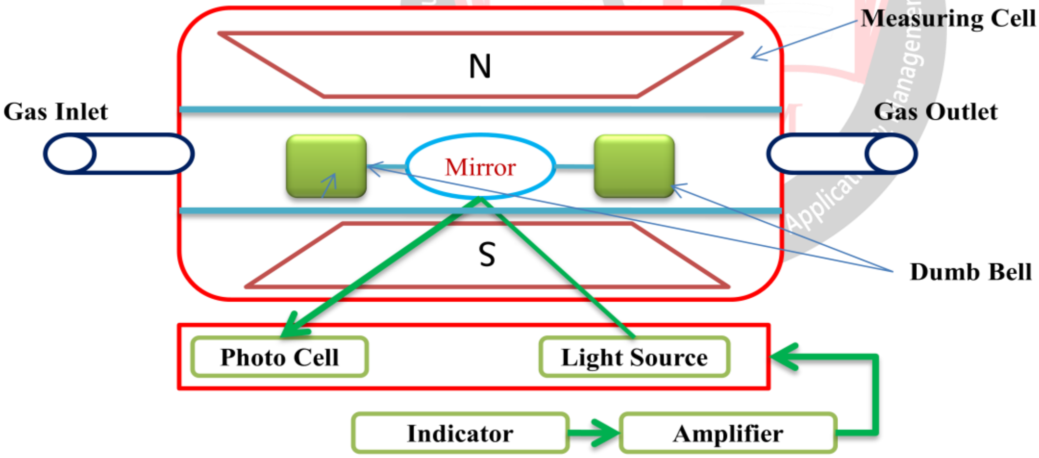

Figure 8 Paramagnetic Gas Sensing Technique[47]

7. Thermo Magnetic O_2-Sensor – In this technique, two Chambers containing one heating wire element located at the centre of chamber are involved. The magnetic field exists in measurement chamber, sample gas is fed to the chamber and oxygen molecules are attracted to magnetic field and heated by heating wire element and flow of magnetic field cool the wire of heating element, intensity of heating is proportional to oxygen content available inside the chamber[48].

7.1Quincke O_2 detector -It utilizes a pneumatic Wheatstone bridge for measurement using differential pressure flow to determine oxygen concentration.

Reference gas, as well as sample gas, is introduced in two different chambers, where reference gas is recombined at the outlet section by dividing it in two paths of flows. A magnetic field is in one arm of the reference gas outlet and creates a back pressure due to presence of oxygen in gas sample along with this, oxygen molecules in the gas are measured and the Range of paramagnetic O_2 Sensor is measured about to 0.05% to 100%.

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Major disadvantages are high cost, low stability in vibration and limited temperature range between 120˚C - 145˚C. and it is used in some petrochemical, chemical and cement industries[49].

VII. Liquid Electrolyte Amperometric Oxygen Sensing Technology

In this method, oxygen measuring instruments contain electrochemical sensor and it is a type of metal air battery with the diffusion-limited barrier type device containing consumable lead anode and cathode. Oxygen sensor generates current which is proportional to oxygen diffusion to the cathode which is limited by diffusion film or capillary barrier and it is prepared by thin, low-porosity Teflon membranes. Membranes perform the function of filter and transfer the proper amount of gas molecules to the device[50][51].

Molecules of gas are reaching to the electrode. Oxygen in contact with cathode is reduced to Di-hydroxyl ions due to balancing reaction of lead oxidation at anode:

$$\text{Cathode: } O_2 + 2H_2O + 4e^- = 4OH^-$$

$$\text{Anode : } 2Pb + 4OH^- \rightarrow 2PbO + 2H_2O + 4e^-$$

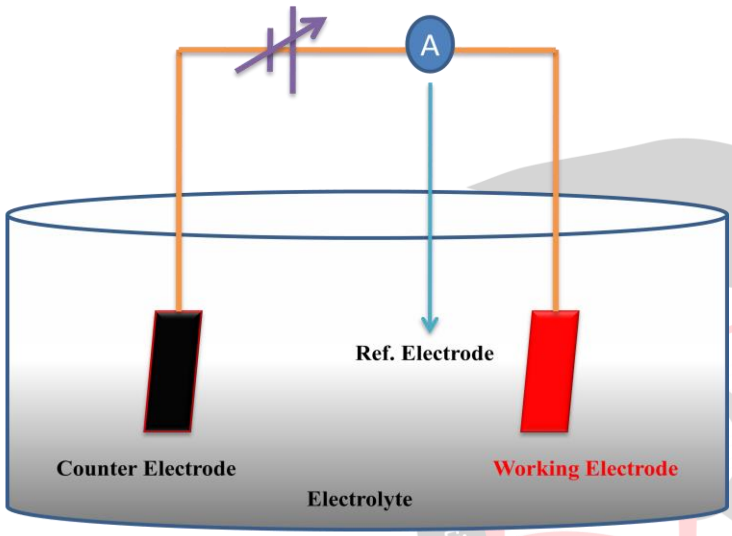

Figure 9 Electrolyte Amperometric Oxygen Sensor

In Fig. 9, the amperometric sensor is placed inside of high concentrate dissolves analytic solution isolating circuit consists of a Working Electrode, counter electrode, and Reference Electrode.

VIII. Conclusion

To maintain the efficiency of the boiler in bagasse plant or gas-fired boiler is the first priority in relevant industry. As maintaining the ratio of air/fuel is the most essential part to increase boiler efficiency, calculation of parameters and prediction of oxygen are of paramount importance for long life of boiler and reduced fuel consumption. In this paper various techniques of oxygen analysis, namely methods using Zr-O_2Analyzer, TDLS Analyzer, Amperometric analysis , Ferromagnetic type O_2 Analysis etc., have been summarized. Now the advancements are taking place by installing CCD module to monitor flame images and calibrating them to enable prediction of oxygen concentration with a soft sensor DBN neural network. For non-linear process, DBN based model is highly efficient, by taking practical data, best result is acquired in 2D images for the prediction of oxygen contents DBN algorithm tool and advanced control algorithm tool can also be applied in Bagasse or Gas fired boiler to predict oxygen and save fuel and energy in a similar manner. In this paper the reader can have bird's-eye view with respect to multifarious approaches of analyzing oxygen content in furnace/ boiler sections.

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