

# SOFCOM – Self-optimising strategy for control of the combustion process

Jonas Funkquist, Volker Stephan, Erik Schaffernicht, Claus Rosner and Magnus Berg

## Kurzfassung

### SOFCOM – Selbstorganisierendes System zur Optimierung des Verbrennungsprozesses in Kohlekraftwerken

Die Verbrennung in kohlenstaubbefeuerten Großkraftwerken ist aufgrund kontinuierlicher Veränderungen der Kohleeigenschaften und deren Verteilung zwischen mehreren Brennern oft nicht optimal.

Das SOFCOM-Projekt entwickelte hierzu einen selbstorganisierenden Ansatz zur weitestgehend vollautomatischen Integration und Auswertung von Hochgeschwindigkeits-Kameradaten. Die darauf aufsetzende adaptive und lernfähige Reglerstruktur ist mit dieser neuartigen Information in der Lage, sich automatisch an Veränderungen des Verbrennungsprozesses anzupassen.

Optimierungsziele sind Lambda-, NO<sub>x</sub>- und CO-Reduktionen sowie verbesserte Aschequalität und verlängerte Kesselstandzeiten.

Die entwickelten Algorithmen funktionieren gut und liefern robuste und stabile Ergebnisse im On-line-Betrieb bei zeitvarianten Prozessbedingungen. Im Vergleich zu Standard-Einstellungen reduziert das SOFCOM-System den Luftüberschuss um 0,7 Volumenprozent und NO<sub>x</sub> um 20 mg/Nm<sup>3</sup>. Das System erwirtschaftet einen zusätzlichen Nutzen von 385.000 € pro Jahr aufgrund von Effizienzsteigerungen, reduziertem Lüfterbetrieb und reduzierten Einspritzwassermengen.

Darüber hinaus wird ein signifikanter Gewinn aus dem verlängerten Vollast-Betrieb der Anlage erzielt.

## Authors

**PhD Jonas Funkquist**  
Vattenfall Research and Development AB  
Stockholm/Sweden

**Dr.-Ing. Volker Stephan**  
Powitec Intelligent Technologies  
Essen/Germany

**Dipl.-Ing. Erik Schaffernicht**  
Technische Universität Ilmenau  
Ilmenau/Germany

**Dipl.-Ing. Claus Rosner**  
Vattenfall Vattenfall Europe Wärme AG  
Heizkraftwerk Tiefstack  
Hamburg/Germany

**PhD Magnus Berg**  
Vattenfall Research and Development AB  
Stockholm/Sweden

## Introduction

In 2004 the combustion control system, the PiT Navigator by Powitec Intelligent Technologies GmbH, was installed at the Vattenfall Tiefstack plant in Hamburg. This system is based on optical information from the flames and neural network models. The results of this system are decreased fuel consumption by 0.8 % and the amount of unburned carbon in fly ash.

One drawback was the system's inability to adapt automatically to changing process conditions. Therefore, an improved system with high-speed cameras and more advanced signal processing and control algorithms was required in order to achieve a more adaptive system.

The new approach comprises two main differences in comparison with the installed PiT Navigator: use of completely new visual high-frequency information provided by CMOS-cameras instead of CCD-cameras. This allows a more detailed and sophisticated description of the combustion process concerning coal particle size, volatiles and ash content. Based on this additional information it was expected that more accurate process models could be produced and thereby achieving a more accurate control.

The second difference is that a human had to define all inputs, all controls and the structure of the whole controller. This process is very time- and cost-consuming and increasing the risk of making wrong decisions. The new system uses instead data-mining techniques to detect relationships between inputs, states and control variables in order to make an automated, designer-independent and purely data-driven controller design.

### Project target and approach

The SOFCOM project was mainly aiming at the development of a system to optimise combustion. This system is based on camera information from the flames in addition to normal process data. The main objective of the project has been to optimise combustion air the distribution in order to:

- reduce the air/fuel ratio (Lambda) below 1.16,
- reduce NO<sub>x</sub> and CO and
- increase ash quality and the boiler lifetime

- using advanced high-speed cameras to capture flame information,
- designing a self-organising system that will automatically
  - extract relevant information from the image data,
  - find relationships between inputs and targets, and
  - select a suitable control strategy.

### Description of the Tiefstack plant

The Tiefstack CHP plant (Figure 1) is located close to the Hamburg city centre. The plant was commissioned in 1993 and generates nearly half of the heat required for the local district heating network.

The thermal power plant consists of a base load plant with two hard coal-fired steam generators and one turbine. The base load plant is of forced flow Benson type with steam data of 180 bar and 540 °C. The maximum thermal power is 285 MW<sub>th</sub> and the maximum electrical power is 205 MW.

The two boilers have three burner levels equipped with two burners each that are fed by one mill for each level. Coal is pneumatically transported to the burners by the staged air flow (Figure 2) comprising of primary and secondary air.

## Theory and methods

### Introduction

The basic theory behind the SOFCOM system is as follows:

- Collect high-dimensional, high-speed data from burner flame camera images,



Figure 1. Photo of the Tiefstack plant.



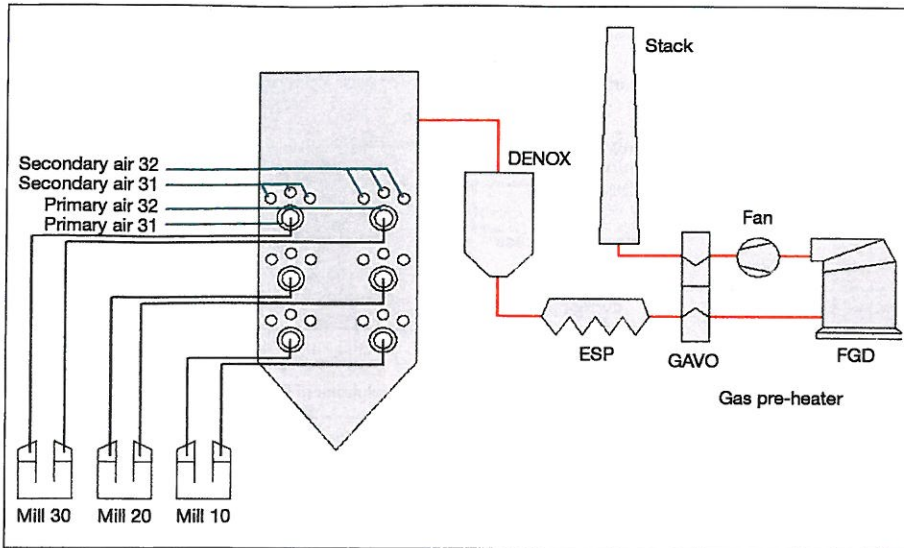


Figure 2. Diagram of the Tiefstack plant.

- Apply signal-processing algorithms that extract camera data information and process data information and aggregate this information into so-called features that can be used for control,
- Apply control algorithms using the extracted data and a chosen set of control commands to optimise both the total air amount and its distribution with respect to the targets of decreased oxygen level, CO content and NO<sub>x</sub> content in the flue gas.

The latter two also include algorithms that are adaptive in order to follow typical process changes caused by e.g. different coal types and fouling.

Camera-based measurement system

Six CMOS cameras have been installed at the Tiefstack plant in Hamburg. Every camera shows one burner from the side. The hardware required by every camera is shown in Figure 3.

Figure 4 depicts a spectrogram from such a high-speed sequence of a CMOS camera. The underlying spectra are computed by a standard Fast Fourier Transformation (FFT) and show the energy distribution over different frequencies of brightness changes over time. It is obvious that most energy is in the area of lower frequencies, but sometimes also higher frequencies of brightness changes occur.

Both, the high-resolution images as well as the spectra calculated from high-speed image sequences, provide the raw data providing primary information about the flames. The following section will describe how to automatically extract control-relevant information from those high dimensional raw data.

Information extraction

There is plenty observable data from the power plant that are delivered by the control system and the camera system. In fact, there is

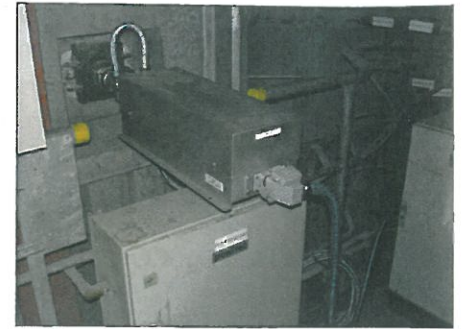


Figure 3. Powitec camera installation for one burner. The upper box contains the CMOS camera, the lower box provides cooling and purging air to keep the lenses clean from dust.

This reduced information is now joined by the normal control system data (DCS) and subject to a final feature selection to decide which channels will be used in the new control strategy.

The feature selection module decides for each available channel if it is relevant enough to be used by the controller. The decision is again based on criteria of information theory. This way it is ensured that only channels are presented to the controller that actually carry information. The final system uses an approach called MIFS (Mutual Information for Feature Selection). It computes the relevance of a given channel with respect to the desired outputs and it also takes into account any redundancies the input channels may contain.

too much data to handle for any artificial intelligent control system. Moreover, several channels are not containing useful information, but only add distractions. Hence, it is required to extract information.

Thereto, raw and high-dimensional CMOS camera data is transformed into so-called features, which are low-dimensional but highly informative. The feature's relevance regarding target prediction is evaluated by an information-theoretic criterion, which is used afterwards to iteratively improve the transformation. This method is called maximise mutual information (MMI)

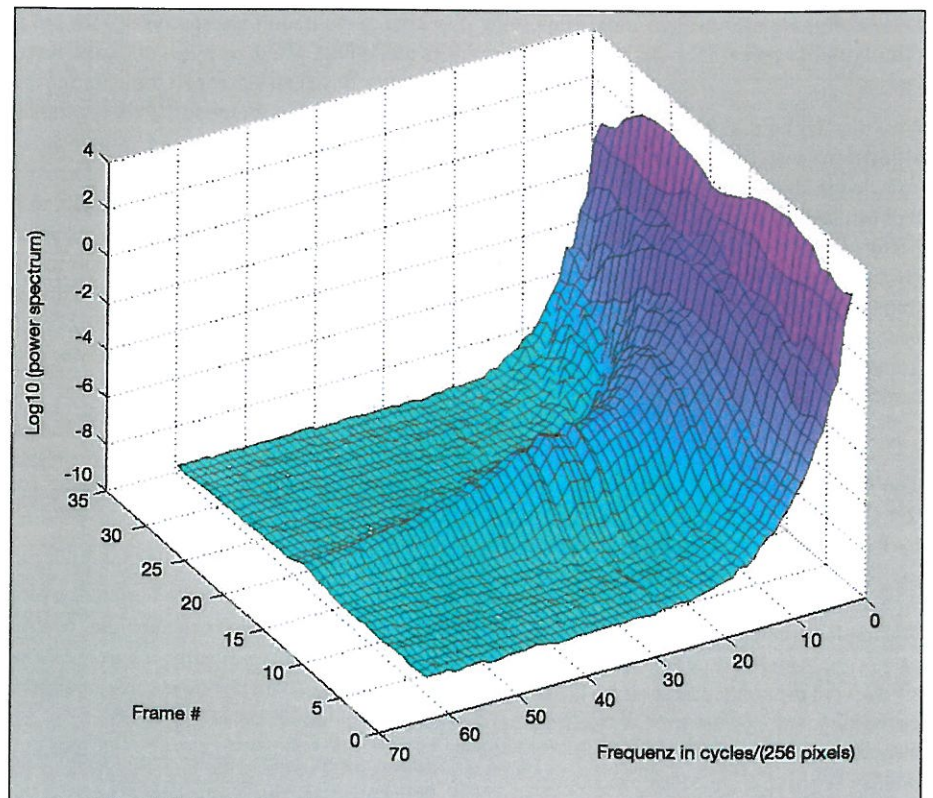


Figure 4. The spectrogram of the CMOS-high-speed image sequence shows the development of power frequency spectrum over time frames.



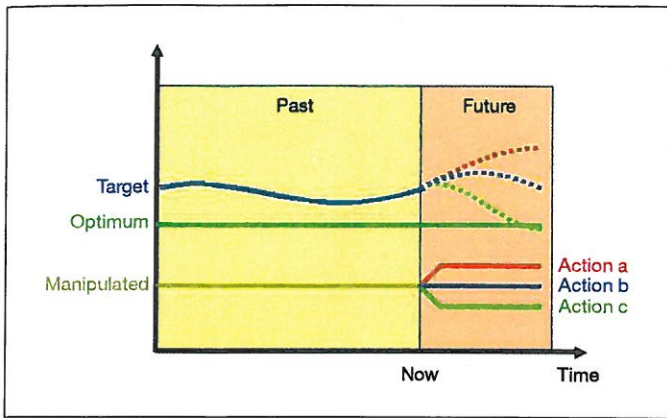


Figure 5. Working principle. An Artificial Neural Network is used to predict the future behaviour of a target given different hypothetical control actions a, b, and c. The one that evaluates best is executed on the real process.

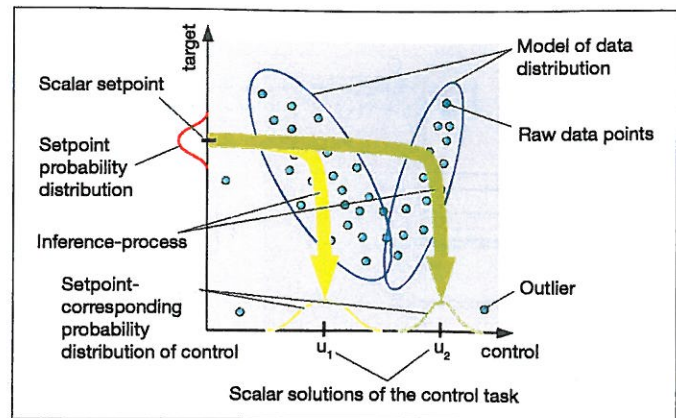


Figure 6. Simplified functioning of Bayesian process control for a single input-single output system (SISO). First, the distribution of raw data is modelled by a number of Gaussians. This so called probabilistic process model is used afterwards in the inference step, where for the given distribution of the target set point possible distributions for control solutions are calculated.

### Control strategy

Traditional control approaches like the Linear Model Predictive Control (MPC) as well as new developments from the Reinforcement Learning Domain like the Cooperative Synapse Neuro-evolution (CoSyNE) and probabilistic approaches are used as control strategy.

In the Reinforcement Learning Paradigm the learner is not told which actions to take, as in most forms of other control methods, but instead it must be discovered which actions yield the most reward by trying them. Actions may affect not only the immediate reward but also all subsequent rewards. These two characteristics – trial-and-error search and delayed reward – are the two most important distinguishing features of reinforcement learning.

Note that during the trial-and-error search, the algorithm will continuously increase the knowledge about the process. This knowledge will be used for future control and the control performance will therefore improve until it has been fully learned. Only when new conditions arise, e.g. if fuel is used that has never been used before, the performance will degrade temporarily until adaptation to the new conditions has been finished.

#### The PiT Navigator

The PiT Navigator is a Model-based Predictive Controller (MPC). It is a standard product by Powitec and was available even before the SOFCOM-project started. The basic idea is to first build a process model and then to use that model to calculate a control sequence that drives the simulated targets as good as possible to the predefined set points. If the process model matches the process well enough, also the real process will be driven to the set points given the same control sequence.

The PiT Navigator uses Artificial Neural Networks to build a process model from histori-

cal data. Afterwards, several hypothetical control sequences are simulated internally and the best evaluated sequence is executed in reality. Figure 5 depicts this principle.

#### The Bayesian controller

The Bayesian controller [10] was motivated by the fact that real and especially industrial processes show uncertainty in many ways. There are for instance noisy, unreliable, or even missing measurements, as well as unknown hidden process states. This results in ambiguous and noisy process data that complicate or even prevent traditional process modelling.

In contrast to traditional approaches for process modelling, which operates on scalar numbers, the Bayesian approach is operating on probability density functions. This way noisy data do not have to be reduced to their mean value; instead they can be described correctly by statistics. Based on that improved data representation, the Bayesian controller uses process data to build a probabilistic process model. Again, this operates on high dimensional probability density functions describing the probability of different process outcomes given an uncertain input constellation.

Figure 6 shows for a very simple system with only one control and one target variable (SISO) the principle functioning of Bayesian process modelling and control.

Once this probabilistic process model is built, it can be applied to a so-called inference-procedure, which is able to calculate that control sequence that most probably drives the process into a desired state. That control sequence will be applied to the real process.

Due to correct, but complex representation of uncertain data, this control approach takes much computational effort, but is still fast enough.

#### The CoSyNE controller

In addition to both control approaches described before, a Neuro-evolution method was tested, called Cooperative Synapse Neuro-evolution (CoSyNE) [9]. CoSyNE applies evolutionary strategies to evolve a non-linear controller (Figure 7) based on recurrent neural networks, which drive the process as fast and accurate as possible into a desired target state.

Unfortunately, evolutionary algorithms for control require extensive tests of individual controllers with the plant in order to determine their performance, the so-called fitness. Obviously, that extensive testing is not applicable for industrial processes with real-world constraints like irreversibility and control cycle periods. Thereto, the original approach was extended by a couple of alternative process models, which replace the real plant for extensive closed-loop controller tests.

Instead of a single process model, a couple of different models were favoured, because that diversity ensures the development of a robust controller. On the contrary, operating on a single process model would be sub-optimal, since any model failure may mislead the evolutionary search process for an optimal controller to a suboptimal solution or even a dead-end.

### Analysis of the information extraction methods

#### Robustness analysis of automatic information extraction

The feature extraction algorithm [7] uses measures from information theory to estimate the mutual information (MI) between channels. It is trained with different settings in order to analyse its robustness with respect to different pre-processing of the raw camera



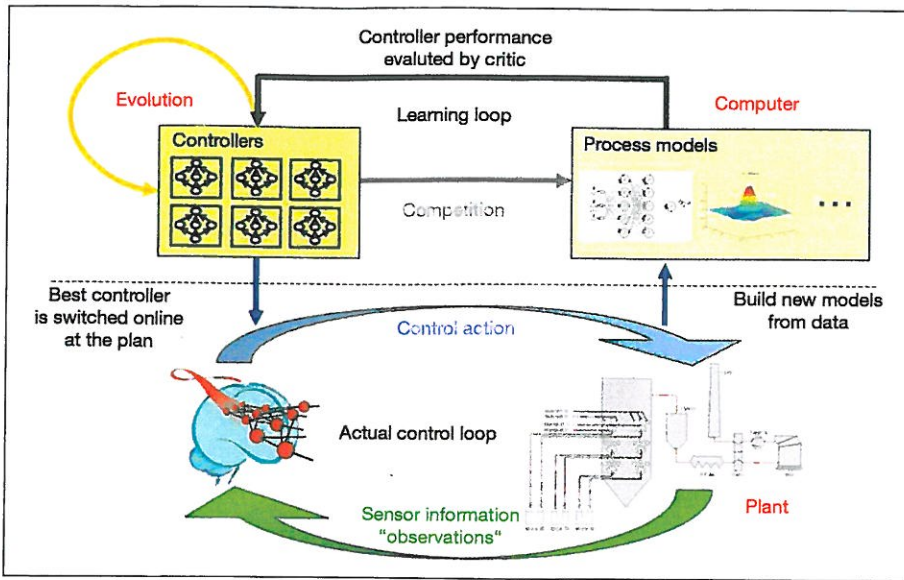


Figure 7. Schematic overview of the CoSyNE control method. The upper half shows the learning cycle of the algorithm. From data acquired in the plant, different models using neural networks are built. Several controllers (neural networks as well) form a population which is evaluated on the models. Good controllers are modified to improve and bad controllers are removed. The best controller of this population is then used to control the plant.

data, different training periods, and different image regions for spectral analysis. From a robust algorithm it is expected to provide similar results on these cases. In summary, this expectation could be fulfilled – the algorithm provided robust results.

*Comparing MMI-based information extraction with traditional PCA*

Based on a parameter study in the previous section, the information content of MMI-based extracted features was compared with those extracted by the standard PCA-approach (Principal Component Analysis).

First, both PCA and MMI were applied to CMOS-image data for all six burners from the Tiefstack plant. Subsequently, neural networks were trained on extracted features in order to learn a prediction of interesting target channels like CO, NO<sub>x</sub>, and O<sub>2</sub>. If the MMI-method is superior to the PCA-approach, one would expect a better prediction of these target channels using MMI-inputs.

It could be stated that the prediction errors of the Neural Networks operating on MMI-based features were lower. That means that the MMI-approach provides more informative features in comparison to standard PCA compression.

*Online behaviour of automatic information extraction approaches*

Since previous investigations stated that the new approach on automatic feature extraction produced robust results and is superior to standard approaches like PCA, a practical application would be the next step. Thereto, an online comparison of the traditional approaches Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) was car-

ried out with the newly developed approach to Maximize Mutual Information.

This investigation with respect to adaptivity is necessary, since it was searched for an architecture that is able to cope with time varying processes in the SOFCOM project. The need for adaptivity not only concerns the controller, but must also be extended to feature ex-

traction to be able to adapt to changing measurements.

The architecture has to be permanently adaptive since there is no a priori information about process changes. To make sure that the controller does not get confused by fast semantic changes of extracted features, only slow and smooth changes of feature extraction are allowed.

After running a stable and robust automatic feature extraction online, also the online behaviour of the feature selection to be finally used by the controller had to be tested. Therefore different parameter settings and different data sets (time ranges) were investigated where additional information-free dummy channels and manually pre-selected informative channels were introduced into the test scenario. The tests demonstrated that the proposed approach for automatic feature selection is usable for online operation.

*Analysis of the control strategies*

*Comparison of control strategies by simulation*

For the first stage of testing different candidate control approaches, a simple combustion simulator mimicking basic relations of combustion was used as benchmark. These tests were focused on different approaches from Reinforcement Learning domain. One contender from each of the three basic groups of Reinforcement Learning was chosen. The

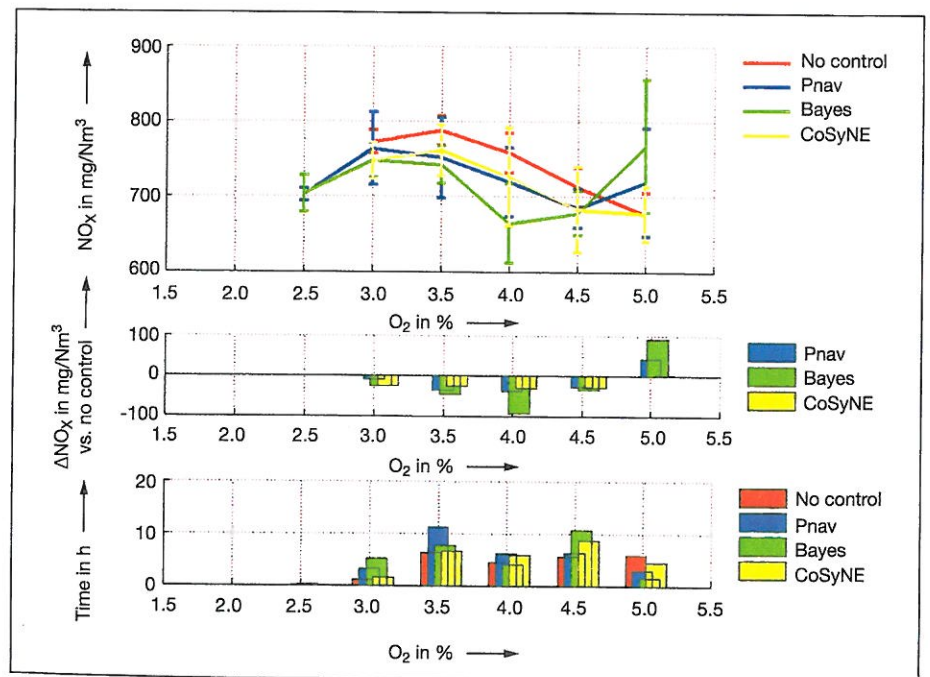


Figure 8. Comparison of four control approaches with respect to NO<sub>x</sub>. Since NO<sub>x</sub> strongly depends on the amount of excess air, data have been split into comparable oxygen classes. The upper diagram shows NO<sub>x</sub> emissions of all four controllers within these oxygen classes. Vertical bars indicate the standard deviation inside that class. The diagram in the middle shows differences between "no-control" mode and the other three controllers. The lower diagram shows a histogram of test data with respect to oxygen. Note that it is important to check this diagram before drawing conclusions since comparisons on more frequent oxygen classes are more reliable than less frequent ones.



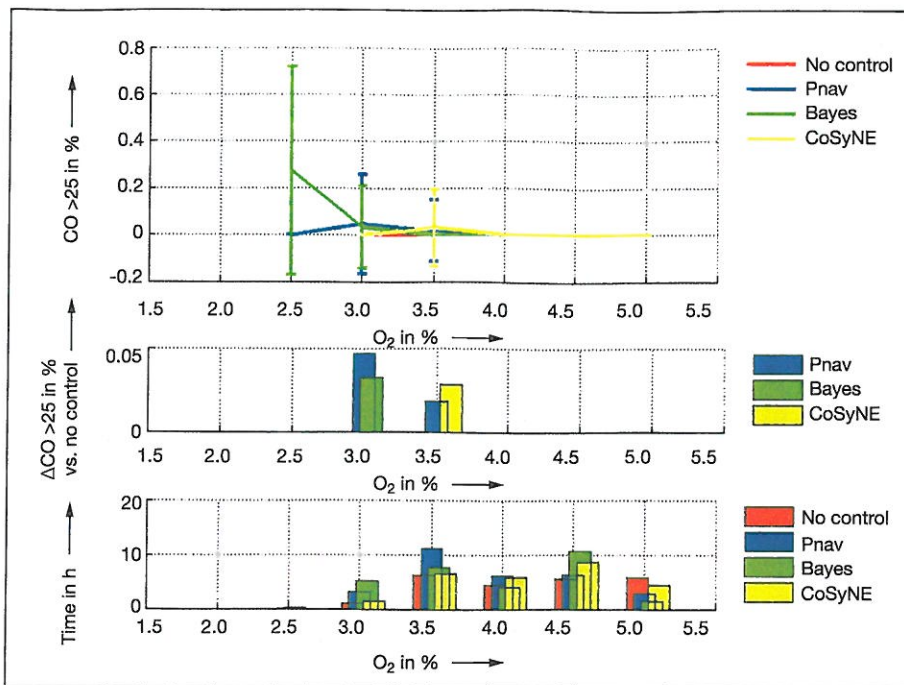


Figure 9. Comparison of four control approaches with respect to CO. Since also CO strongly depends on the amount of excess air, data were split into comparable oxygen classes. The upper diagram shows the number of CO peaks of all four controllers within these oxygen classes. A CO peak is considered to be higher than  $25 \text{ mg/Nm}^3$ . Vertical bars indicate the standard deviation inside that class. The diagram in the middle shows differences between “no-control” mode and the other three controllers. The lower diagram shows a histogram of test data with respect to the oxygen classes.

CoSyNE approach proved to be the most successful method. Afterwards the CoSyNE, the most successful representative of the Reinforcement Learning group, was compared against a Bayesian Process Controller and a Model Predictive Control approach.

For the Model Predictive Control approach, it was concluded that the simple and straightforward version with consecutive linearisation of the non-linear process model was not able to satisfactorily control the Simple Combustion Simulator.

As a result of simulator tests, it was concluded to implement the Bayes controller and the CoSyNE controller in the Tiefstack power plant because both methods reached smallest set point deviations.

#### Comparison of different control approaches in closed loop plant operation

The following control approaches were implemented and tested at the Tiefstack plant:

- “No control”: This control mode refers to original plant operation, where air is distributed by a fixed setting between all three burner levels, between two burners of each level, and also between secondary and tertiary air. Furthermore, the amount of total air is not reduced at all, i.e. oxygen is expected to be controlled by the  $\text{O}_2$  controller of the DCS system at pre-defined load dependent set points.
- Pnav: This control mode refers to “old” PiT Navigator that has been installed in the first

stages of the SOFCOM project for comparison to newly developed controllers. PiT Navigator adjusts air distributions according to its internal model predictive control strategy (MPC). It then uses some manually selected DCS channels and some manually selected features from cameras. In contrast to “no control”, an additional oxygen optimiser tries to reduce the amount of total air as far as possible. The limits for that air reduction were defined by the plant operator from a safety perspective and care about calculated oxygen, CO emissions and steam temperature.

- CoSyNE: The newly developed CoSyNE control mode applies its control policy that was found using evolutionary algorithms. In contrast to the Pnav, it does not operate on manually extracted or selected features instead it uses the newly developed approaches for automatic feature extraction as well as selection from both DCS- and camera data. As in the Pnav-mode, the same oxygen optimiser reduces excess air as low as possible.
- Bayes: The newly developed Bayes probabilistic control approach operates as well as CoSyNE on automatically extracted and selected features from both DCS- and camera data. As in the Pnav- and CoSyNE-mode, the oxygen optimiser reduces excess air as low as possible.

As motivated in detail in the previous section, these tests were run in normal daily operation with typical load changes and different coal

types. The four control modes were run sequentially for 10 hours each. To make a fair comparison, the following time ranges were excluded from further evaluation:

- Plant load below 30 %,
- Powitec-system not activated by the plant operator. This is mainly the case in abnormal plant situations like shutdown or restart procedures,
- Plant load changed by more than 10 % within the last hour. This is not done because the controller would not work, but the number of those transient parts would be different for all tested controllers and this comparison would not be fair,
- 30 minutes after switching the operating controller, because the process takes some time to adjust to the new control settings,
- Exploration time ranges of all controllers: These take about two hours and are used to explore other control settings in order to detect process changes and to improve.

To make the resulting data comparable, data from only the same coal type were compared. To get rid of load case impacts and air to fuel ratios, the evaluations were split into different load and oxygen classes. Figure 8 shows a comparison of all four control approaches with respect to  $\text{NO}_x$  emissions. Except for the 5 %-oxygen class, all three controllers outperform the “no-control”-mode. The Bayesian controller performs best.

Figure 9 shows the corresponding evaluations for CO. Neither of the controllers increase the number of CO peaks to a considerable extent. All controllers keep the number of CO peaks at the same level.

Figure 10 finally plots the total amount of oxygen that was reached. All three controllers can reduce the oxygen level in comparison to “no-control”-mode, which represents original plant operation with a pre-defined load dependent oxygen level.

The same evaluation that has been presented in Figure 8 to Figure 10 has been performed for 12 other coal types from April until October 2009. To compress these very detailed comparisons, total reductions in CO peaks,  $\text{NO}_x$ , and  $\text{O}_2$  were calculated for each coal type, weighted by their reliability. The result is shown in Figure 11. All controllers’ performances correlates with “coal type”. On the one hand, there are coal types that cause problems for all approaches, on the other hand, combustion of some coal types can be improved strongly. It has to be noted that a major plant inspection was carried out between coal type K and L. As can be seen, the investigated controllers cope well with all process changes caused by that plant overhaul.

In order to compress these results even further, average reductions for all emissions



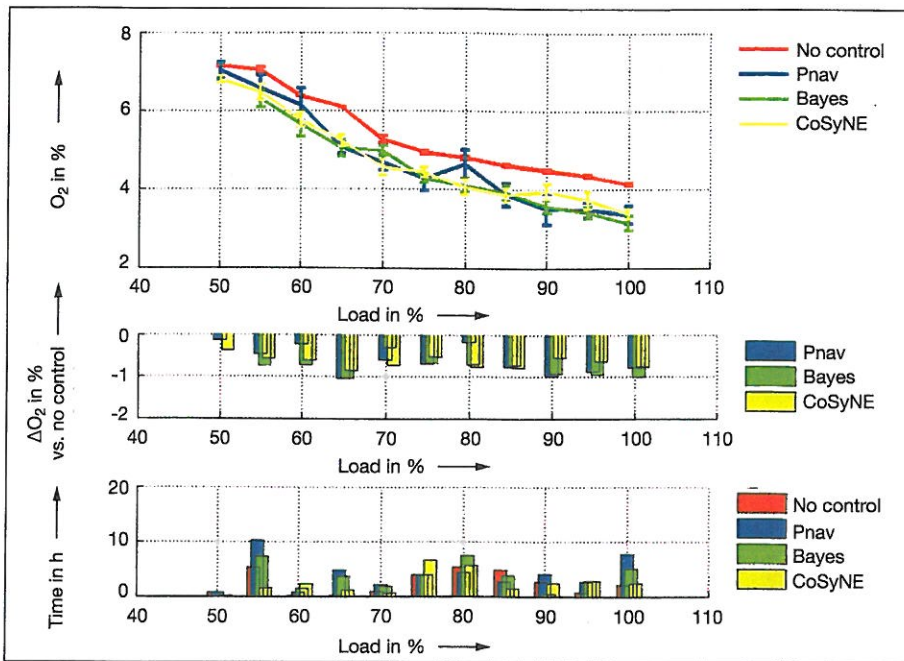


Figure 10. Comparison of four control approaches with respect to O<sub>2</sub>. Since O<sub>2</sub> strongly depends on plant load, test data was split into comparable load classes. The upper diagram shows average oxygen levels that were reached by the oxygen optimiser in cooperation with all four controllers, separated by load classes. Vertical bars indicate the standard deviation inside that class. The diagram in the middle shows differences between “no-control” mode and the other three controllers. The lower diagram shows a histogram of test data with respect to load classes.

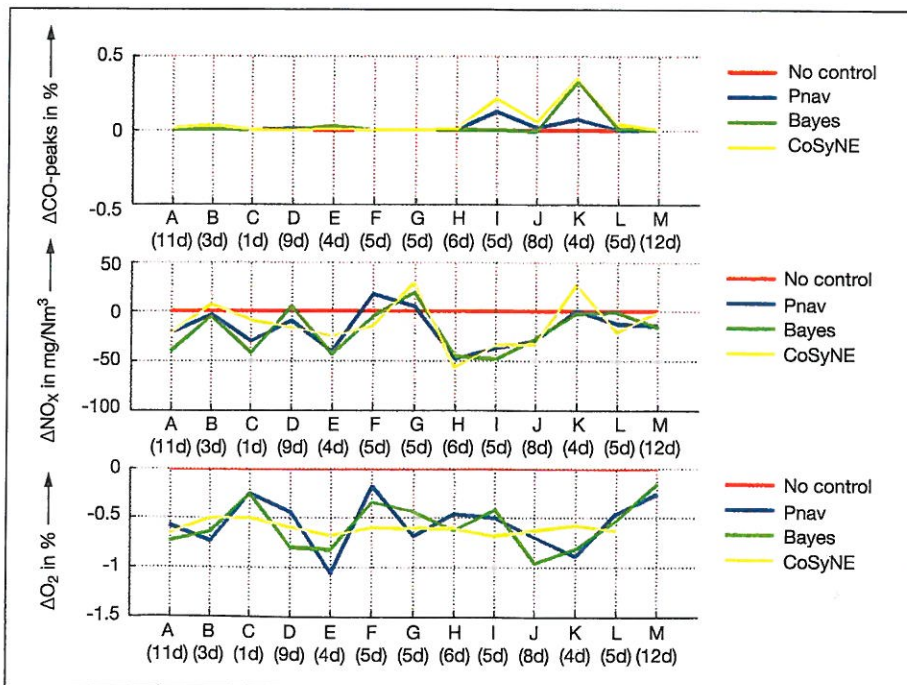


Figure 11. Comparison of all four control approaches for all comparable coal types between April and October 2009. Note the different durations of these coal types (shown within parenthesis in days). The comparison is made in relation to the “no-control” mode, which is the zero-level in these plots.

weighted by the duration of corresponding coal type were calculated. Figure 12 shows the results. There are no considerable increases in CO peaks for any of the controllers. NO<sub>x</sub> emissions could be significantly reduced by all controllers by approximately 20 mg/Nm<sup>3</sup>. Note that for all controllers real NO<sub>x</sub> reduction exceeds this number, because in this comparison the impact of oxygen reduction is

intentionally excluded! At best performs the Bayesian controller, who slightly outperforms the Pnav and CoSyNE. The largest reduction of excess air measured by oxygen is achieved by the Bayesian controller, which could reduce O<sub>2</sub> by 0.66 %. This value is clearly above the average of all load cases and all coal types. Also CoSyNE works better than the Pnav by 0.04 %.

### Economical results

Four main causes for economical results through the SOFCOM system have been identified:

- Increased efficiency due to a continuous reduction of excess air,
- Reduction of air and its impact on maintenance,
- Reduction of air fan operation (decreased energy consumption),
- Reduction of spray water for steam temperature control.

In the following sections the economical benefits are assessed.

#### Boiler oxygen reduction

Calculations about the economical savings due to the reduction of oxygen by reducing excess air are based on the following assumptions:

- Full load operation (5,500 hrs/y): SOFCOM with  $\lambda = 1.16$  versus manual operation with  $\lambda = 1.24$ , equals to 5.4 Nm<sup>3</sup>/s less excess air,
- Part load operation (2,500 hrs/y): reduction of 2.7 Nm<sup>3</sup>/s of excess air
- Gas enthalpy = 159 kJ/Nm<sup>3</sup>
- Calorific value coal  $\approx 25,000$  kJ/kg
- Coal price incl. CO<sub>2</sub> emission costs  $\approx 100$  €/t

This results in a yearly savings of  $(859 \text{ kJ/s} \cdot 5,500 \text{ h} + 429 \text{ kJ/s} \cdot 2,500 \text{ h}) / 25,000 \text{ kJ/kg} \cdot 3,600 \text{ s/h} \cdot 100 \text{ €/t} \approx 83,500 \text{ €}$

#### Reduced fan operation costs

The economical benefits resulting from reduced fan operation due to less excess air are estimated on the basis of the following assumptions:

- Efficiency in condensation operation: 37.5 %.
- Electric savings ID-fan  $\approx 125$  kW, FD-fan  $\approx 40$  kW.

This results in yearly savings of  $8000 \text{ h} \cdot 3,600 \text{ s/h} \cdot (125 \text{ kW} + 40 \text{ kW}) \cdot 100 / 37.5 \% / 25,000 \text{ kJ/kg} \cdot 100 \text{ €/t} \approx 50,000 \text{ €}$

#### Spray water reduction

The turbine has a high-pressure and a low-pressure steam cycle. Two spray water temperatures control the HP-part steam temperatures one the RH-part. The most theoretical efficient operation would be to eliminate RH-injection.

From operational experience with the SOFCOM-system, optimising both air distribution and air amount, the heat distribution has improved in a way that less spray water is used in the RH-part by about 1 kg/s. Assuming the following



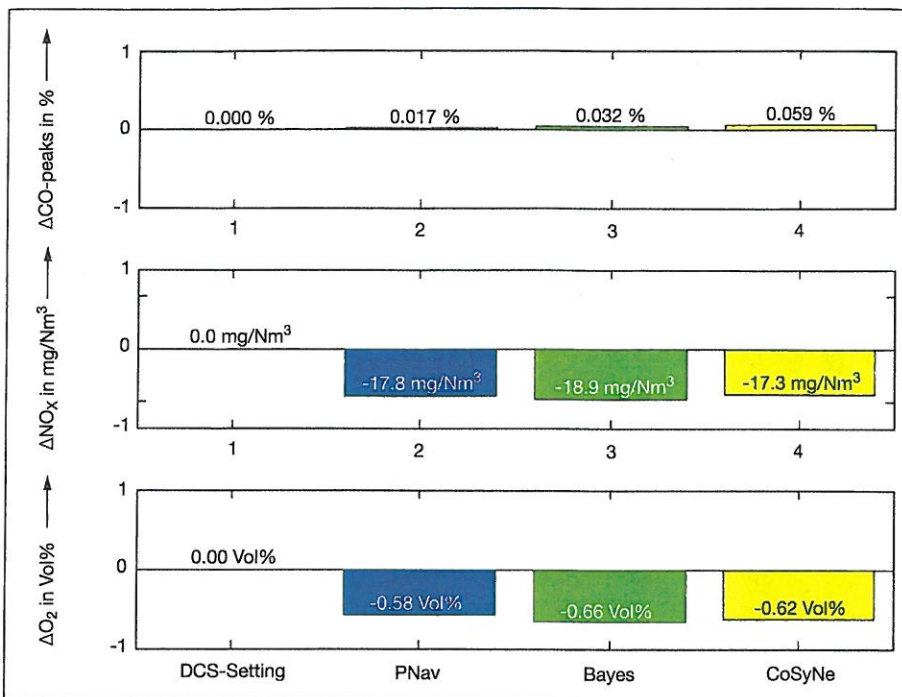


Figure 12. Comparison of all four controllers for CO peaks, NO<sub>x</sub> and O<sub>2</sub>.

- Total amount of spray water is 76 kg/s,
- Coal consumption ≈ 250,000 t/y,
- Boiler efficiency ≈ 93 %.
- 1 % spray water reduction = efficiency factor increase of 0.13 %

results in yearly savings of

$$250,000 \text{ t/y} - (250,000 \text{ t/y} \cdot 93 \% / (93 \% + 1 \text{ kg/s} / 76 \text{ kg/s} \cdot 0.13 \%)) \cdot 100 \text{ €/h} \approx 45,500 \text{ €}.$$

Prolonged time of full-load operation

Due to excess air reduction the plant can run longer at full load. Especially shortly before an inspection, fans are polluted and their efficiency is reduced. At some point, fans cannot transport all exhaust gases, even if they run at maximum speed. In this case, the plant's load has to be reduced. It is hardly possible to reliably calculate the economical impact of that effect, because there are many external influences like heat demand, weather conditions, generator limits and coal types. However, it is the opinion of plant personnel that the prolonged boiler run-time significantly increases income.

#### Summary

In total, all savings total to about 179,000 € a/boiler. For the two boilers at the Tiefstack site the savings are 358,000 €/a.

Additionally the plant generates increased income due to the possibility to run the plant at full load. This effect is, however, very hard to estimate in economical terms.

## Conclusions and future work

### Conclusions

The combustion control system at the Tiefstack plant was improved. Camera-based flame information and advanced algorithms are used in an adaptive system to control distribution and total air amount.

The technical conclusions from the project can be summarised as follows:

- The SOFCOM system reduces excess air by 0.7 volume-%, and NO<sub>x</sub> by 20 mg/Nm<sup>3</sup>. In spite of these reductions the increases of CO peaks is only 0.03 % (same oxygen level in flue gas). If it is taken into account that O<sub>2</sub> is reduced by the controller, NO<sub>x</sub> will be reduced even further.
- With much less human effort, the new automatic control architecture in the SOFCOM system achieves slightly better improvements compared to the Pnav, the predecessor of SOFCOM. Installations in different plants will require less effort, still reaching optimum control.
- The developed signal processing algorithms, the automatic feature extraction and feature selection, are working well in online operation under time varying process conditions, provide robust and stable results, and outperform traditional approaches like Principal Component Analysis (PCA).

- The economical benefits of the developed combustion control solution have been estimated and can be summarised as follows:
- With SOFCOM the plant works at a minimum excess air, leading to increased efficiency and yearly savings of about 83 500 €.
- Reduced air fan operation and reduced temperature control spray water adds 95,500 € per year.
- In total the SOFCOM system saves Vattenfall Tiefstack approximately 358,000 € per year (179,000 € per boiler).
- Due to the reduction of excess air, the boiler may also be run longer at full load, especially before inspection. This increases substantially the income which is very hard to estimate in economical terms.

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