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Combustion Optimization at Duke Energy's Gibson Station

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Abstract: Combustion optimization has been deployed on a 670 MW wall fired unit at Duke Energy's Gibson Generating Station. The goals achieved by the deployment include 1) control of NO_x to a desired setpoint, 2) balancing of combustion and reheat steam temperatures across the boiler, and 3) maximization of boiler efficiency. The combustion optimization approach is based upon building a dynamic model of the unit that represents the effects of changes in manipulated variables, such as O_2 bias, burner register biases, over-fire air register biases, and fuel burner biases, on a set of controlled variables including NO_x, O_2 profile, and reheat steam temperatures. An optimizer uses the dynamic model to control NO_x and maximize boiler efficiency while maintaining safety and operational constraints such as excess O_2 and reheat temperature profiles. To provide prompt response to external, unmeasured changes (such as changes in fuel characteristics or ambient conditions), an adaptive feedback algorithm updates the models every 30 seconds. The combustion optimization system uses the updated models to compute new set points or biases for the manipulated variables at each execution to achieve the desired goals while also respecting operational constraints. The underlying combustion optimization technology, its implementation, and operational results are presented.

1.0 Introduction

A power plant furnace is a complex environment where power generation must be balanced with both equipment and environmental constraints. Nitrogen oxides (NO_x) are formed in the power plant furnace and emitted to the atmosphere in the exit flue gas. The level of NO_x formation is dependent upon 1) the local fuel/air stoichiometry in the furnace, 2) burner configuration, and 3) the nitrogen content of the fuel [1]. Unit 2 at Duke Energy's Gibson Generating Station has been equipped with low NO_x burners, over-fire air, and a Selective Catalytic Reduction (SCR) system for NO_x reduction.

The combination of these technologies introduces combustion imbalances to the process, which are difficult for the operator to control. This is particularly true for Gibson Unit 2, which is used for regulation and changes load frequently. The combustion imbalances for this unit are indicated by imbalances in the oxygen analyzer profile and the reheat temperatures. The potential adverse consequences of the combustion imbalances include increased fouling/slagging and corrosion due to localized oxygen deprivation in the furnace and lower reheat temperatures (with a corresponding loss of boiler efficiency). NO_x control is also an important objective, as it stabilizes SCR operation.

A combustion optimization system has been deployed on Unit 2 to address the combustion imbalance issues while maintaining control of furnace NO_x emissions and respecting other equipment constraints (such as average oxygen and fan limitations).

Previously, significant NO_x reductions have been reported for coal fired units using a combination of neural network modeling approaches and nonlinear optimization techniques [2,3,4]. This paper presents results from implementation of combustion optimization to balance oxygen profile and steam temperatures while respecting operational constraints and maintaining, (rather than minimizing) NO_x generation in the furnace.

The next section of this paper describes the need for combustion optimization in this application. The third section presents the combustion optimization technology used on this project. The fourth section presents results, and the final section provides a conclusion.

2.0 The Need for Combustion Optimization

NO_x generation in the furnace is controlled by adjusting over-fire air registers, burner air registers, and excess oxygen. Operational constraints on slagging/fouling and corrosion limit how far excess oxygen can be reduced for this unit. The combustion process (indicated by the individual oxygen analyzer readings) and the reheat steam temperatures are balanced by manipulating the over-fire air registers and the burner registers. Any changes in register positions to balance the combustion or reheat steam temperatures must be made such that the furnace NOx generation remains at its target value.

The problem of balancing combustion and reheat steam temperatures in conjunction with NO_x control is made more challenging because the relationships between the variables constantly shift due to disturbances such as changes in fuel characteristics, boiler conditions, mill conditions, and ambient conditions. For example, changes in the nitrogen content of the fuel cause the furnace outlet NO_x to change. Responding to this change in NO_x can affect both combustion balance and reheat temperature balance.

Because the relationships shift for a given load, it is not possible to determine a single optimal operating point for excess oxygen and register positions at a given load. Furthermore, as load changes, it is not possible to determine a single optimal curve for these variables as a function of load.

Reheat steam temperature balance adds to the complexity of the problem. There are two reheat steam temperature measurements (east and west). The DCS controls the maximum reheat steam temperature by adjusting reheat and superheat damper positions. Balancing the reheat temperatures allows the DCS to increase the average reheat steam temperature and improve boiler efficiency while reducing thermal stress on the equipment. The interaction of the burner and over-fire air registers with reheat steam temperatures and combustion balance make this a problem that is difficult for the plant operators to address because it requires frequent adjustments in response to multiple objectives. Safety constraints on reheat steam temperatures further complicate the problem. A high reheat steam temperature requires quick response to prevent it from exceeding maximum allowed value.

To balance combustion and steam temperatures while controlling NO_x requires a system that recognizes the current operating conditions of the furnace and constantly updates the excess oxygen set point and air register positions based upon these conditions. Instead of using a fixed curve that is a function of load, the curve is constantly recomputed based upon a known model of the process and current process values.

Finally, because individual oxygen readings and reheat steam temperatures can change significantly in less than a minute due to disturbances such as changes in fuel characteristics, the set points of the manipulated variables need to be update every 30 seconds to guarantee optimal performance. Thus, an optimization system that incorporates a model of the furnace that is updated frequently (every 30 seconds) is needed to solve this problem. The combustion optimization system used to solve this problem at Gibson Unit 2 is described in the next section.

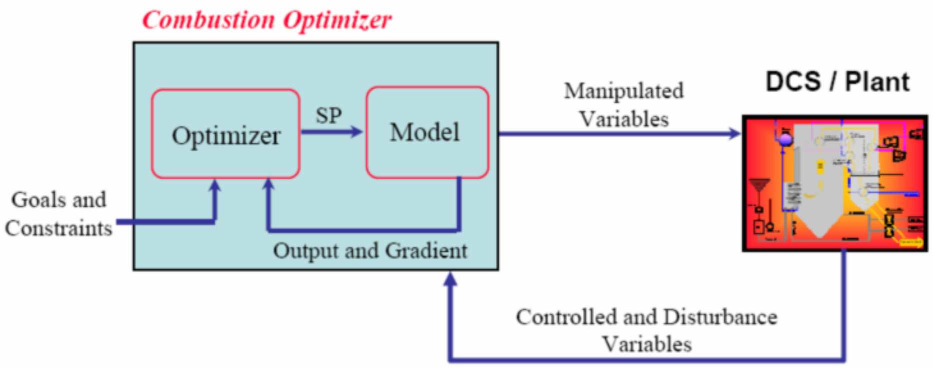

Figure 1: Overview of a combustion optimization system connected to a DCS/plant.

3.0 Combustion Optimization System

Figure 1 shows an overview of the combustion optimization system that is used to control Gibson Unit 2. The optimization system, which was installed on a separate computer, communicates directly with the DCS.

The optimization system reads the current values of the manipulated variables and controlled variable through this link every 30 seconds. It also reads the current values of any measured disturbance variables such as load or ambient conditions. (Disturbance variables are variables that affect the controlled variables but cannot be manipulated by the operator.)

As described below, the optimization system computes an optimal set of set points for the manipulated variables based upon current conditions and sends these to the DCS. The operator determines which manipulated variables the combustion optimization system is allowed to adjust. Thus, the optimization system runs in closed loop adjusting the manipulated variables every 30 seconds.

The optimization system shown in Figure 1 contains two components, an optimizer and a model. The model is used to represent the relationship between the manipulated/disturbance variables and the controlled variables. The optimizer is used to compute the optimal set of manipulated variables for the desired goals of balancing combustion, balancing reheat steam temperatures, and controlling NO_x production in the furnace. Both the model and optimizer are described in further detail below.

3.1 Nonlinear Dynamic Model

To properly capture the relationship between the manipulated/disturbance variables and the controlled variables, the model of the furnace has the following characteristics:

- **Nonlinearity:** A nonlinear model is capable of representing a curve rather than a straight line relationship between manipulated/disturbance and controlled variables. For example, a nonlinear, curved relationship is often observed between over-fire air dampers and NO_x.
- **Multiple Input Multiple Output (MIMO):** The model must be capable of capturing the relationships between multiple inputs (manipulated/disturbance variables) and multiple outputs (controlled variables).
- **Dynamic:** Changes in the inputs do not instantaneously affect the outputs. Rather there is a time delay and follow by a dynamic response to the changes. It may take 15-30 minutes for changes in the inputs to fully propagate through the system. Because the

optimization systems executes every 30 seconds, the model must represent the effects of these changes over time and take them into account. Because the process dynamics are also a function of load, the model must also account for nonlinearity in the dynamics.

- **Adaptive:** The models must be updated at each optimization cycle (every 30 seconds) to reflect the current operating conditions of the furnace.
- **Derived from Empirical Data:** Because each furnace is unique, the model must be derived from empirical data obtained from the plant. (First principles based models are too expensive to develop and are often not accurate enough or able to run fast enough to use for on-line optimization.)

Given these requirements, a neural network based approach is the best available technology for implementing the models. Neural networks are developed based upon empirical data using advanced regression algorithms [5]. Neural networks are capable of capturing the nonlinearity commonly exhibited by boilers. Neural networks can also be used to represent systems with multiple inputs and outputs. In addition, neural networks can be updated using either feedback biasing or on-line adaptive learning.

Dynamic models can also be implemented in a neural network based structure. A variety of different types of model architectures have been used for implementation of dynamic neural networks [6-7]. However, many of these structures require a large amount of data to successfully train the dynamic neural network. A novel neural network structure, which may be trained using a relatively small amount of data, was developed in the late 1990's and has been used on a variety of projects. Complete details on the dynamic neural network based structure may be found in [8].

Given a model of the furnace, it is possible to compute the effects of changes in the manipulated variables on the controlled variables. Furthermore, since the model is dynamic, it is possible to compute the effects of changes in the manipulated variables over a future time horizon (multiple changes rather than a single change).

If the relationships between inputs and outputs are well represented by the model described above, an optimizer is then required to calculate the values for the inputs needed to achieve the goals while observing the constraints? The next section describes this approach.

3.2 Optimizer

An optimizer is used to minimize a cost function subject to a set of constraints. The cost function is a mathematical representation of the desired goal. For this implementation, the cost function includes terms for combustion balance (indicated by oxygen analyzer readings), reheat steam temperature balance, maximum individual reheat steam temperature, and NO_x target.

Because the model is dynamic, the effects of changes must be taken into account over a future time horizon. Therefore, the cost function includes terms over a future horizon of one hour, which is typical for combustion optimization. Because the model is used to predict over a time horizon, this approach is commonly referred to as model predictive control (MPC) [9].

Constraints may be placed upon both the inputs and outputs of the process over the future time horizon. Typically, constraints on the inputs are consistent with the DCS limits for these manipulated variables. Constraints on the outputs are determined by the problem formulation. For this application, constraints are placed on the reheat steam temperature difference and individual reheat steam temperatures.

Because a nonlinear model is used to compute the relationship between the inputs and outputs of the furnace, a nonlinear programming optimizer is used to solve the optimization problem. This dynamic optimizer could run every 30 seconds for this problem formulation. More details on the formulation of the cost function and constraints are presented in [8].

The optimizer computes the full trajectory of manipulated variable moves over the future time horizon (one hour for this application). For an optimization system that executes every 30 seconds, 120 values are computed over a one hour future time horizon for each manipulated variable. Because the model or goals/constraints may change before the next optimization cycle, only the first value in the time horizon for each manipulated variable is output by the combustion optimization system to the DCS as a set point.

At the next optimization cycle (30 seconds later), the model is updated based upon the current conditions of the furnace. The cost function and constraints are updated if they have changed. (Normally, the cost function and constraints are not changed.) The optimizer then recomputes the manipulated variables over the time horizon and outputs the first value in the time horizon to the DCS. The combustion optimization system repeats this cycle at each time interval, thus, constantly addressing the operating objectives as the boiler is affected by changes in load, ambient conditions, boiler conditions, and fuel characteristics. As described in the next section, this approach significantly improves reheat steam temperature control and combustion balance while maintaining the NO_x emissions generated in the furnace at a desired target.

4.0 Results

The application was initially commissioned in April 2006 and has been operating in closed loop control over 90% of the time since April 15, 2006. Figure 2 shows utilization over a 10 week period from April 16, 2006 to June 25, 2006. Utilization for this period averaged 96%, indicating excellent acceptance of the combustion optimization system by the unit operators.

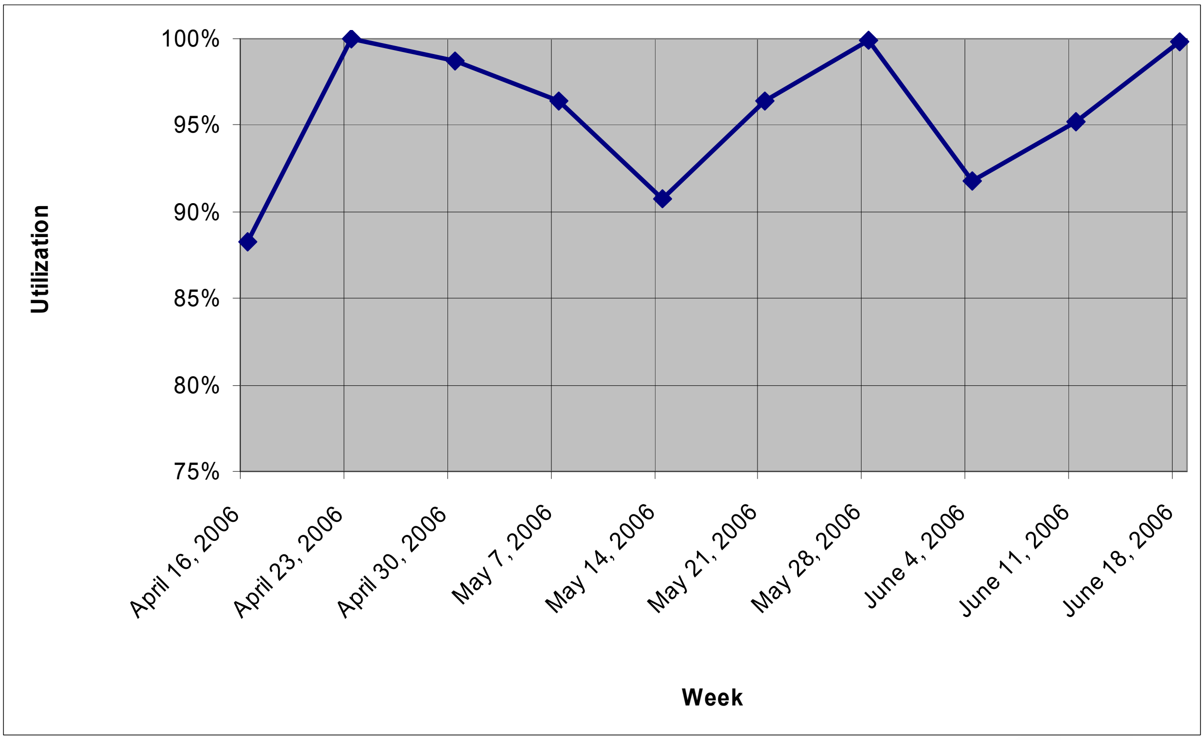

Figure 2: Combustion Optimization System Utilization from April 16, 2006 to June 25, 2006.

Figure 3 shows the average reheat steam temperature distribution for comparable 8-week periods without combustion optimization (May 1, 2005 to June 26, 2005) and with combustion optimization (April 30, 2006 to June 25, 2006). Average reheat steam temperature increased by 3.5 °F with combustion optimization. Average reheat steam temperature excursions above 1020 °F have decreased by 81% (from 0.046% to 0.009% of the time for the corresponding 8-week periods).

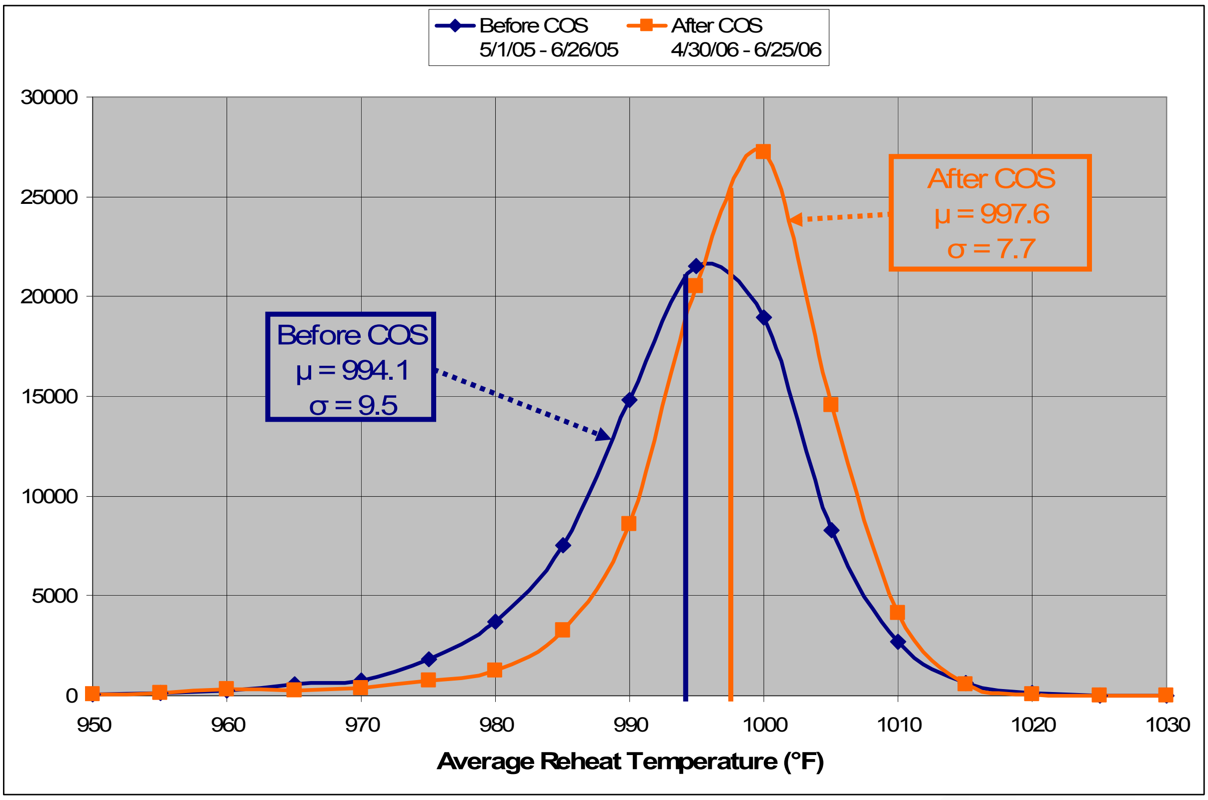

Figure 3: Average Reheat Steam Temperature (°F) Distribution for Gibson Unit 2.

Figures 4 - 7 show the offset of each oxygen analyzer from target. The reductions in standard deviation for each analyzer offset were:

Analyzer	Reduction
A	45%
B	38%
C	28%
D	66%

The reductions in variation show improved control of the oxygen profile in the unit. The Gibson Unit 2 combustion optimization system has shown the ability balance combustion or balance reheat steam temperatures independently. However, these two objectives are often in conflict. The desired oxygen profile is +0.30% on the outer analyzers (A and D) and -0.30% on the inner analyzers (B and C). To achieve this profile, the reheat steam temperatures would be driven too far apart, resulting in both a loss in efficiency and added thermal stress on the reheat steam header. Similarly, reheat steam temperatures can be totally balanced, but this would result in low oxygen values on analyzer B, which can result in a localized increase in fouling/slagging as well as excessive water wall corrosion. Figures 3 - 7 show how the combustion optimization system has balanced the need to keep reheat steam temperatures within 15 °F of each other while avoiding localized low oxygen values.

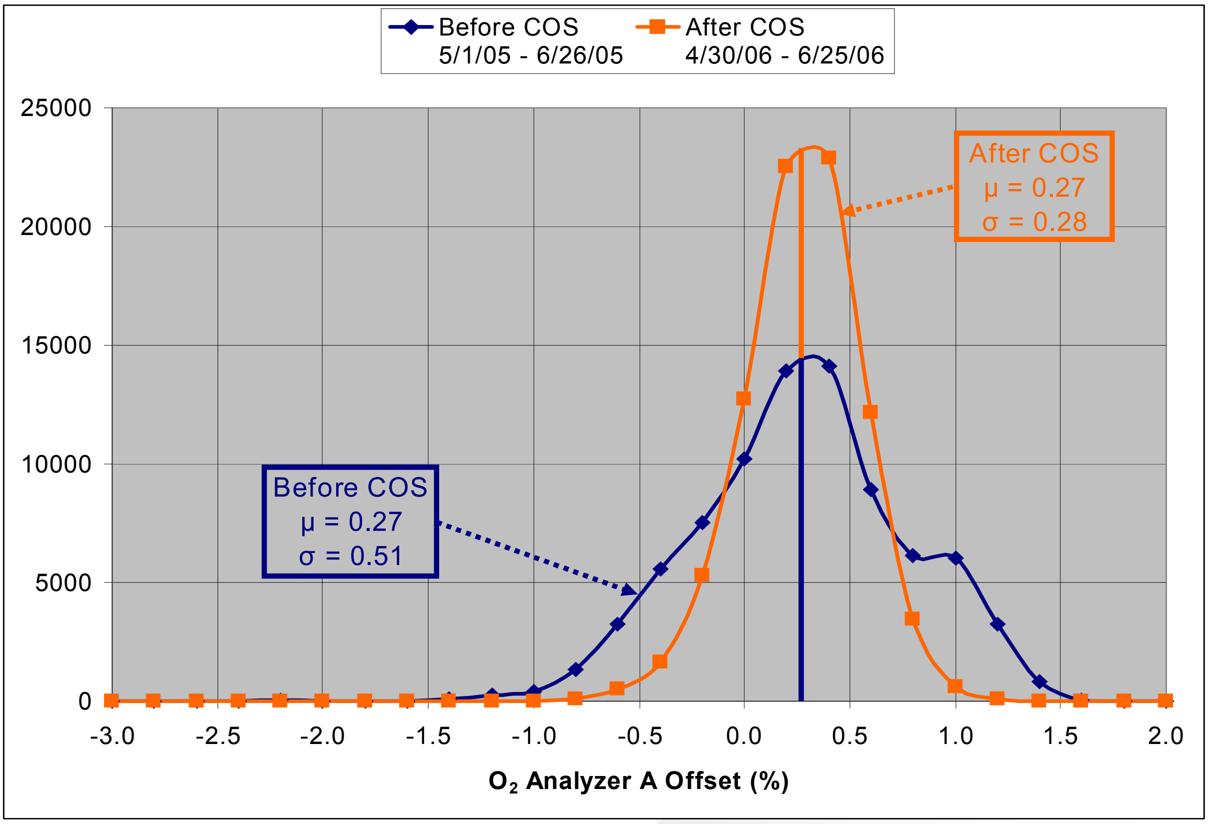

Figure 4: Oxygen Analyzer A Offset from Setpoint (%) for Gibson Unit 2.

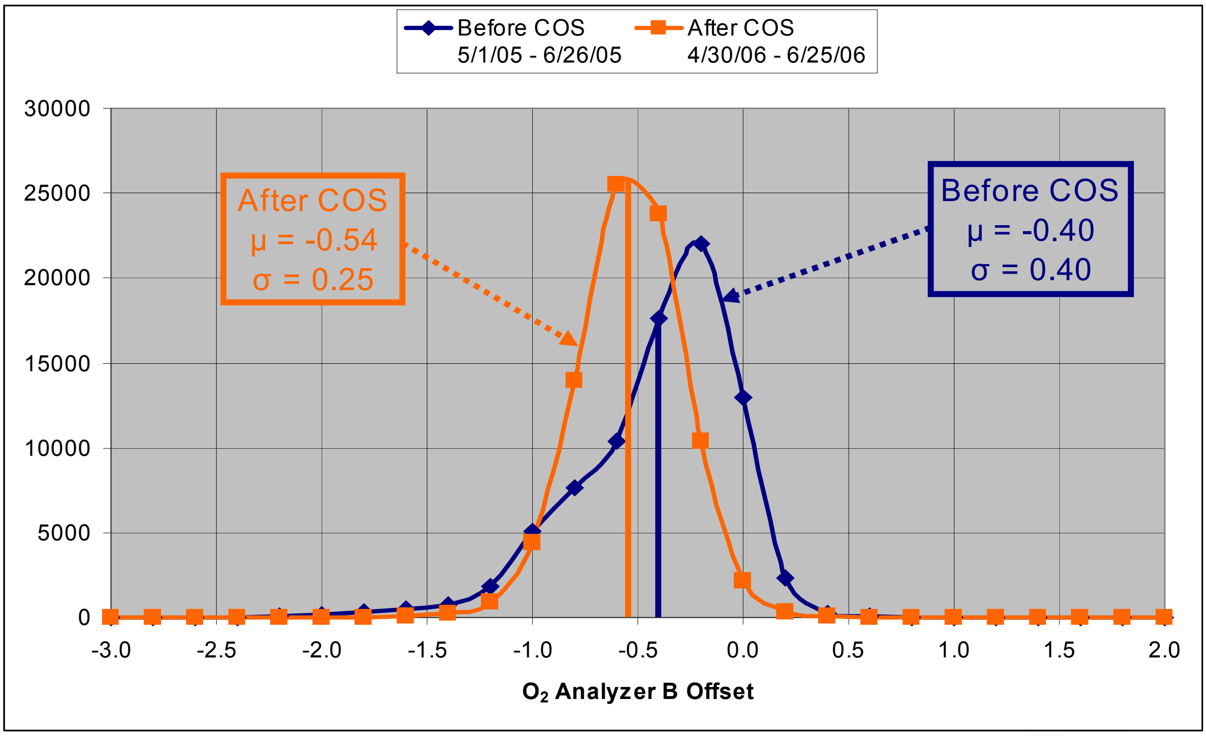

Figure 5: Oxygen Analyzer B Offset from Setpoint (%) for Gibson Unit 2.

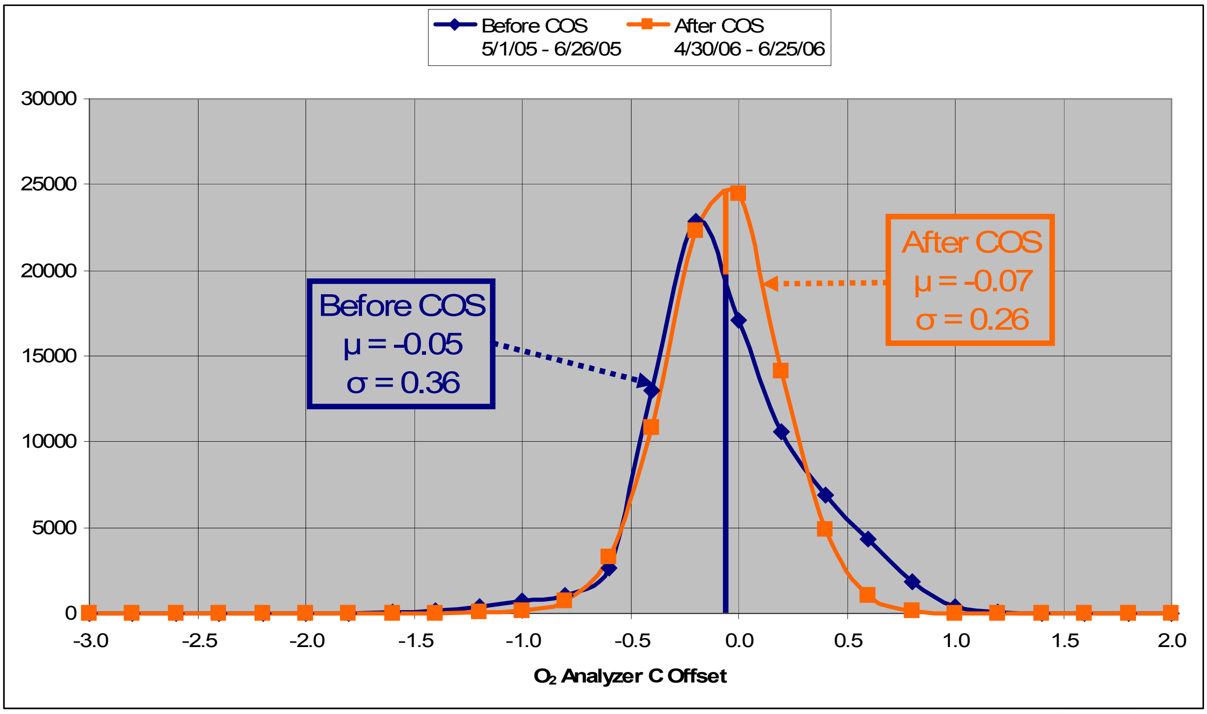

Figure 6: Oxygen Analyzer C Offset from Setpoint (%) for Gibson Unit 2.

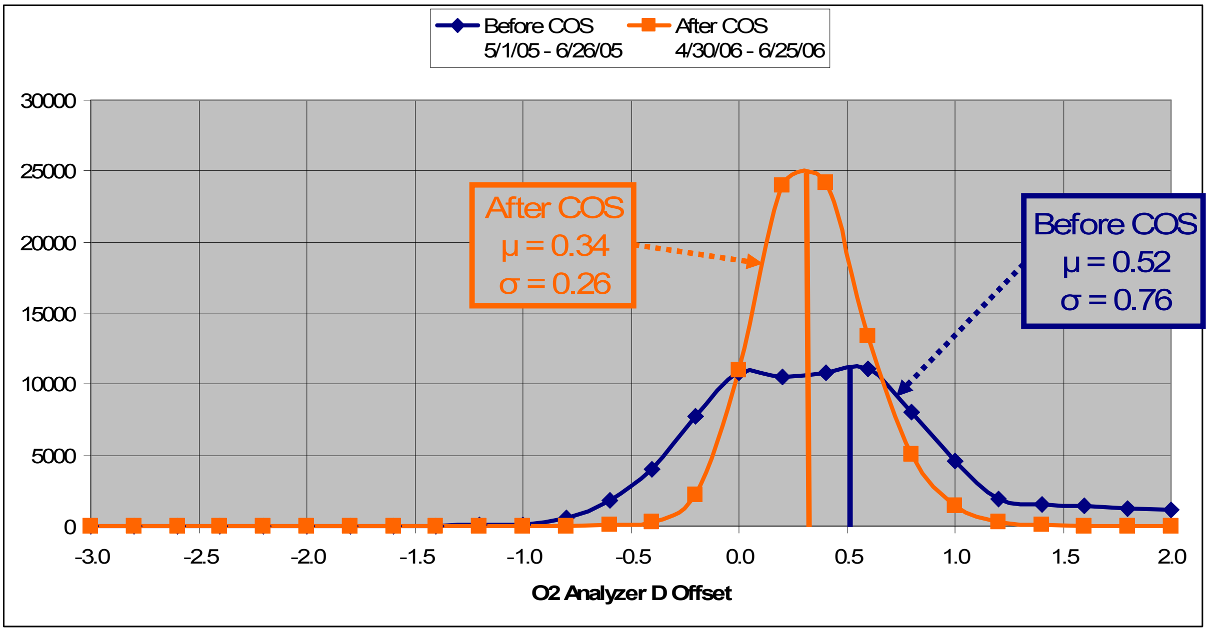

Figure 7: Oxygen Analyzer D Offset from Setpoint (%) for Gibson Unit 2.

Figure 8 shows NO_x emissions distribution for comparable 8-week operating periods. The data is presented as deviation from target, since the NO_x target varies with load. These values are based on the average of the SCR inlet analyzers. Variability has been reduced by 44%, and SCR inlet NO_x is being maintained closer to its target.

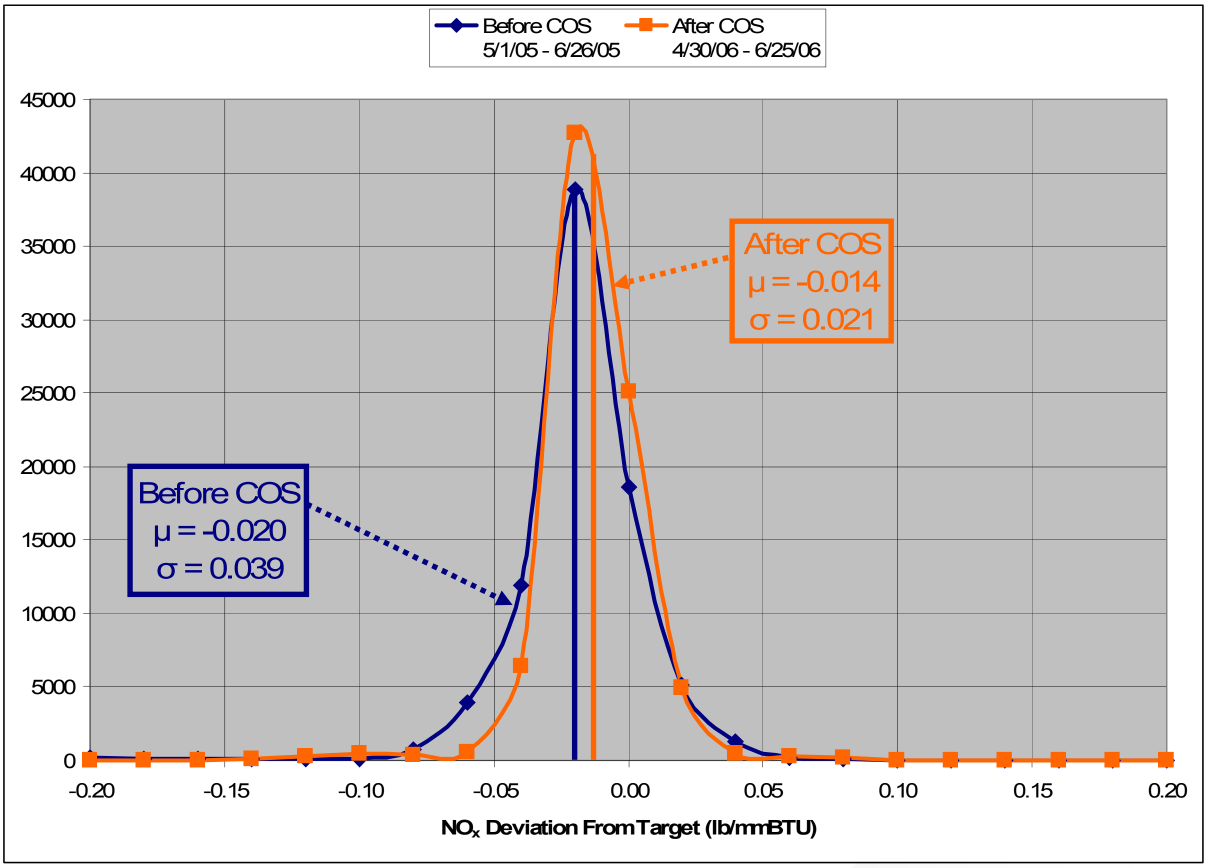

Figure 8: NO_x Deviation from Target (lb/MMBTU) for Gibson Unit 2.

5.0 Conclusions

At Gibson Unit 2, the combustion optimization system is a valuable tool that allows the operator to address multiple (and often conflicting) objectives in a continuous manner. Since commissioning, the system has operated in closed-loop control 96% of the time. Using this system, reheat steam temperature has been increased 3.5 °F, while average reheat temperature excursions above 1020 °F have been reduced by 81%. Combustion balance (shown by reduced variation in the individual oxygen analyzer readings) has simultaneously been improved across the furnace, resulting in more uniform boiler fouling/slagging and water wall corrosion. At the same time, the system maintains NO_x slightly closer to target, while reducing the NO_x variation by 44%. The Gibson 2 combustion optimization system demonstrates the value of this technology in addressing applications beyond NO_x minimization.

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