Proceedings of the American Control Conference
Anchorage, AK May 8-10, 2002

Combustion Optimization with Inferential Sensing

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Abstract

The paper presents development and implementation of Advanced Combustion Controller (ACC) for a coal-fired boiler. The solution consists of Combustion Controller (multi-variable predictive controller) and Combustion Optimizer (cautious strategy stochastic optimizer).

Optimization is based on a model of the CO and NO_x emissions. The model is used to calculate the setpoint of the optimal air/fuel ratio(s) maximizing the efficiency of the plant under constraints given by emission limits.

1 Introduction

The objective of application of model-based predictive control technology for boiler control is to enable tight dynamical coordination of selected controlled variables, particularly the coordination of air and fuel flows during the transients. This approach can be used – in connection with excess air optimization – to increase the boiler efficiency by 1–2% while considerably reducing the production of NO_x by 15-20%. One of the important features of the predictive controller developed is the control of the trajectory of the ratio of selected controlled variables [5]

While the standard air-fuel interlock provides acceptable steady-state performance, the solution based on classical PID controllers may not be fully satisfactory during the transients, e.g. for boilers operating in cycling regimes, particularly if low-NO_x burning with reduced excess air is used.

The controller cooperates with combustion optimizer, providing the optimal air to fuel ratio(s) setpoints, based on maximizing the efficiency of the plant under constraints given by emission limits. Optimization of combustion products must involve a suitable model describing the dependency of product concentrations on manipulated and measured variables.

Unfortunately, the models provided by the theory of combustion are too complex and involve difficult-to measure variables [2]; therefore they cannot be easily used for control. Practically usable models usually represent a trade-off between model complexity and accuracy [4, 7]. This text describes a second generation of such model, based on well-established *grey-box modelling* paradigm: combine the prior information resulting from first principles models with the posterior information (adaptive features) provided by the data. Realistic approach to combustion modelling is to suppose the following measurable variables: rate of fuel feed to the pulverizers, air flows (primary, secondary, tertiaty/overfire if applicable) to the burners and concentrations of the $[NO_x]$, $[CO]$, and $[O_2]$ in the output flue gas.

For the two key products, carbon and nitrogen monoxides, generation mechanism is highly influenced by temperature distribution and mixing (velocity/turbulence) in the combustion area. Unfortunately, these parameters are not available in real-time. Presented model is based on the idea that the $[CO]$ and $[NO_x]$ concentrations are functions of fuel and air flow rates in the boiler and additional unknown factors (related to the temperature/degree of turbulence in the boiler) that can be modelled as a stochastic process. This idea was verified empirically and the evaluation indicates that the air and fuel masses actually burnt are disturbed by irregularities in the transport ("blasts" in the flow).

An essential property of the model is *adaptivity*, i.e. its parameters must be recursively estimated from the data to reflect current state of the process, fuel quality etc. With nonlinear models it is difficult to adapt model parameters recursively, because nonlinear statistical estimation methods are mostly iterative. One of the few exceptions is the linear regression model which lends itself to numerically reliable yet simple recursive parameter estimation.

2 Modelling of combustion products

2.1 Combustion optimizer architecture

The optimizer architecture is depicted in Figure 1. The air and fuel supply dynamics are represented by two separate blocks P1 and P2. Combustion is modelled

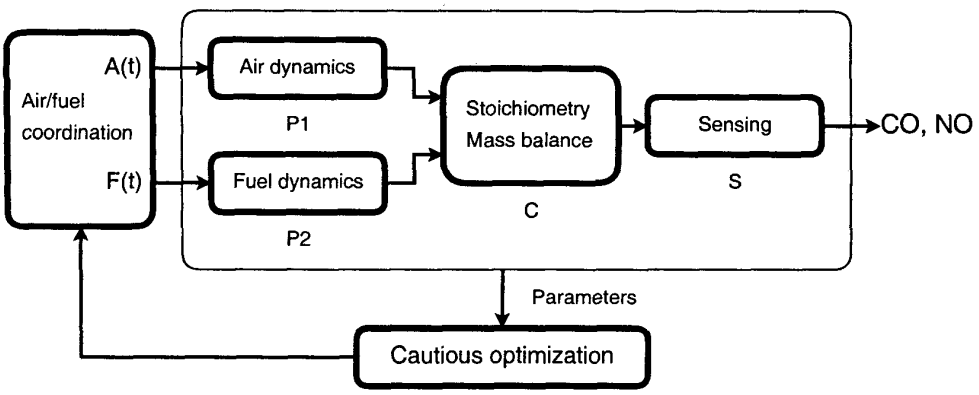

Figure 1: Architecture of the combustion optimizer.

by the block C, S represents the dynamics of flue gas transport and flue gas analyzers.

Our first-generation model used for the optimization purpose was based on modelling concentration of pollutant X as a nonlinear function of air A to fuel F ratio combustion chamber, with the transport dynamics represented by FIR (finite impulse response) models

$$[X](t) = f\left(\frac{\sum_{\tau=1}^{T} g^F(\tau)F(t-\tau)}{\sum_{\tau=1}^{T} g^A(\tau)A(t-\tau)} + \varepsilon(t)\right)$$

with unit gain (resulting from mass conservation) $\sum_{\tau=1}^{T} g^F(\tau) = \sum_{\tau=1}^{T} g^A(\tau) = 1$. This model is insufficient, particularly for $[CO]$.

Better representation of the prior information, that the settling time is in an interval $T \in [\underline{T}, \overline{T}]$ and the gain is unity, can be approximated by a FIR

$$y(t) = \sum_{k=0}^{N} g(k)u(t-k),$$

with the prior information about uncertainty of the dynamics expressed as probability distributions of the terms

$$h(t) = \sum_{\tau=0}^{t} g(t) \sim N(\hat{h}(t), \sigma_h^2(t)).$$

An example of *ucertainty propagation* resulting from uncertain dynamics is depicted in Figure 2. note the increase of uncertainty during the transients.

2.2 Combustion process

The combustion process is very complex and nonlinear. The only prior information we were effectively able to incorporate into the model is related to the stoichiometric and mass balance considerations.

For the prediction of CO concentration, the following variables are relevant (neglecting NO_x and SO_2 components):

Variables:

	symbol	unit
CO_2 production	CO_2	mole s^{-1}
CO production	CO	mole s^{-1}
N_2 production	N_2	mole s^{-1}
carbon contributing to CO_2	C^1	mole s^{-1}
carbon contributing to CO	C^2	mole s^{-1}
oxygen O_2 contributing to CO_2	O_2^1	mole s^{-1}
oxygen O_2 contributing to CO	O_2^2	mole s^{-1}
unburnt oxygen	O_2^3	mole s^{-1}
nitrogen N_2 in the air	N_2^1	mole s^{-1}
wet flue gases	Y	mole s^{-1}
input air	A	mole s^{-1}
water vapor	W	mole s^{-1}

Constants:

	symbol	range
wet/dry flue gas ratio	ν	$\frac{Y_{\text{dry}}+W}{Y_{\text{dry}}}$
fraction of C contributing to CO	δ_1	$[0,1]$
fraction of unburnt C	δ_2	$[0,1]$
fraction of O_2 in the air	P_{O_2}	0.21
fraction of N_2 in the air	P_{N_2}	0.79

A system of linear equations can be derived based on mass balance and reaction stoichiometry. For example reaction $C + O_2 \rightarrow CO_2$ entails algebraic equations

$$\begin{aligned} O^1 - CO_2 &= 0, \\ C^1 - CO_2 &= 0. \end{aligned}$$

and the mass balance equations

$$\begin{aligned} Y &= O_2 + CO + CO_2 + N_2 + W(\text{wet output}) \\ A &= N_2 + O_2 \end{aligned}$$

In the vector form the equation reads

$$M[C^1, C^2, CO, CO_2, \ldots, Y, W]^T + N[F, A]^T = 0$$

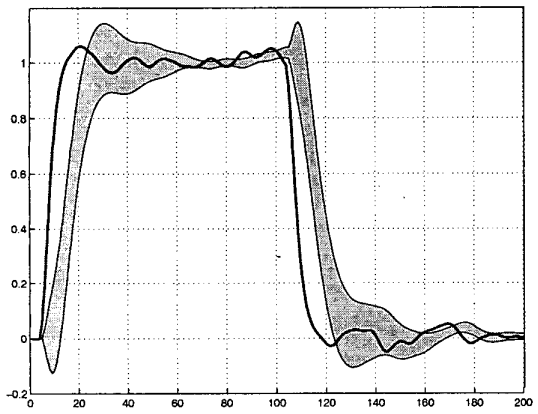

Figure 2: Modelling of air and fuel dynamics with uncertainty propagation.

where

$$M = \begin{array}{c} \begin{array}{cccccccccc} C^1 & C^2 & CO & CO_2 & O_2^1 & O_2^2 & O_2^3 & N_2 & Y & W \end{array} \\ \left(\begin{array}{cccccccccc} 1 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & -1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & (\nu-1) & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \end{array} \right) \end{array}$$

The CO and O_2 concentrations in flue gas are defined as fractions $CO/Y = [CO]$, $CO_2/Y = [CO_2]$, and $O_2^3/Y = [O_2]$, i.e. fractions of certain linear functions of the two mass supply rates $A(t)$ and $F(t)$

$$\begin{pmatrix} CO \\ O_2 \\ Y \end{pmatrix} = \begin{pmatrix} \delta_1 & 0 \\ a_{11} & a_{12} \\ \delta_1 & a_{22} \end{pmatrix} \begin{pmatrix} F \\ A \end{pmatrix}$$

$$[O_2] = \frac{a_{11}F + a_{12}A}{\delta_1 F + a_{22}A} \qquad [CO] = \frac{\delta_1 F}{\delta_1 F + a_{22}A}$$

For both CO and NO_x the formation mechanism depends mainly on temperature and turbulence parameters and the stoichiometric equation captures only a part of model. A thorough data-analysis show that the stoichiometric part of the mechanism is relevant for high-frequency part of the model, whereas the parameter δ_1 changes slowly but in a random manner. Further improvement is reached if also the correlation between $[CO]$ and $[NO_x]$ is used.

2.3 Air and fuel flow analysis

The previous subsection has shown the output concentrations to be certain linear rational functions of the supply rates. Unfortunately these supply rates at the input of the combustion block C in 1 are not measurable. They are estimated as outputs from the transport dynamics blocks P1 and P2; estimates are represented by mean value and dispersion. Moreover, it is necessary to reflect the fact the boiler draws false air and the mass fraction of carbon the fuel also varies, which can be approximated as

$$\begin{aligned} F &= \hat{F}\kappa + \epsilon_F \\ A &= \hat{A}_W + \Delta A + \epsilon_A \end{aligned}$$

with air supply rate bias

$$\Delta A = \hat{F}\theta_F[\Delta] + \hat{A}_W\theta_A[\Delta] + \theta_1[\Delta],$$

using variables

θ_k	False air draught parameters
κ	Carbon [mole] fraction in the fuel [kg]
ϵ_F	uncertainty of carbon supply rate; dispersion σ_F
ϵ_A	uncertainty of air supply rate; dispersion σ_A
$\hat{A}_W$	Wet air supply rate set-point, [mole s^{-1}]
$\hat{F}$	Fuel supply rate set-point, [mole s^{-1}].

Supposing independent sources of uncertainty, resulting equation for least squares estimation of unknown parameters reads

$$\begin{aligned} \epsilon\sqrt{(a_{11}\sigma_F/z)^2 + \sigma_A^2} &= \\ &= \left[\hat{A}_W z, \hat{F}z, z, a_{11}\hat{F}, \hat{A}_W z\right]^T \times \\ &\quad \left[\theta_A, \theta_F, \theta_1, \kappa, 1\right]. \end{aligned}$$

where $z = (a_{12} - a_{22}m_{O_2})$ and $\epsilon \sim \mathcal{N}(0,1)$. This equation supplies the posterior information about the masses instantaneously burnt in the boiler, using $[O_2]$ measurement to improve A and F tracking.

The stoichiometric and mass balance equations would solve the CO generation problem completely provided the parameter δ_1 is known. In fact it is not and it depends on unknown factors in a unknown way. It can supposed that that δ_1 is a low-order linear stochastic process, with settling time (estimated from the data) more than 200 seconds. No significant correlation between δ_1 and any other measurable variable was found. Apart from δ_1, the dynamics of the combustion block C is considered to be much faster than the other blocks and it is neglected.

2.4 Logarithmic version

The stoichiometric equations can be more conveniently expressed in a logarithmic form. For $a_{11} = 1$ we get

$$\log F - \log A - \log(O_2 a_{22} - a_{12}) = 0$$

Approximation of the term $\log(O_2 a_{22} - a_{12})$ with a normal random variable ξ. can be done by fitting the first two moments. The measured concentration of oxygen $m = [O_2]$ is supposed to be uniformly distributed on $[\underline{m}, \overline{m}]$. Then $\xi = \log(O_2 a_{22} + a_{12})$ has distribution

$$p(\theta) = \frac{1}{|\underline{m} - \overline{m}|} \frac{\exp \xi}{a_{22}}$$

for $\xi \in [\log(a_{22}\underline{m}+a_{12}), \log(a_{22}\overline{m}+a_{12})]$ with first and second moments

$$\begin{aligned}\mathcal{E}\{\xi\} &= [(\xi-1)\exp\xi]_{\log(a_{22}\underline{m}+a_{12})}^{\log(a_{22}\overline{m}+a_{12})} \\ \mathcal{E}\{\xi^2\} &= [(\xi^2-2\xi+2)\exp\xi]_{\log(a_{22}\underline{m}+a_{12})}^{\log(a_{22}\overline{m}+a_{12})}\end{aligned}$$

Logarithm of the CO equation for $\delta_1 \ll 1$ reads

$$\log F + \log\delta_1 + \log(CO) - \log A - \log a_{22} = 0$$

For the logarithmic model, $\log\Delta A = \theta_A \log\hat{A} + \theta_F \log\hat{F} + \theta_1$ is used.

For the purpose of prediction, it is necessary to translate distribution of $\log A$ to distribution of A. Suppose x is uniformly distributed on $[a,b]$. Then

$$p(\exp(x)) = \frac{1}{|b-a|}\frac{1}{\exp(x)} \text{ on } x \in [a,b]$$

and the first two moments are

$$\begin{aligned}\mathcal{E}\{\exp(x)\} &= \frac{\exp(b)-\exp(a)}{b-a} \\ \mathcal{E}\{\exp^2(x)\} &= \frac{\exp(2b)-\exp(2a)}{b-a}\end{aligned}$$

As a result, we have the following linear regression model for the logarithms of combustion products

$$\begin{aligned}\log F - \log A - \log(O_2 a_{22} - a_{12}) &= 0 \\ \log\delta_1 + \log F - \log A - \log a_{22} + \log(CO) &= 0 \\ \theta_A[NO_x]\log A + \theta_F[NO_x]\log F + \theta_1[NO_x] + \epsilon_{NO_x} &= 0\end{aligned}$$

where each entry is supposed to be a normally distributed random variable with known mean and variance and can be described as

$$\begin{aligned}\log F(t) &= \log\hat{F}(t) + \log\kappa + \epsilon_F(t) \\ \log A(t) &= \log\hat{A}(t) + \theta_A[\Delta]\log\hat{A}(t) + \\ &\quad + \theta_F[\Delta]\log\hat{F}(t) + \theta_1[\Delta] + \epsilon_A(t) \\ \log\delta_1(t) &= \theta_A[\delta_1]\log\hat{A}(t) + \theta_F[\delta_1]\log\hat{F}(t) + \\ &\quad + \theta_1[\delta_1] + \epsilon_{\delta_1}(t) + \ldots + \epsilon_{\delta_1}(t-n)\end{aligned}$$

These equations are coupled by the two random variables A and F – the air and fuel masses burned instantaneously in the boiler. All the unknown parameters in these equations are denoted as $\theta[\ldots]$ and can be estimated recursively. The equations may be made further coupled by a correlation of a noise term in NO_x and CO equations, which seems to be proven by the data-analysis.

2.5 Uncertain flue gas analyzer dynamic

The sensors measuring CO, O_2 and NO_x must be modelled as dynamic elements. Similarly as for the two P1 and P2 blocks, the settling time is known only approximately $T \in [\underline{T}, \overline{T}]$ and first order delay is supposed. Let us denote the input to the S block as $u(t)$ and output as $y(t)$. Then the first order random dynamics $u(t) \rightarrow y(t)$ as follows can be described as

$$\begin{aligned}y(t+1) &= y(t)a(t) + (1-a(t))u(t) \\ a(t) &\sim \mathcal{U}(\underline{a}, \overline{a}).\end{aligned}$$

i.e. it is uniformly distributed on $\langle\underline{a}, \overline{a}\rangle$. The inverse dynamics can be used to approximate the instantaneous gas concentration $u(t)$ as

$$u(t) = y(t) + \frac{y(t+1)-y(t)}{1-a} = y(t) + \Delta(t)$$

where $\Delta(t)$ is an unknown correction term with probability distribution

$$\begin{aligned}F_\Delta(\Delta_0) &= P\{\Delta < \Delta_0\} = \int_{-\infty}^{1-\frac{y(t+1)-y(t)}{\Delta_0}} p_\Delta(\Delta)d\Delta \\ F_\Delta(\Delta_0) &= F_\Delta\left(1 - \tfrac{y(t+1)-y(t)}{\Delta_0}\right)\end{aligned}$$

For $a \sim \mathcal{U}(\underline{a}, \overline{a})$ we get

$$p_\Delta(\Delta) = \left|\frac{\partial F_\Delta}{\partial\Delta_0}\right|_\Delta = \frac{1}{\overline{a}-\underline{a}}\frac{y(t+1)-y(t)}{\Delta^2}$$

for $\Delta \in \langle\frac{y(t+1)-y(t)}{1-\underline{a}}, \frac{y(t+1)-y(t)}{1-\overline{a}}\rangle$. and the first and second moment of distribution $p_\Delta(\Delta)$ are

$$\begin{aligned}\mathcal{E}\{\Delta\} &= \frac{y(t+1)-y(t)}{\overline{a}-\underline{a}}\int_\Delta 1/\Delta d\Delta = \\ &= (y(t+1)-y(t))\frac{\log(\overline{a}-1)-\log(\underline{a}-1)}{(\overline{a}-\underline{a})} \\ \mathcal{E}\{\Delta^2\} &= \frac{y(t+1)-y(t)}{\overline{a}-\underline{a}}\int_\Delta 1/\Delta d\Delta = \\ &= \frac{(y(t+1)-y(t))^2}{(\overline{a}-1)(\underline{a}-1)}\end{aligned}$$

Hence we are able to approximate the instantaneous gas concentration dynamics by means of the mean value and dispersion. In steady state the dispersion approaches zero and the model is rapidly adapted.

2.6 Heteroscedastic model

In the previous sections, incorporation of prior information into the model was described. The CO production was modelled by a set of linear regression models. The difference between the actual CO concentration and predictions provided by the model is a prediction error (residue) $r(t)$ with time-varying variance of "burst" nature. The variance of the residua can be modelled using an ARCH model (stands for Auto-Regressive Conditional Heteroscedasticity) [B1986].

Using the ARCH approach, the log-variance of the prediction error is given by an auto-regressive random process

$$\log\sigma_{\delta_1}(t) = \sum_k a_k \log\sigma_{\delta_1}(t-k) + \log|\epsilon(t)|$$

or using $\mathcal{Z}$–transformation

$$A(z)\log\sigma_{\delta_1}(z) = \log|\epsilon(z)|$$

The equation for prediction error $r(t)$ based on the driving noise $\epsilon_{\delta_1}(t)$ with time-invariant variance reads

$$\log r(z) - \log|\epsilon_{\delta_1}(z)| = \log\sigma_{\delta_1}(z)$$

and after substitution for $\log\sigma_{\delta_1}(z)$ we get

$$\log r(z) = \frac{1}{A(z)}\log|\epsilon(z)| + \log|\epsilon_{\delta_1}(z)|$$

This is an output error model that can be handled using pseudo-linear regression. This type of model where the amplitude of the prediction error ϵ_{δ_1} is modulated by occasional bursts of the prediction error is particularly efficient for the $[CO]$ modelling.

3 Combustion Optimizer

The Combustion Optimizer is based on cautious optimization strategy, i.e. it uses the full information about the uncertainty/distribution of combustion product concentrations (e.g. peaks in CO production). The optimizer adjusts the air supply rate in an adaptive manner, so that the changes of fuel quality and additional air are compensated for. Optimization of the total amount of combustion air requires inferential sensor for false (sucked-in) air that is not part of the measured/controlled air flows. This inferential sensor is part of the presented combustion model To be able to close a reliable feedback from flue gas analyzers (typically, O_2 and a subset of CO, CO_2, SO_x and NO_x concentrations may be available), sensor diagnostics based on sensor cross validation is also implemented in the Combustion Optimizer.

The purpose of the model is to calculate the "optimal" air to fuel ratio(s). The optimality index is related the plant efficiency $\eta(A/F)$, which is a function of the air to fuel ratio. The efficiency is maximized subject to inequality constrains

$$A^*(t) = \arg\max_{A(t)} \eta\left(\frac{A(t)}{F(t)}\right)$$

subject to

$$\begin{aligned} P\{[CO] > [CO]_{\mathrm{MAX}}\} &< \alpha_{CO} \\ P\{[NO_x] > [NO_x]_{\mathrm{MAX}}\} &< \alpha_{NO_x} \end{aligned}$$

i.e. the probability that the actual concentration values will exceed limits is constrained. In the case this optimization problem is infeasible, the constrains are replaced by a penalty function, i.e. if it is impossible to find $A^*(t)$ so that all concentration are within given limits, it is still possible to find $A^*(t)$ minimizing the violation of these limits.

The $[CO]$ and $[NO_x]$ abatement require exact coordination of the air and fuel supply rates so that A/F entering the combustion is constant and optimal. As the dynamics P1 and P2 is uncertain, the A/F ratio is reduced when the boiler is working near the steady state conditions, and increased to guarantee the combustion quality during the transients when exact coordination of the fuel and air flow cannot be guaranteed.

3.1 Implementation

The solution is implemented as an open solution (independent of a particular DCS) on Windows NT node. The communication with boiler regulatory control is via OPC (OLE for Process Control standard) client-server technology. Use of the OPC link also enables use of the ACC as a full-featured trainer running on a boiler simulator (including regulatory control layer) with OPC server.

Currently, ACC is running on three industrial size boilers (125 ton/hour, 9.4 MPa, 540 °C) and the ACC controller is distributed worldwide as a solution for power generation and industrial energy. Typical benefits of ACC is $1-2\%$ efficiency increase and reduction of NO_x emission by $15-20\%$. A typical screen showing the estimated uncertainty of CO emission as a function of excess air level is depicted in Figure 3.

3.2 Current developments

Current development is focussed on combustion optimization with more complex (staged) air distribution, multi-fuel fired boilers and link between the ACC and Economic Load Allocation (ELA) package.

Note that the boiler efficiency curve depends on the achievable excess air ratio. For several boilers operating to a common steam header(s), the link enables propagation of the efficiency curves of individual boilers (resulting from the optimized combustion efficiency) to the load allocation level. This bottom-up approach minimizes the burden of building and maintaining a separate model for the Real Time Optimization level when the information relevant for economic optimization is available on the process control level. Another benefit of this approach is event-driven real time responsiveness to varying economic environment (e.g. changes in input/output costs and constraints propagation) typical for power sector as a result of unbudling/deregulation.

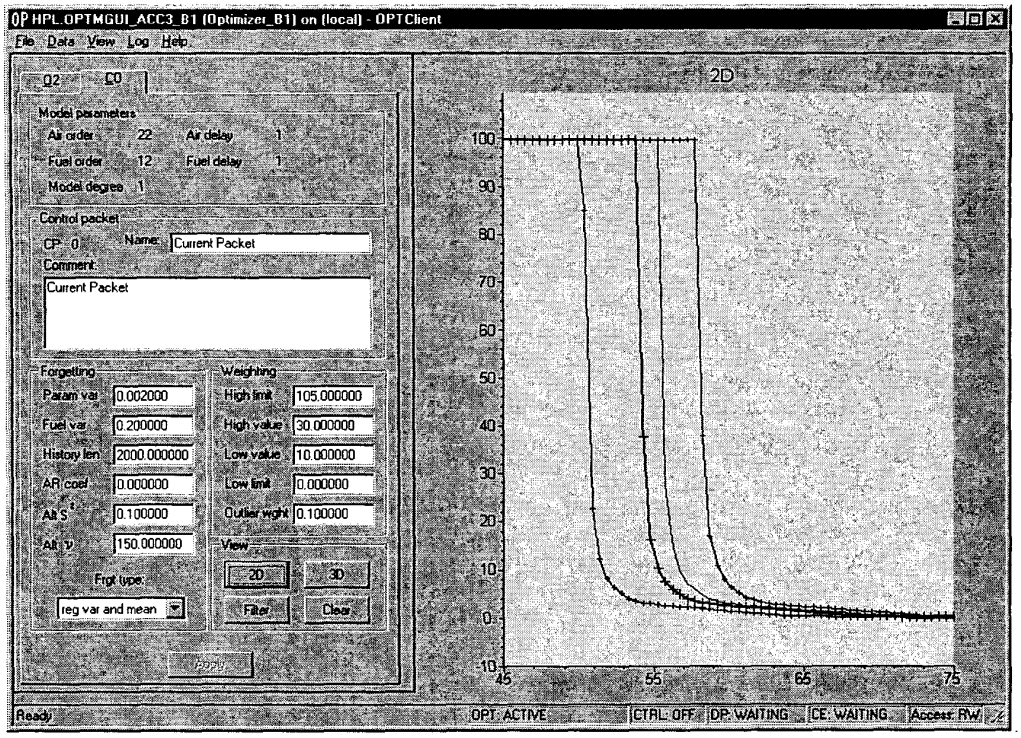

Figure 3: GUI of combustion optimizer showing the CO uncertainty.

4 Conclusion

including pilot testing on a pulverized-coal fired boiler

We have presented a comprehensive model of combustion products generation with uncertain transport and sensing dynamics and estimated false air ratio. The model is based on a grey box combustion model. The uncertain dynamics are not identified, however, the contribution of uncertain dynamics to the overall uncertainty is systematically propagated. The model of combustion is based on stoichiometric equations and mass balance equations, combined with the posterior information from flue gas analyzers. The paper concentrated mainly on $[CO]$ prediction, which is most difficult to model.

Acknowledgment: This research was partially supported by the Grant Agency of the Czech republic, grant 102/01/0021

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