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Smartsheet Tool applied to Boiler Performance Analysis and Economic Optimization of a Circulating Fluidized Bed Boiler

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Abstract

In the current deregulated competitive electricity market and with tighter environmental regulations, it is an important goal that power plant boilers are operated and controlled in the most efficient, economic and cleanest manner while fulfilling the grid load demand requirements. This paper presents the development and testing results of a boiler performance analysis and optimization tool referred to as "Smartsheet", capable of assisting plant owners and operators in meeting the stated optimization goals. The Excel based tool includes a neural network process model, economic relationships, an optimization solver and a number of user functions and interface for use in the analysis and the operational optimization of a circulating fluidized bed (CFB) boiler. In view of the fact that a CFB boiler process is nonlinear with strong interactions among process variables, an artificial neural network (ANN) based model was developed to capture the nonlinear relationships between the variables representing operating conditions and the variables that relate to operating costs. The tool has been tested at the AES Thames, station in Uncasville Connecticut. The validation testing involved developing two orthogonal test matrices based on Design of Experiments (DoE) methods that were then used to carry out two independent tests in the Alstom supplied CFB boiler (100MW). The test data collected from the first set of tests was used to train the ANN model and the data from a second set of tests was used for the model validation. The model was combined with the other software developed functions into a tool to support power plant engineers and operators in boiler and total plant performance analysis. The tool is specifically designed to assist in generating economically optimal operating plant settings based on a utility's specified current cost and emission credit factors. The optimization results to date show that the optimized operating settings can save, on average, more than 2% of operating costs over the current operating conditions, which have been fine tuned by almost 20 years of operating experience. Additional validation tests of the optimal operating conditions suggested by the optimization tool have been planned with the customer to further validate the tool.

Keywords: CFB boiler, Economic Optimization, Neural network, Genetic algorithm.

1. Introduction

In the current deregulated competitive electricity market and with tighter environmental regulations, it is an important goal that power plant boilers are operated and controlled in the most efficient, economic and cleanest manner while fulfilling the grid load demand requirements. Boiler operators and engineers can use the wealth of knowledge they have about boiler design and operating parameters and their effect on key economic variables such as fuel consumption, emissions, etc. to improve the operating profits. Nevertheless, determining the "best" combination of operational settings for multiple variables out of all the possible condition combinations that will achieve maximum operating profit is a very challenging human problem. To determine all the possible operating condition, honor plant constraints and then find the set of many variables that establishes the operating conditions that minimize operating costs requires the aid of a computational tool. In addition, ever changing with time electricity prices, fuel costs and emission credits make the boiler optimization problem much more difficult where a software tool will aid the operator in selecting optimal parameters.

This paper presents the development and testing results of a boiler performance analysis and optimization tool, "Smartsheet", capable of assisting plant owners and operators in meeting the stated optimization goals. The Excel based tool includes a nonlinear process model based on neural network, economic relationships, a global optimization solver and a number of user functions and interface for the analysis and the operational optimization of a circulating fluidized bed (CFB) boiler. The tool can be either used in an offline engineering mode or in online supervisory control mode.

2. Circulating Fluidized Bed Boiler Plant

Circulating fluidized bed (CFB) (Semedard, et al., 2005) combustion technology is relatively new, yet mature solid-fuel firing technology developed in last forty years. CFB boilers can be designed to fire essentially any combustible material, and also can be designed to fire a wide range of fuels in a given boiler (Abdulally and Darling, 2007). While there are many differences between CFB and other available boiler technologies, one of the most important is furnace temperature, with CFBs operating at much lower furnace temperatures than pulverized coal boilers. The relatively low furnace temperature is the source of most key benefits of fluidized bed firing; NOx levels are low because no atmospheric nitrogen is converted to NOx, SO2 levels are low because SO2 can be efficiently absorbed via limestone injection to the furnace, and fuel flexibility results because the ash stays in solid form, so fuel ash characteristics do not impact the design. CFB boilers also have a high solids residence time in the furnace, which compensates for the relatively low furnace temperature, allowing high combustion efficiency and limestone utilization.

The circulating fluidized bed (CFB) boiler under consideration is a coal-fired 100 MW Alstom designed drum-type subcritical boiler (see Bozzuto, 2009; Marchetti et al., 2003) similar to the diagram shown in Figure 1. It also supplies steam (in the range of 100 K lb/hour) to a processing plant.

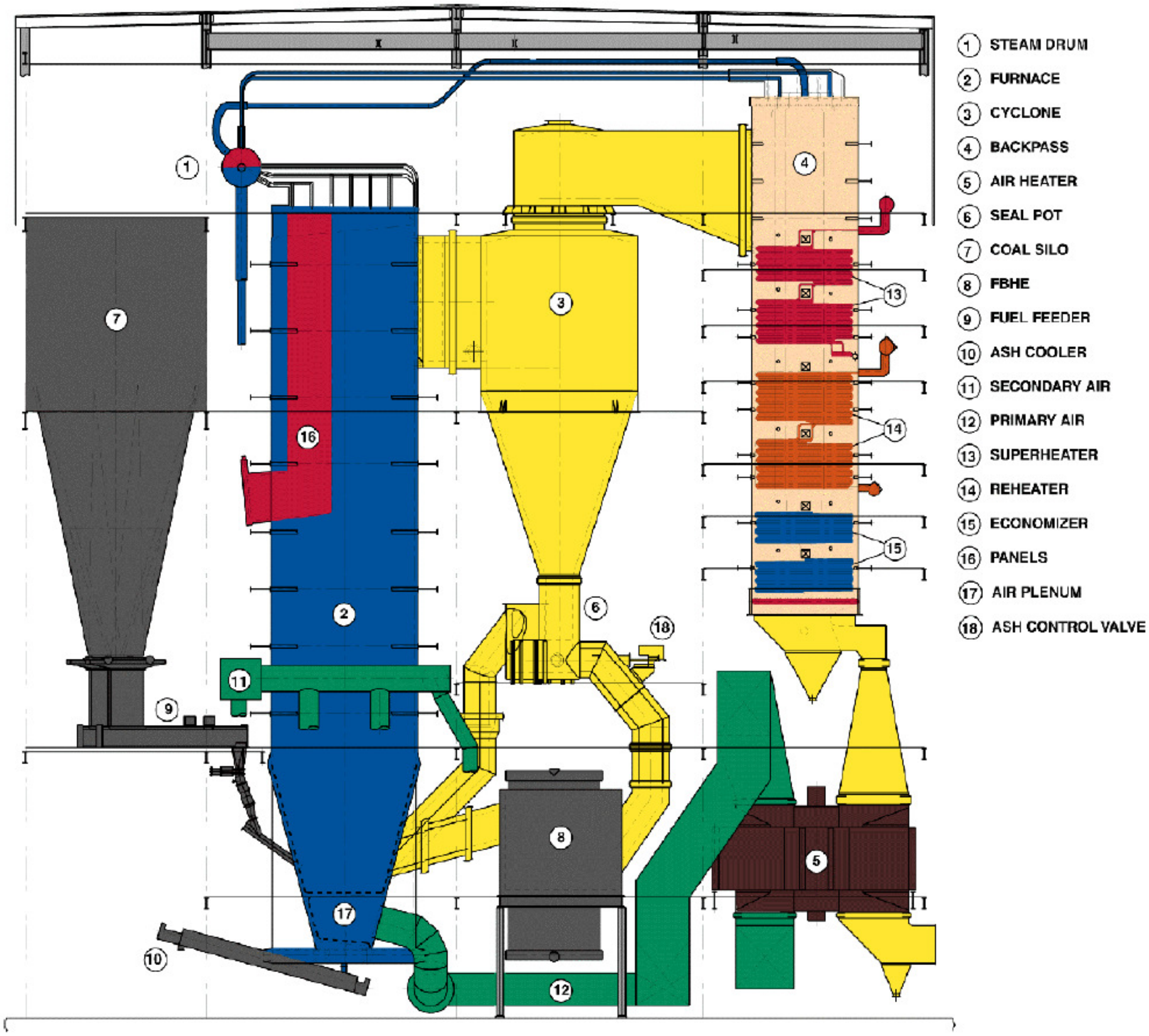

Figure 1. Elevation View of an Alstom CFB Boiler

3. Performance Analyses and Economic Optimization Tool

The performance analyses and economic optimization tool, Smartsheet, developed and applied here for a CFB boiler hinges on two components: an artificial neural network based steady state nonlinear boiler model and a genetic algorithm based global optimization solver. Using these two components and economic relationships, different boiler performance analyses and economic optimization functions can be performed. These Smartsheet functions are discussed in the sub-sections below. A glimpse of the Excel based Smartsheet tool and its ranges of functionality is shown in Figure 2. The tool can be either used in an offline engineering mode or in online supervisory control mode.

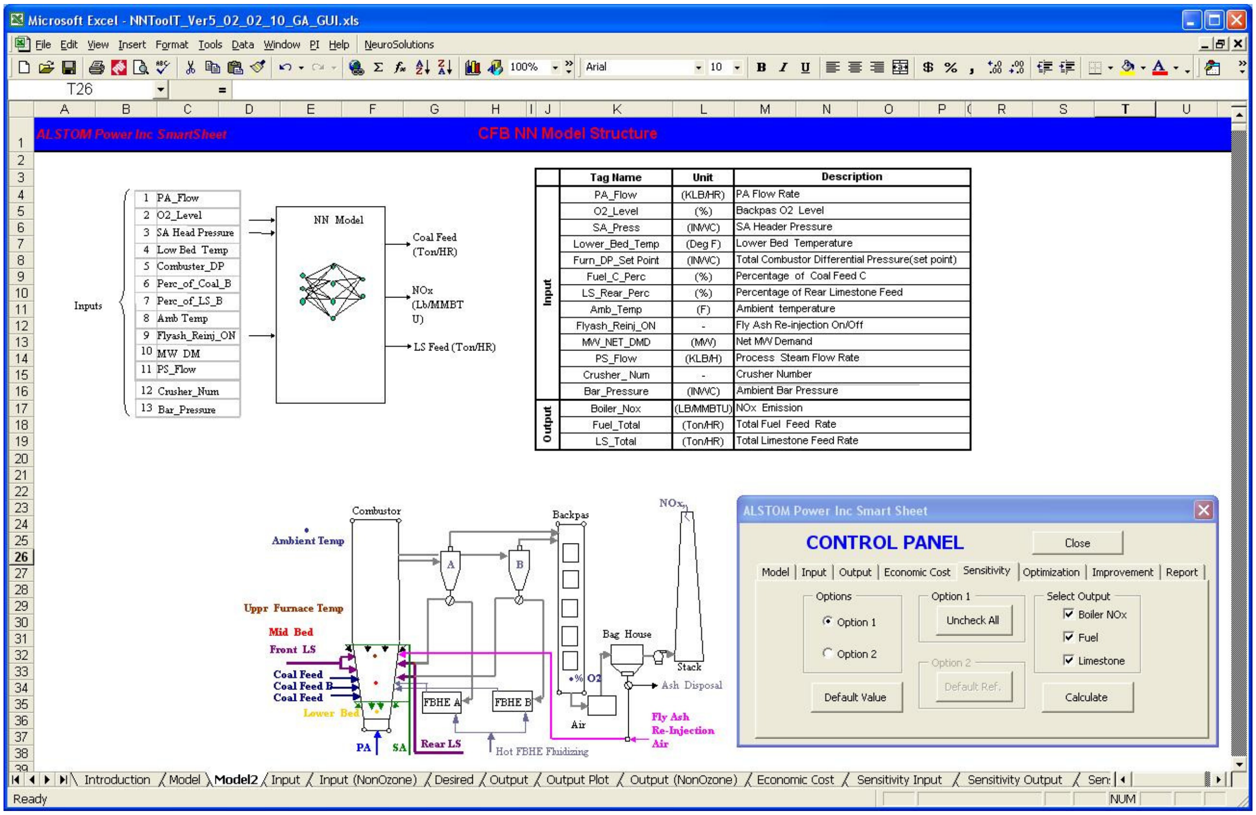

Figure 2. A Glimpse of the Excel Tool

3.1. Artificial Neural Network Model

The artificial neural network (ANN) based nonlinear process model of the CFB boiler is one of the key components of the Excel Smartsheet tool. The Boiler process has been identified as a time-varying nonlinear process over the different loads and operating conditions. Therefore, the artificial neural network, which has been widely and successfully utilized to model nonlinear relationships between variables in boiler process (Joshi, et al., 2008), was adopted to develop a CFB process model. Neural network model coefficients are estimated (referred to as neural network training) by using test data and numerous studies available in literature have found that the ANN has abilities to capture input-output relationship in the data accurately.

The development of a neural network boiler model for boiler optimization typically involves three steps: 1) Defining input-output model structure, 2) Test matrix design & boiler test execution, and 3) Neural network model training & validation using test data.

Defining the input-output structure for the ANN model is an important step and requires deep process and boiler equipment understanding. Exclusion of a key boiler process variable in the model may affect the operating cost calculations and inclusion of an unnecessary variable in the model prolongs the test and model building time. In addition, the input-output list was also verified and trimmed based on thorough analysis of historical operation data. A neural network input-output model structure for the CFB boiler is depicted in Figure 3. As seen in the figure, there are two categories of inputs to the model: 1) Manipulated and 2) Disturbance. Manipulated variables (MV's) are those variables that can be changed by the operator when necessary. Disturbance variables (DV's) are those that affect the defined model outputs but cannot be changed at will, such as ambient air temperature, external steam flow, etc.

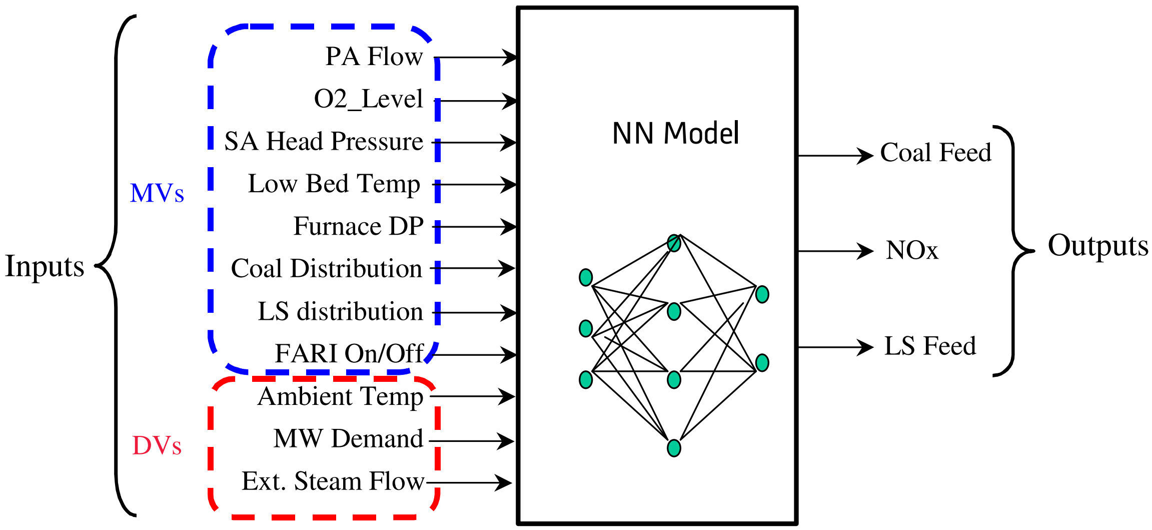

Figure 3. A neural network input-output model structure for a CFB boiler

In the next step, two sets of test matrices with statistically independent test cases in each test matrix were designed based on a design of experiments (DoE), by including all the manipulated variables that are identified as inputs to the neural network model. Each test matrix included a series of tests with a limited number of values for each manipulated variable that span its full range. Two test datasets were collected from the tests conducted on the CFB utility boiler and then processed. The first dataset was utilized for the model development and the second for checking the developed model for its accuracy. The neural network structure used for the model development was so called multi-layer perceptron (MLP) with one hidden layer, i.e. there are three layers – an input layer, a hidden layer and an output layer as seen in Figure 3.

The development of the neural network model includes iterative estimation of model coefficients (referred to as training) with a checking mechanism (called cross-validation) and model testing by using the dataset. The cross-validation mechanism helps avoid the neural network model from over-fitting the dataset during its training. Model over-fitting may give very good predictions for the particular dataset but will perform very poorly for other datasets not used in training. The dataset is normally divided into three data subsets: training, cross-validation and testing data for this purpose. The prediction data from the resulting neural network model and the actual measured plant data are plotted in Figures 4-6. As seen in the figures, the prediction from the neural network model gives a good match with the actual plant data. The actual values of the outputs have not been shown, as they are confidential information.

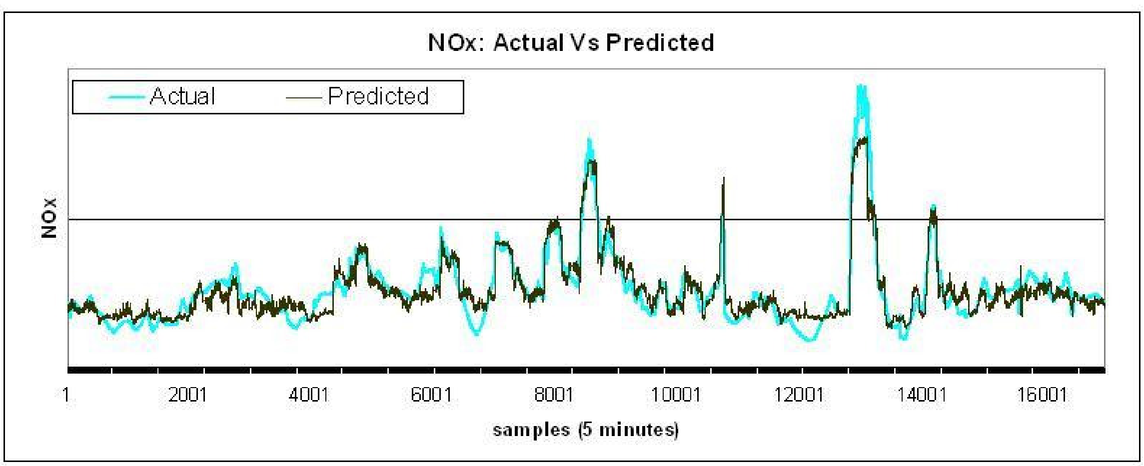

Figure 4. Predicted and actual plant data for NOx

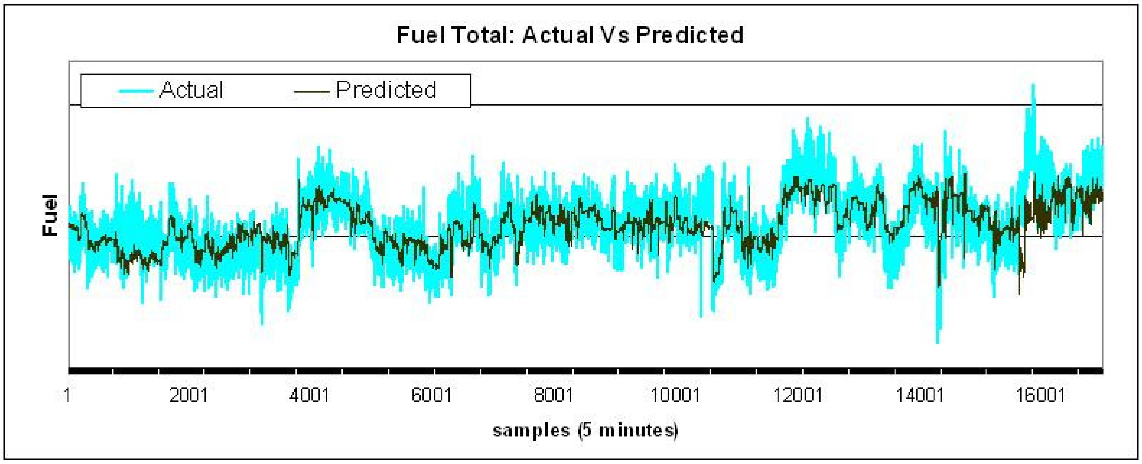

Figure 5. Predicted and actual plant data for Total Fuel

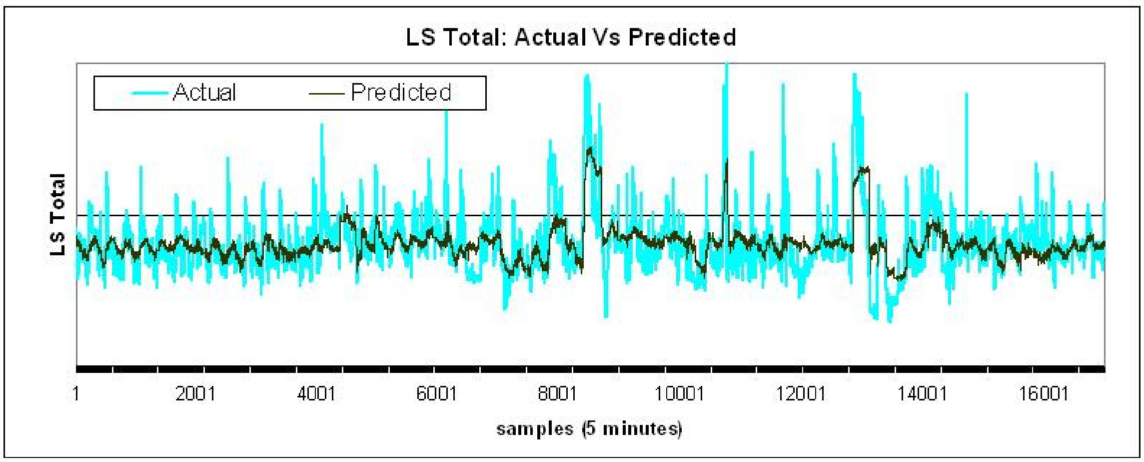

Figure 6. Predicted and actual plant data for Total Limestone

3.2. Genetic Algorithm for Global Optimization

The genetic algorithm (GA) based global optimization solver is the next important component of the Smartsheet ™ tool. As mentioned above the neural network boiler model is nonlinear, and therefore, the resulting optimization problem to be defined in Section 3.4 becomes nonlinear and often tends to be non-convex, i.e. it can have multiple locally optimal solutions across the range of input values. Since conventional gradient-based optimization solvers are designed to converge to a local optimal point, they often fail to find the global optimum solution among the various local optimal points. Therefore, a genetic algorithm based optimization solver was developed and incorporated in the tool. A genetic algorithm is a class of stochastic search techniques influenced by evolutionary biology, such as inheritance, mutation, selection, and crossover. The steps by which an optimization problem is solved using a genetic algorithm (refer to Gen and Cheng, 2000 for more details) are as listed below. The steps are also presented as a flow chart in Figure 7.

Step 0: Initialize. Choose GA parameters, e.g., size of the population, mutation rate (a parameter that represents the probability of occurrence of mutation, which is explained in Step 2), maximum number of iterations, minimum difference in the value of the objective function (as defined in equation 1 in Section 3.4) of the best solution in successive iterations, etc. Minimum and maximum bounds of the inputs also needs to be defined. Go to Step 1.

Step 1: Create initial population of chromosomes. A 'chromosome' is an array of input values (as seen in Figure 3) included for optimization. Individual elements in a chromosome representing individual inputs are called 'genes'. In this step, a population of chromosomes is generated by randomly picking a value for each gene (input) within its lower and upper bound. For each chromosome, its associated objective function value is calculated and the chromosomes are arranged in the order with the best solution first. Go to Step 2.

Step 2: Crossover, Mutation and Elitism: This step produces a next generation population (group) of chromosomes with an expectation of improvement in the best solution from the last generation by the mechanisms of crossover, mutation and elitism. During a 'crossover', two chromosomes (parents) from the last generation population are randomly selected and a new chromosome is created by randomly selecting a gene from either of the parents. During a mutation, a chromosome is randomly selected from the last generation population and undergoes a mutation condition test where a random number is generated to see if it is below the mutation rate (chosen in Step 0). If the mutation test is passed, a new chromosome is created from the selected one by randomly selecting a gene and altering it with a random number within the bounds of the particular input. The selection of chromosomes from the last generation for crossover and mutation is done in such a way that there is a higher probability for a chromosome with better objective function value to be selected. 'Elitism' means to transfer the chromosome with the best objective function value from the last generation population to the new generation population.

Since genetic algorithm is a stochastic search method, the solution it gives may or may not be a stationary point with slightly better solution in its immediate neighborhood. To address this issue, the elitism mechanism has been extended such that not only the chromosome with the best objective function value but also few more chromosomes that are slight variants of the current best are introduced to the next generation population. Go to Step 3.

Step 3: Evaluation. The objective function value for each chromosome in the current generation population is calculated and the chromosomes are arranged in the order with the best solution first. If the improvement in the objective function value of the best chromosome in the current generation population and compared to the best chromosome in the last generation population is larger than a minimum difference value (chosen in Step 0), and if the maximum number of generations (iterations) has not been surpassed, then go to Step 2. Otherwise go to Step 4.

Step 4: Termination. The chromosome with the best objective function value is the optimal solution to the optimization problem.

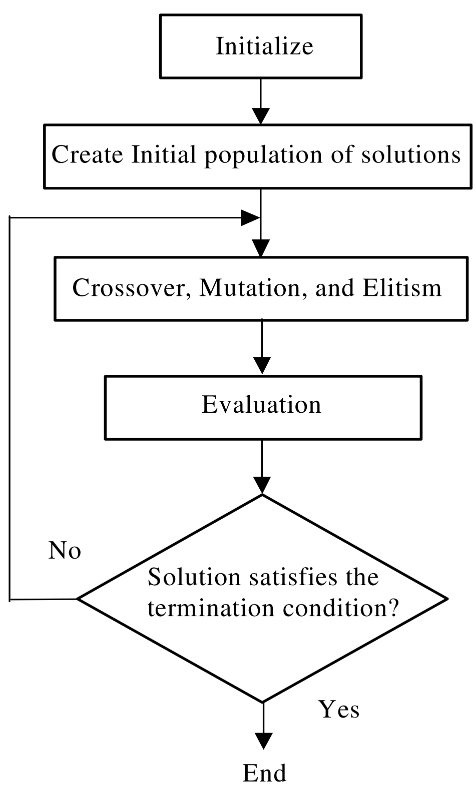

Figure 7. A Genetic Algorithm flow chart

3.3. Boiler Sensitivity Analysis

The boiler sensitivity analysis function allows engineers and operators to understand the relationships between all the input and output variables. Although power plant engineers with their wealth of experiences have a good understanding of some of these relationships, there are relationships among some variables that are hard to discern. Two types of sensitivity analyses methods were incorporated in the tool: 1) Basic - one input one output sensitivity curves and 2) Advanced - sensitivity curves with an additional input variable in the sensitivity plots.

The basic sensitivity curve gives one-to-one functional relationship between an input variable and an output variable while other inputs are fixed to a nominal value. The basic sensitivity curves for the three outputs with respect to temperature are shown in Figure 8. Basic sensitivity curves give an idea of where outputs will be at different input settings.

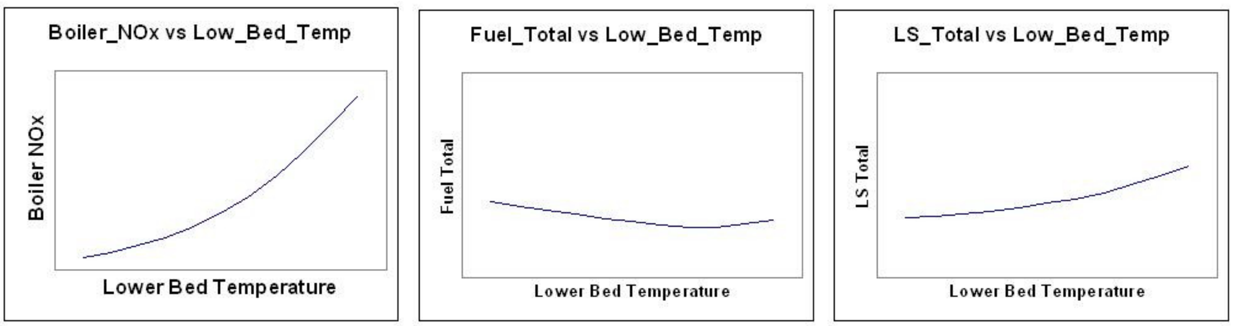

Figure 8. Basic sensitivity curves for three outputs with respect to an input

The advanced sensitivity curve gives functional relationships between an input and an output while a third input is at different discrete values, and other inputs are fixed to a nominal value. An advanced sensitivity curve for an output with respect to an input for five discrete values of another input is shown in Figure 9.

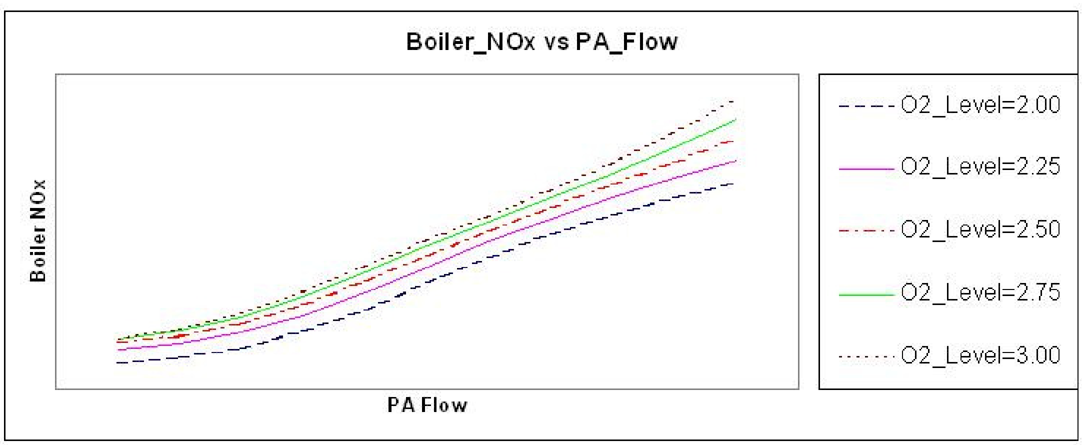

Figure 9. Advanced sensitivity curve for NOx with respect to PA Flow at five discrete values of O2 Level

3.4. Boiler Economic Optimization

The foremost objective of developing the Smartsheet tool was to carry out economic optimization of the boiler/plant and compute the most profitable operating settings for the given power demand and input/output prices. Power plant engineers and managers with a their know-how and experience can change the boiler/plant input settings towards more profitable conditions in terms of, say, two or three variables. However, it is very difficult to find an overall true mathematically based economic optimal operating settings that involves many input and output variables. Furthermore, with constant changes in prices of outputs (electricity) and inputs (fuel, sorbent, etc.), finding the most profitable condition at frequent intervals is almost impossible without an appropriately designed optimization tool.

The economic optimization problem (with an objective function and constraints) for this work is formulated as

$$\min_u J, \quad with\ J = C_{NOx}\ y_{NOx} + C_{Fuel}\ y_{Fuel} + C_{LS}\ y_{LS} + C_{Ash}\ y_{Ash}\,, \qquad (1)$$

subject to

$$y = f_{NN}(u, \theta)\,,$$

$$u_{\min} \le u \le u_{\max}\,,$$

where y = [y_{NOx}, y_{Fuel}, y_{LS}, y_{Ash}] is a vector of model outputs; u is a vector of model inputs, e.g., O_2 level, bed temperature, etc.; C_{NOx}, C_{Fuel}, C_{LS}, and C_{Ash} are unit costs of the model outputs y; f_{NN} is the neural network model; u_{min} and u_{max} are minimum and maximum bounds of inputs, respectively; and θ is a set of model coefficients. Although y_{Ash} (total ash output) is not predicted by using the neural network model, it can be calculated based on total fuel and limestone values, their composition, and estimated calcination and sulfur capture ratio. The unit cost C_{NOx} of NOx output can be positive or negative (with different values) depending on NOx production is above or below the allowed limits, respectively. The cost function used in the optimization problem above may not be the actual total cost of producing a unit of power, nevertheless, it covers major costs of operation in the form of fuel, limestone, and NOx costs/credits.

The Smartsheet tool developed can provide basically three types of optimization solutions: 1) Enumeration solution, 2) Globally optimal solution and 3) Guided optimal solutions. For each solution type, a subset of inputs can be selected for optimization.

The first solution type is based on enumeration, which gives a solution based on an exhaustive search of the input space with a number of discrete input points. This is a crude and simple method and may work with few variables and when a reasonably good solution is sufficient, but the problem size and the computation time increases very quickly with increase in variables and required resolution.

The second solution type is globally optimal and computed based on genetic algorithm as discussed in Section 3.2. To provide more freedom for the engineers and operators, the global optimal solution is displayed with a number of near-optimal solutions from the last population for their reference in operational decision making. The operators may have preferences for one set of input settings that provides almost as much cost savings as the globally optimal set of input settings.

The third solution type is similar to the second type but guided to a small number of partitioned regions. Since many experienced operators feel comfortable running a boiler with certain variables in certain preferred regions (e.g. operation of boiler at lower O2 in order to stay away from ID fan motor limits during the summer), this solution type provides solutions from searches at different regions in the input space.

4. Optimization Results

The Smartsheet tool presented in Section 3 has been extensively tested to generate economically optimal input setting for different optimization cases by using current prices of fuel and limestone and NOx credits. The tool was also used to run optimization cases to evaluate potential improvement that could have been made in past operations. An improvement test case over duration of a month is shown in Figure 10, which compares the incurred total cost based on current settings and the optimized total cost. The cost numbers are confidential and hence are not revealed. As seen in the figure, the operating cost could have been reduced for all but one sample. Extrapolating the improvement results, the Smartsheet tool suggests savings of, on average, more than 2% of the current operating costs.

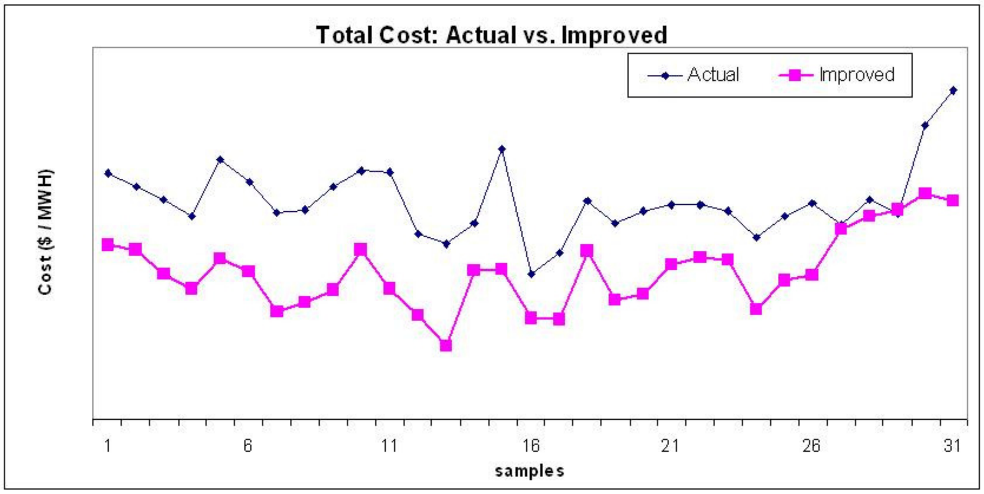

Figure 10. Total cost: Actual and Improved

The results within the tool have been very encouraging to both Alstom and the AES power plant team members. To validate the optimization results in the field, about a month long plant tests have been planned for the near future.

5. Summary and Conclusions

Smartsheet is an Excel based tool for the performance analyses and economic optimization of operating PC or CFB boilers. The initial application testing completed for a CFB plant was presented. Enabling the powerful optimization functionality of the tool are its computational engine components including: neural network based process model and a global optimization solver. The neural network model was trained and validated using actual boiler plant test data, which was derived and collected by implementing a systematic DoE orthogonal based set of test matrices. The resulting model is used for Boiler process behavior prediction and sensitivity analyses. The Smartsheet tool also includes economic relationships tailored to the Utility operations, which are used together with the model and the solver to provide different analyses of the boiler performance and to carry out economic optimization cases to derive the best operating points.

The results from the tests so far show that this new tool is capable of supporting engineers in carrying out boiler performance and optimization analyses. The results also suggest that there are tangible savings that can be made by adjusting some of the boiler parameters even on units that have been working over many years to optimize operations. Additional Plant tests have been planned to further validate the optimization results.

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