More efficient operation of coal fired power plants using nonlinear models

ABSTRACT

Coal fired power plants should be operated in such a way that the emissions are kept clearly below desired limits and the combustion efficiency is as high as can be achieved. This requires a lot of quantitative knowledge of the effects of the process variables and fuel characteristics on the emissions and efficiency. Mathematical models can be developed with different approaches. Physical models are too slow to be used for on-line process guidance, and require too many assumptions and simplifications. It is feasible to develop empirical or semi-empirical models from normal production data of the power plant. This technical communication explains with an example of a coal fired power plant how nonlinear models are an effective means of determining the best operating conditions at any given load for a given type of coal.

1. INTRODUCTION

Coal fired power plants are looked upon as dirty by the general public, partly because that is how most coal fired power plants used to be operated just a couple of decades ago. Pressure from the public as well as environmental regulations have improved the situation significantly, and today, technology is capable of producing power from coal with very modest emissions with a fairly good combustion efficiency. Emissions can be reduced by either adding new equipment like more efficient burners, or by better operation of the power plant by better tuning of the process variables. This article focusses on the latter. Even if new equipment is added, the opportunity to operate it more efficiently remains. In addition to environmental regulations, power plant managers are under constant pressure to improve their production economics, which has only increased with the sharp increase in fuel prices in the last two years.

Turku receives much of its electricity from Fortum's power plant in Naantali, built in 1964. It has been generating electric power for about 50 years. The Naantali power plant comprises three 46 metre high boilers of the once-through type. Russian coal is the main fuel, while oil is normally used as the starting fuel. Saw dust is also added to coal, which accounts for at the most 2% of the energy.

The Naantali 2 boiler was supplied in 1964 by Gebr. Sulzer AG, and turbogenerators by Kraftwerk Union of Siemens. The boiler can burn upto about 44 tons/hour (worth 315 MW) of coal, producing either 90 MW electricity and 175 MW heat, or 120 MW electricity. The boiler typically produces 117 kg of steam per second at a pressure of 180 bar, and a temperature of 535 °C. The turbogenerator can produce between 40 and 120 MW electricity, depending on the output of steam and district heat. The steam output, meant for industrial consumption, can be upto 50 MW.

2. NONLINEAR MODELING

Mathematical models contain knowledge of quantitative effects of relevant variables in a concise and precise form. They can be used instead of experiments if they are accurate and reliable enough. Mathematical models also allow the user to carry out several kinds of calculations, which can be used to improve the cost efficiency. Mathematical modeling can be done in various ways, and different ways are suitable in different situations.

Physical modeling is not very effective for predicting emissions or combustion efficiency. Physical modeling for coal and saw dust combustion in a boiler requires solving the partial differential equations of heat transfer, mass transfer and fluid dynamics coupled with multiple chemical reactions. This requires plenty of assumptions and simplifications. The reactions taking place at different temperatures are poorly known, let aside their kinetics. Even if possible, the solution of those partial differential equations tends to be very slow, with each run taking days, making it unsuitable for on-line process guidance.

On the other hand, empirical and semi-empirical modeling does not need any major assumptions or simplifications. Empirical models simply describe the observed behavior of a process, and are developed from recorded data. Empirical modeling is feasible when the relevant variables are measurable, as is usually the case with most boilers. Conventional techniques of empirical modeling, however, are linear statistical techniques. These have severe limitations because nothing in nature is very linear, and particularly so in process engineering. It therefore makes sense to use better techniques of empirical and semi-empirical modeling which take nonlinearities into account.

processMax+

Nonlinear modeling

Nonlinear modeling is empirical or semi-empirical modeling which takes at least some nonlinearities into account. The older techniques include polynomial regression, linear regression with nonlinear terms and nonlinear regression. These techniques have several disadvantages compared to the new techniques of nonlinear modeling based on free-form nonlinearities.

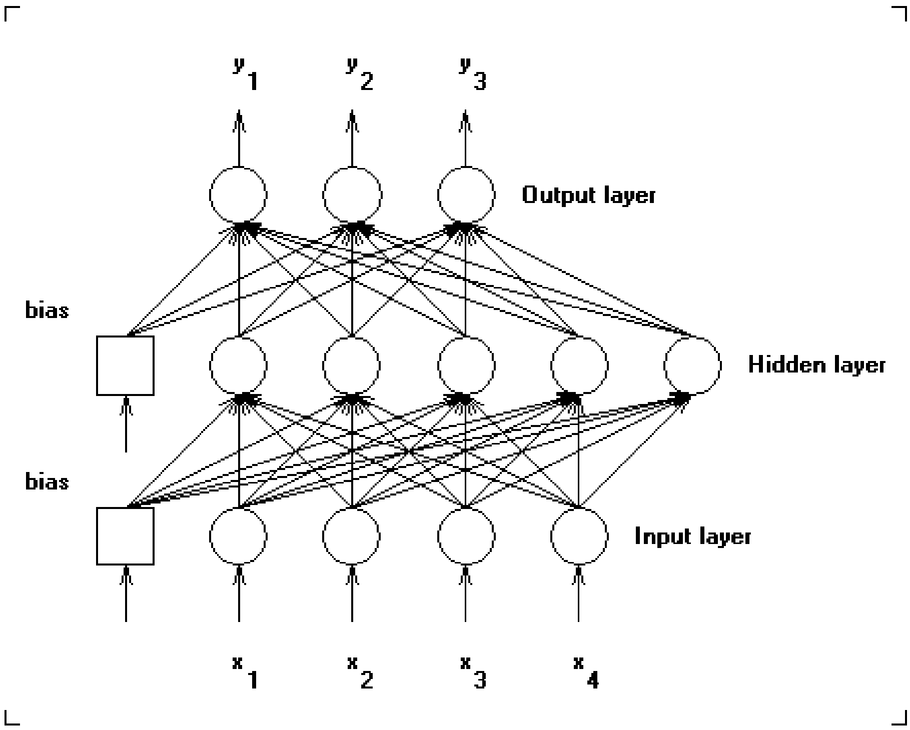


Figure 1. A typical feed-forward neural network has an input layer, an output layer and one or two hidden layers.

Nonlinear models can also be developed with feed-forward neural networks, series of basis functions, multivariate splines, kernel regression and other techniques. Among these new techniques, feed-forward neural networks have turned out to be particularly valuable in process modeling [1, 2]. Feed-forward neural networks have several features which make them better tools for nonlinear empirical modeling. Besides the universal approximation capability [3], it is usually possible to produce nonlinear models with some extrapolation capabilities with feed-forward neural networks. Artificial neural networks usually consist of neurons in layers directionally connected to others in the adjacent layers. Multilayer perceptron (Figure 1) is a kind of a feed-forward neural network.

Besides power generation sector [4], nonlinear modeling has been used successfully in several other industrial sectors including plastics, metals, concrete, glass, pharmaceuticals, medicine, biotechnology, mineral wools, semiconductors and food. It has been successfully utilized for a variety of purposes including quality control, product development, process guidance, software sensors and fault detection. Process modeling, however, dominates the list.

2.2. Nonlinear modeling of industrial processes

Different industrial processes have different characteristics - different raw materials, different products, different process variables, different kinds of constraints. The process may be a batch process, a continuous process or a fed-batch one. However, some things are common to process modeling of various kinds of processes.

Usually, the plant operator has several degrees of freedom in terms of process variables, and in some cases, the feed characteristics which could be different amounts of different raw materials. One would like to determine the best values of the feed characteristics and/or process variables such that the product properties, emissions and other consequences of the process are within desired limits, and preferably, a production economic variable (e.g. production rate, raw material consumption, energy efficiency, purity, number of defects, emissions or whatever) is maximized or minimized.

In power plants, the feed (fuel) characteristics can be constants. In case of Fortum's power plant in Naantali, there is at least one degree of freedom there. Different amounts of saw dust can be mixed with coal. In less common situations, the process variables may be constant or dependent variables and the only degrees of freedom in process development may be the composition of the feed, the amounts of raw materials. Sometimes the raw material (feed) characteristics vary, over which we have no control, and the task is to determine the best values of process variables every time the raw material characteristics change.

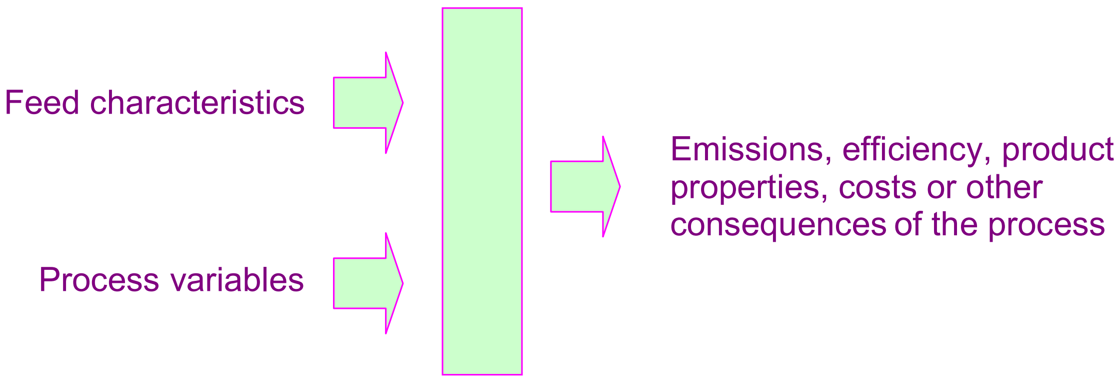


Figure 2. A typical model configuration for process development

The problem is similar from the process modeling point of view for a wide variety of processes. Emissions, efficiency, product properties, costs, etc. are consequences of feed characteristics and process variables, as summarized in Figure 2.

3. OBSERVATIONS FROM THE BOILER

Nonlinear models are developed using measured data from processes. Selected observations from normal operation of the power plant were collected. A total of 11 input variables to be used in the models were selected. The input variables should be independent variables, if the models are to be used for better control of the process. Several consequences of the process were considered for output variables.

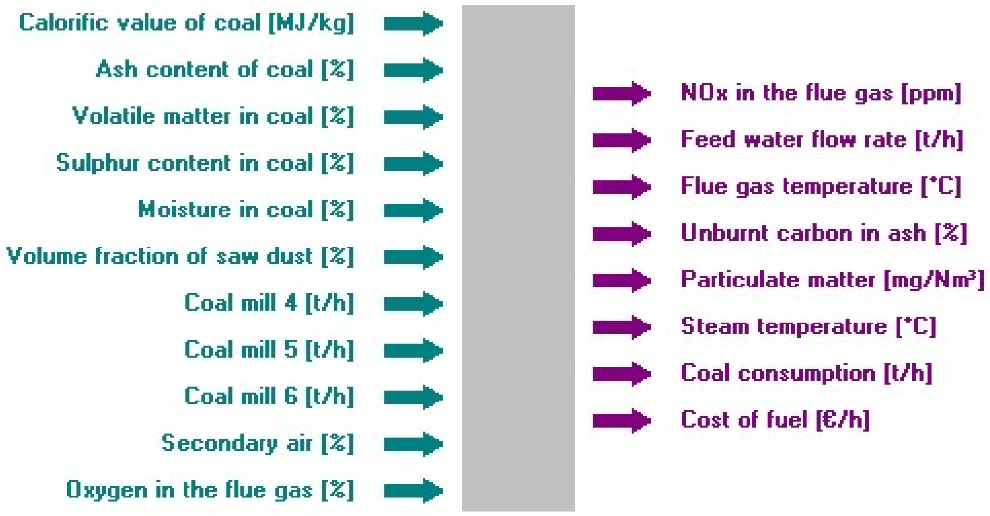


Figure 3. Input variables used in the nonlinear models are on the left side; possible output variables on the right

As can be seen from Figure 2, input variables comprise feed characteristics and process variables. Figure 3 shows the selected input variables on the left. Feed characteristics including fraction of saw dust and coal characteristics were included as input variables. As process variables coal flow rates from three mills to burners at three levels, secondary air flow rates and oxygen in the flue gas, a variable indirectly indicating excess air, were selected for the model development work. The output variables included emissions, the amount of feed water as a measure of the power generated, unburnt carbon in ash, flue gas temperature and steam temperature. Two simpler consequences of the process include coal consumption and its cost. Once implemented along with other models in suitable software, optimisation of cost is also straightforward.

Observations from the production database were carefully selected, all of which were from normal operation without any deliberate changes in the process variables. The selection resulted in a good variation in each of the variables of interest. Developing models from industrial production data is more complicated. Input variables which should be independent variables will still tend to have internal correlations.

4. NONLINEAR MODELS OF EMISSIONS AND OTHER CONSEQUENCES

Nonlinear models could predict NO_x emissions quite well. Secondary air has the strongest effect on NO_x in the flue gas. With a large fraction of the air fed in as secondary, NO_x emissions reduce a lot. Fuel feed to the burners at different levels also affect the NO_x emissions significantly. Figure 4 shows plots of NO_x emissions against secondary air at different values of fuel feed rate from coal mill 4, while keeping other variables constant.

Figure 5 shows plots of NO_x emissions against secondary air at different values of fuel feed rate from coal mill 5. Not feeding coal from coal mill 4 helps a lot in reducing NO_x to a large extent, but it limits the amount of power that can be generated. This is also unfavourable from the point of view of unburnt carbon in ash.

Similarly, saw dust also tends to reduce the NO_x in the flue gas to a small extent, as can be seen from Figure 6, but this too comes at the cost of feed water flow rate, or the amount of steam or power generated.

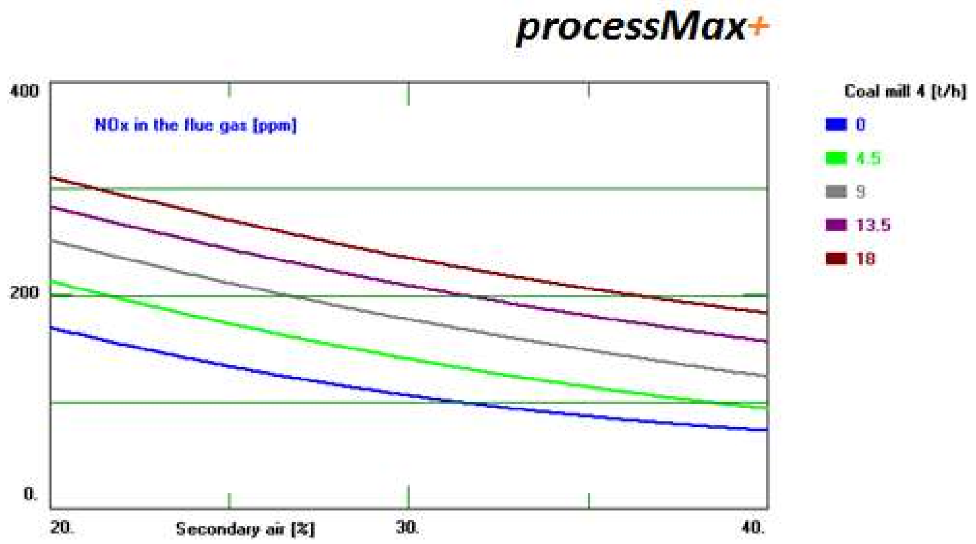


Figure 4. Effect of fraction of secondary air on NO_x at different fuel flow rates from coal mill 4

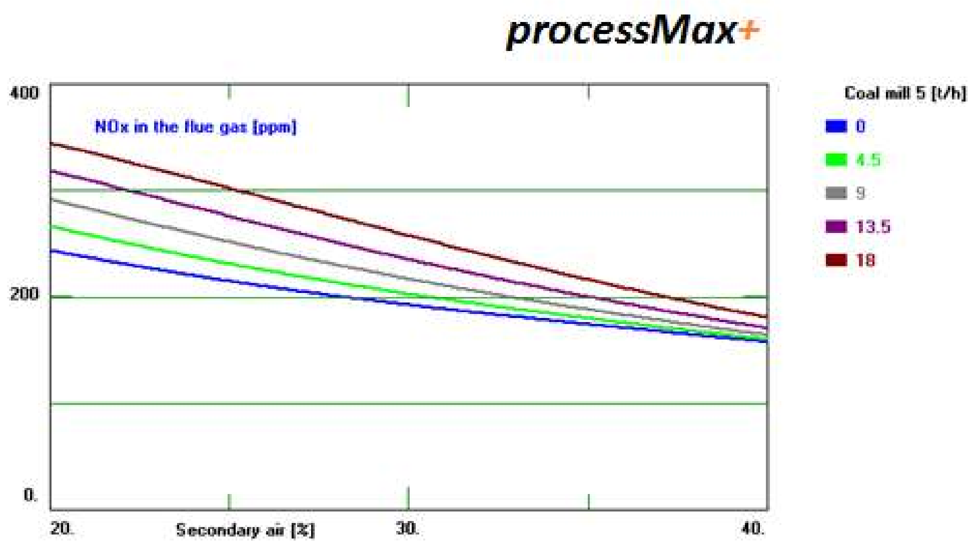


Figure 5. Effect of fraction of secondary air on NO_x at different fuel flow rates from coal mill 5

The effect of fuel feed rates from the three coal mills should be linear and directly proportional to the feed water flow rate (indirectly, power generated) if the combustion efficiency remains constant. This is, however, clearly not the case. Figure 7 shows plots of feed water flow rate against secondary air at different fuel feed rates, while keeping other input variables constant. It is easy to see that secondary air has a beneficial effect on combustion efficiency.

Figure 8 shows contours of unburnt carbon in ash with oxygen in the flue gas and fuel flow rate from coal mill 6 as the two axes. From the point of view of unburnt carbon in ash, higher values of oxygen in the flue gas (excess air) are desirable. This brings down the energy produced from the same amount of coal as well as steam temperature.

From Figure 9, one can see maxima in the curves of steam temperature vs coal mill 4 at diiferent fractions of secondary air. The location of the maximum varies with several other variables including secondary air.

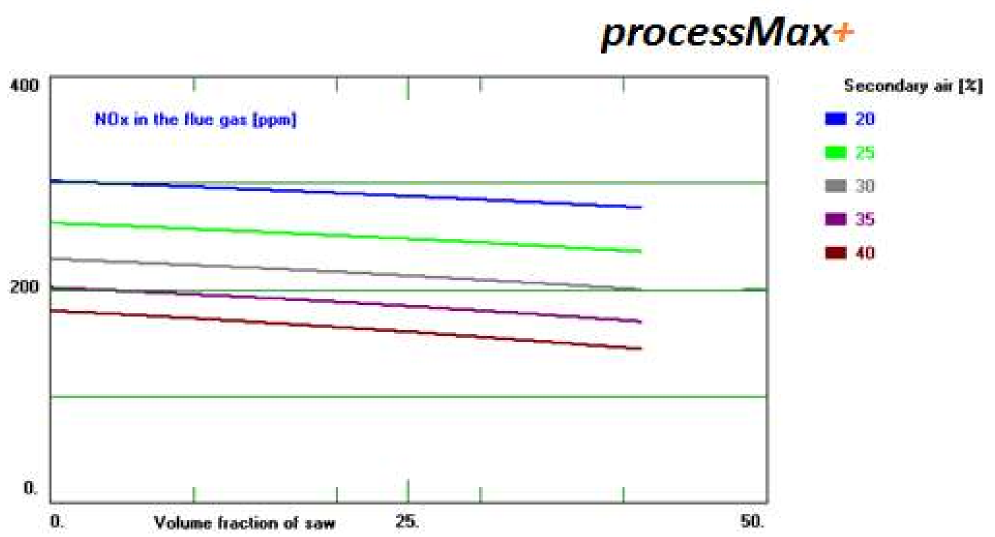


Figure 6. Effect of volume fraction of saw dust on NO_x at different amounts of secondary air

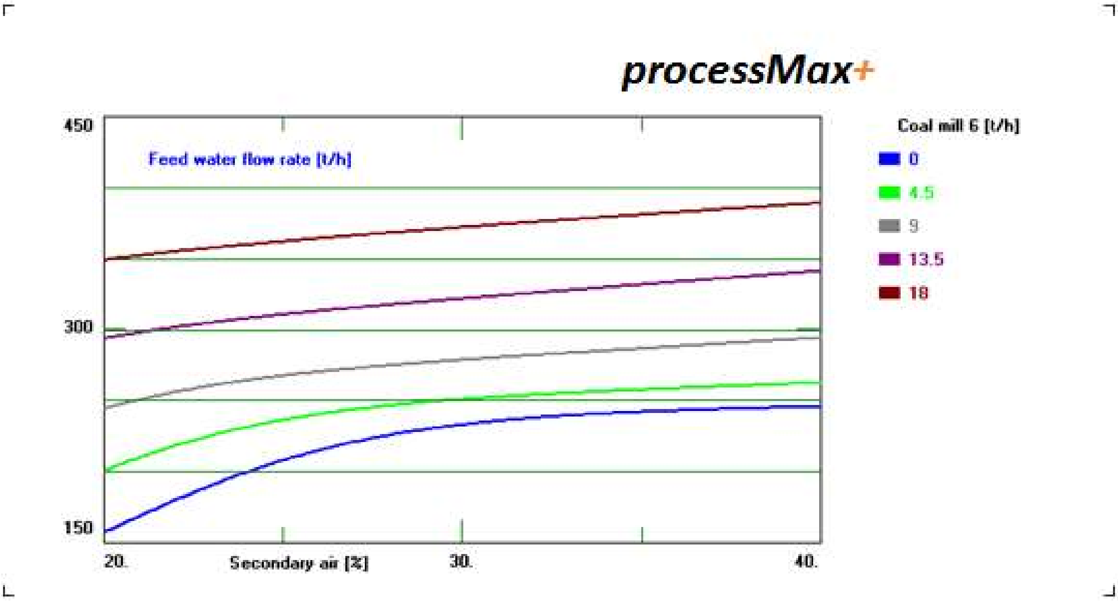


Figure 7. Effect of secondary air on feed water flow rate at different flow rates from coal mill 6

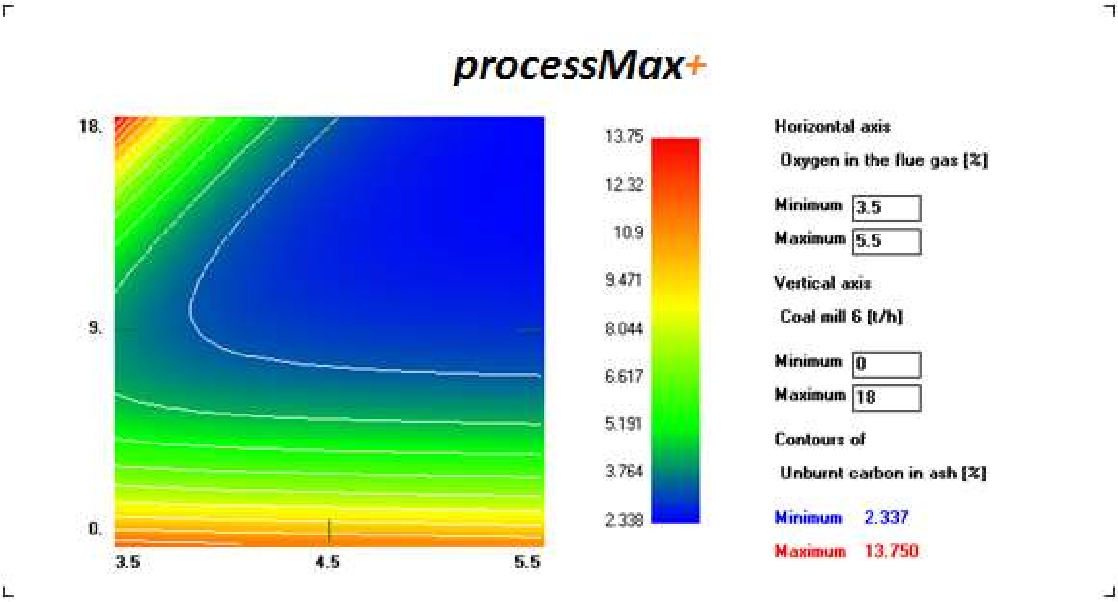


Figure 8. Contours of unburnt carbon in ash

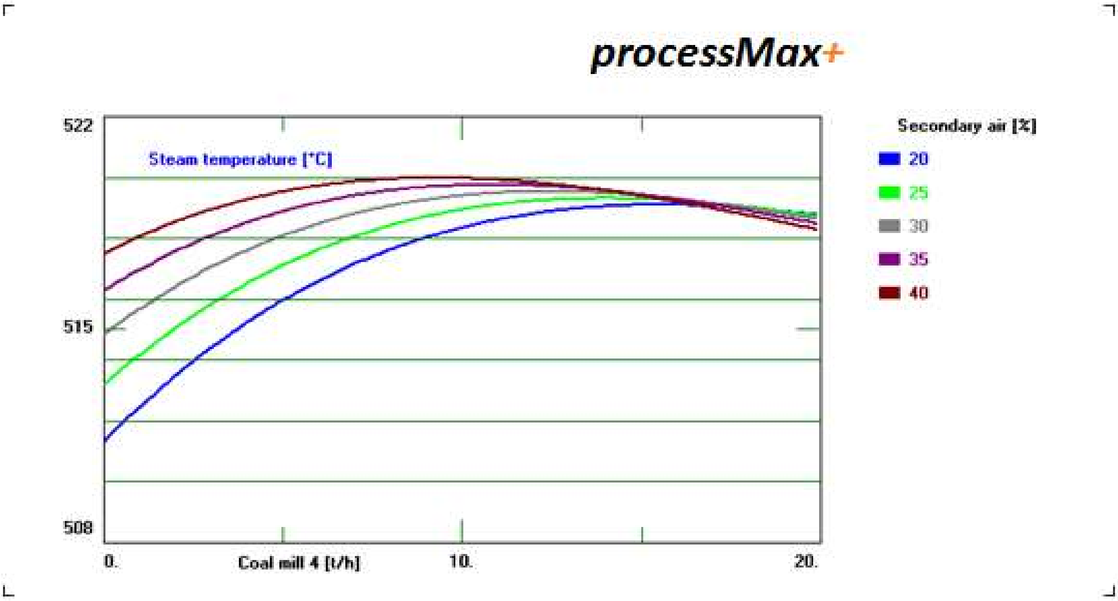
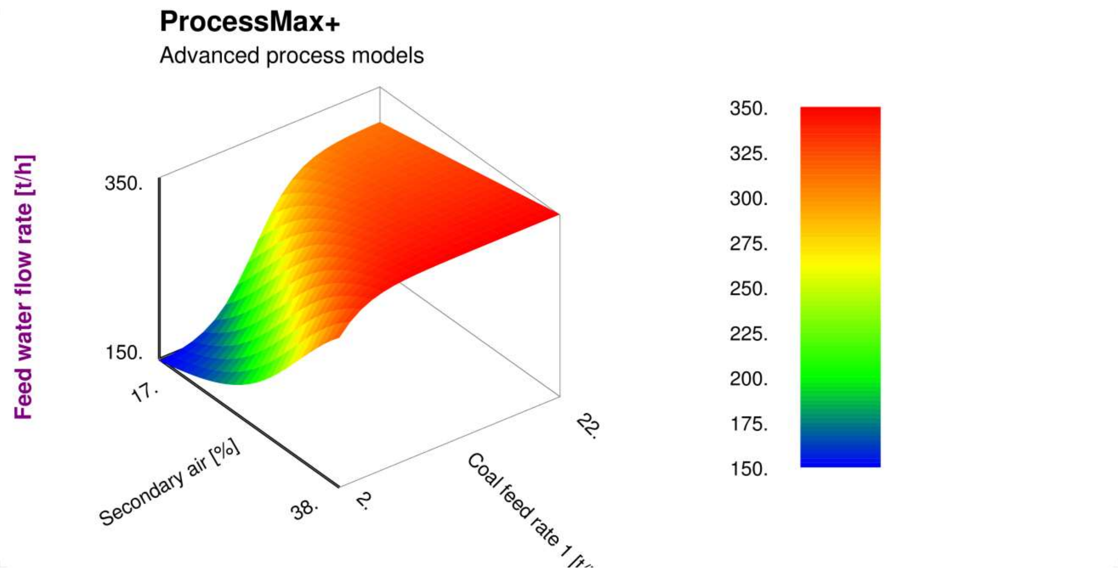


Figure 9. Effect of fuel flow rate from coal mill 4 on steam temperature at different fractions of secondary air



Thus, there are several variables which have beneficial effects on some consequences and deleterious effects on others, which make it difficult for operators to decide what a good compromise should be. Mathematical models which can quickly predict the consequences can help the operators determine the best values of process variables. However, engineers and plant operators in power plants cannot be expected to be familiar with nonlinear modeling. Therefore a set of software components has been developed over the years which allows facile use of the nonlinear models without needing to know the details of the mathematics underlying them. Depending on the end use, some of these software components are assembled into a software package, referred to as a *PROCESSMAX+* system

.

Such *PROCESSMAX+* systems have many different functionalities, besides simply being able to predict the values of the output variables. For example, effects of input variables, or pairs of input variables can be plotted in different ways. Figures 4 to 9 have been prepared in a *PROCESSMAX+* system with several nonlinear models implemented in it. Besides these, *PROCESSMAX+* systems can also have facilities for calculating the best values of process variables in presence of constraints and optimisation objectives [5]. In some cases, a software component allowing for updating the models is also included. These systems have allowed much better use of nonlinear models.

processMax+

	minimum	maximum	answer
Calorific value of coal [MJ/kg]	22.73	22.73	22.73
Ash content of coal [%]	12.70	12.70	12.7
Volatile matter in coal [%]	40.06	40.06	40.06
Sulphur content in coal [%]	0.383	0.383	0.383
Moisture in coal [%]	14.16	14.16	14.16
Volume fraction of saw dust [%]	10	15	13.990
Coal mill 4 [t/h]		10	2.8438
Coal mill 5 [t/h]			15.007
Coal mill 6 [t/h]	15		15.16
Secondary air [%]	25	35	28.958
Oxygen in the flue gas [%]	4.0	5.0	4.1584
NOx in the flue gas [ppm]		180	152.38
Feed water flow rate [t/h]	315	325	324.02
Flue gas temperature [°C]	141	148	146.93
Unburnt carbon in ash [%]		4	3.2753
Particulate matter [mg/Nm³]			22.827
Steam temperature [°C]	510		519.19

Figure 10. Determining a way to operate the boiler such that some variables stay within specified upper and/or lower limits.

As mentioned earlier, the objective of nonlinear models is often to determine the best values of the variables which are operator's degrees of freedom. Figure 10 shows one such calculation where upper and/or lower limits have been specified on some variables. This kind of a calculation usually takes less than a minute. For coal characteristics, there are no degrees of freedom. Whatever coal is available is used. Coal characteristics are what they are, and the upper and lower limits essentially specify the values of the coal characteristics. If the suggested solution does not look good from the point of view of some variable, one can tighten the limits and calculate again. Alternatively, one can ask for maximising or minimising one of the variables in addition to specifying limits on other variables. If cost per MW or combustion efficiency are implemented in processMax+ system, it would be natural to minimise the cost or maximise combustion efficiency while specifying limits on emissions, unburnt carbon, feed water flow rate and steam temperature.

5. CONCLUSIONS

Coal fired power plants should be operated in such a way that the emissions are kept clearly below desired limits and the combustion efficiency is as high as can be achieved. This requires a lot of quantitative knowledge of the effects of the process variables and fuel characteristics on the emissions and efficiency.

In coal fired power plants, there are several variables which have beneficial effects on some consequences and deleterious effects on others, which make it difficult for operators to decide what a good compromise should be. Mathematical models which can quickly predict the consequences can help the operators determine the best values of process variables. Physical models are too slow to be used for this purpose, and require too many assumptions and simplifications. It is, however, feasible to develop empirical or semi-empirical models from normal production data of power plants.

Nonlinear models of several variables were developed for the second boiler of the Fortum's coal fired power plant in Naantali and implemented in suitable software for use by the plant operators.