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New approach to optimizing combustion in power boilers using software inspired by the immune system integrated with an in–furnace temperature monitoring system

Łukasz Śladewski*, Konrad Wojdan, Konrad Świrski

Institute of Heat Engineering, Warsaw University of Technology, 21/25 Nowowiejska Street, 00-665 Warsaw, Poland

Abstract

This paper presents a new approach in combustion process optimization using an integrated solution of immune inspired optimizer (SILO) and acoustic temperature measurement system (AGAM). The solution maintains optimal temperature distribution by on-line, automatic and model based process control. The goal is to increase boiler efficiency, improve process parameters and minimize the environmental impact. This paper includes a description of system components—SILO and AGAM— and the designed solution for an existing, coal-fired power unit. The unit is already equipped with the AGAM system and identification tests conducted previously informed the design.

Keywords: combustion process; advanced control; optimization; acoustic temperature measurement; efficiency

1. Introduction

A range of advanced solutions for control, optimization and monitoring of industrial processes are available on the market. Most of them, like combustion optimization systems, have been developed on the basis of experience from many deployments, making them more suitable for their role. This is a key factor in achieving improved results in process performance. Future development of software optimization systems for industrial processes should focus on integration and utilization of information from other advanced systems, e.g., gas temperature measurement systems. In power boilers, the temperature distribution of combustion gases, measured on-line and directly in the furnace, provides valuable information about the quality of the combustion process. It is a good indicator of whether the fuel and combustion air are distributed properly. An imbalance in the gas temperature indicates an imbalance in the fuel and combustion air distribution. This, in consequence, causes higher CO, NO_X emissions and an imbalance in steam temperatures—higher cooling spray flow and higher excess air. All those parameters have a negative influence on the performance of the combustion process—boiler efficiency and environmental impact. This imbalance in gas temperature can be reduced by adjustments in fuel and combustion air distribution [1, 2].

The combustion process in coal-fired, power boilers is a complex process, with a large number of input, output and disturbance signals. Mostly, it is not stable due to the load profile and the accompanying change of operating coal milling configuration or coal quality, resulting in permanent imbalances in gas temperatures. By monitoring the temperature distribution and adjusting the fuel and combustion air distribution systematically these imbalances can be reduced. Central to achieving this aim is maintaining the combustion process at the optimal point at all times and across the whole range of boiler load. SILO and AGAM are applied to help meet this goal.

2. Acoustic gas temperature measuring technology—AGAM

Since contactless temperature measuring technology has proven its ability in industrial applications, in-furnace gas temperature distribution has become a very important indicator of the quality of the combustion process. It has a direct influence on all combustion parameters and, consequently, on efficiency and environmental impact.

Conventional measuring systems e.g. thermocouples measure temperature only at a single point and their maximum range reaches only 1300°C. Additionally, to measure the temperature distribution on a horizontal cross section of the furnace, multiple sensors are required, which is a challenge in light of the in-furnace conditions. This and radiation error are the main reason why a new generation of measur-

*Corresponding author

Email addresses: lukasz.sladewski@itc.pw.edu.pl (Łukasz Śladewski), konrad.wojdan@itc.pw.edu.pl (Konrad Wojdan), konrad.swirski@itc.pw.edu.pl (Konrad Świrski)

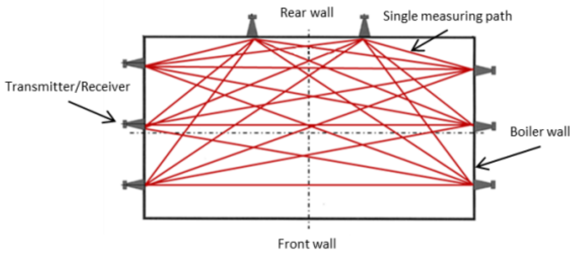

Figure 1: An example of industrial application of an AGAM system

ing technology—contactless measuring—is becoming more popular.

In power boilers contactless technologies enable on-line measurement of gas temperature and its distribution across the furnace. There are two, well known, physical principles used to develop commercial systems: dependency of light absorption (laser) and dependency sound speed (acoustic) on temperature of the medium being measured. In this paper the authors focus only on acoustic technology [3].

The physical principle behind acoustic technology is the relation between temperature, chemical properties of a gas, and the sound speed in the gas. The following equation represents this relation:

$$C = \sqrt{\frac{\kappa \cdot B}{M} \cdot T} \tag{1}$$

where: C—speed of sound, κ—adiabatic coefficient, B—universal gas constant, M—molecular weight, T—gas temperature.

In industrial applications, the system consists of transmitters and receivers placed at the same level of the furnace. The distance between transmitter and receiver creates a single measuring path. The set of transmitters and receivers creates multiple paths, which in turn create a measuring surface. In Fig. 1 an example configuration of an AGAM system is presented, from an existing power plant: Rybnik, unit 4.

The configuration consists of 8 transmitters/receivers. It creates 21 measuring paths.

The system measures temperature through each path based on the "flight time" of sound impulses. In each loop a single transmitter generates a sound impulse and all receivers are "listening". After receiving the impulse, the system calculates the flight time—the time difference between the sending and receiving of the sound impulse. Once all transmitters have finished, the system calculates final temperatures through each path. The results may be presented as an isothermal contour plot and average temperature of sub-areas. The example results are presented in Fig. 2.

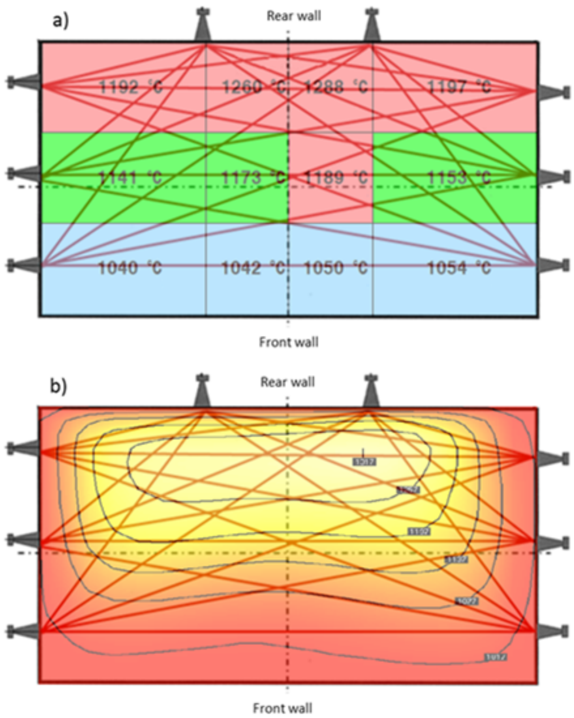

Figure 2: AGAM results presentation a) average temperature of sub-areas; b) isotherms plot

3. Combustion process optimization software—SILO

The combustion process in power boilers is highly complex. It is characterized by a large number of control signals e.g. fuel and air distribution; process parameters e.g. NO_X, CO emission, steam and flue gas temperatures, boiler efficiency; disturbance signals e.g. boiler load, operating coal milling configuration or coal quality. Additionally, this is a dynamic and non-linear process with long response time. That is why it is not easy for operators to maintain the process at optimal point using standard SISO (Single Input Single Output) control algorithms.

SILO is a software system designed for advanced control of MIMO processes (Multi Input Multi Output), especially the combustion process. It is inspired by the immune system of living creatures and represents a new approach in advanced control of industrial processes. The most commonly used solutions are based on predictive control algorithms with receding horizon. Each MPC (Model Predictive Control) controller computes setpoints in control vector for consecutive moments, based on a dynamic model of the process. This control trajectory seeks to minimize the difference between process output signals and their demand values in the corresponding consecutive moments.

Despite all the advantages of MPC controllers, there are also significant disadvantages, which become more meaningful, when it comes to the combustion process. The disadvantages were described in [4], but here cited briefly. One of them is the cost of implementation due to the long and labor-consuming parametric tests needed to define the dynamic, mathematical model of the process.

The second disadvantage of MPC solutions is their weak ability to adapt to long-term changes in process characteristics. Changes can be observed in every industrial process.

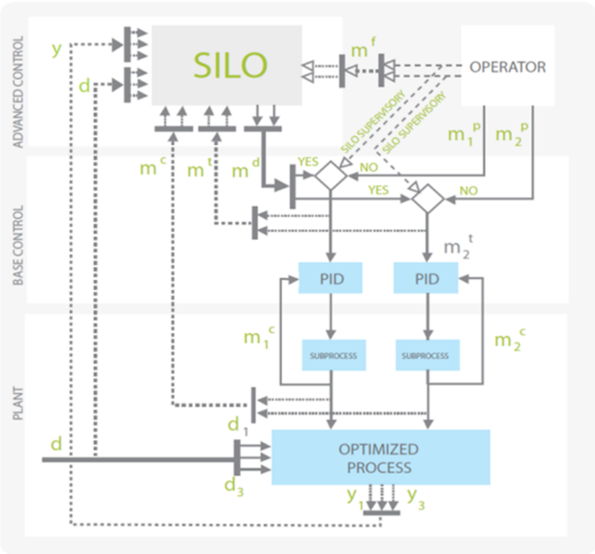

Figure 3: The architecture of SILO implementation in layered control structure

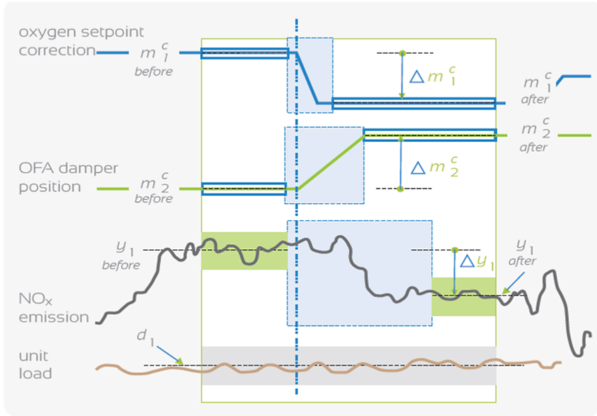

Figure 4: An example time window of Knowledge Gathering module

In the case of combustion, changes in process characteristics may be caused by factors such as wearing or failure of boiler devices, reconfiguration of the boiler construction (deNOX) or changes in chemical properties of the substrates e.g. fuel. To keep the high effectiveness levels of MPC controllers, the mathematical model has to be fine-tuned periodically. This means that parametric tests must be repeated and, consequently, the cost increases. The other solution is to implement an automatic adaptation method. This, however, implies further problems like estimation of model parameters of highly noised signals with low changeability or estimation of model parameters when operating in normal conditions, in closed loop.

Those two disadvantages of MPCs—high implementation cost and weak adaptability motivated researchers to develop a new solution. SILO eliminates the disadvantages of MPC solutions by its architecture, which is inspired by the immune system of living creatures.

SILO seeks to perform automatic, on-line optimization of industrial processes at the current operating point. In other words, through integration with DCS (Distributed Control System), the optimizer monitors process output signals and, based on mathematical model of the process and optimization priorities, calculates setpoints of the controlled signals [5]. The general architecture of the layered control structure with SILO is presented in Fig. 3.

Operators are the main supervisors of the process. So, SILO requires their permission to start operating, as well as permission to use particular controlled devices during optimization. After the operators start the optimization, the system calculates setpoints or setpoint corrections for control structures, which operate in the base control layer e.g. the PID controller of O_2 content in flue gases. If the optimization is stopped, SILO tracks the operators' setpoints.

In general, SILO consists of two main, independent modules: the Optimization module and the Knowledge Gathering module. During optimization the system updates decision vector m^d periodically. The time between subsequent changes of the m^d vector cannot be shorter than the time needed to reach a new process steady state (e.g. 5 to 20 minutes for the combustion process). Independently from the Optimization module, the Knowledge Gathering module monitors input—m^c, output—y and disturbance—d signals to collect new knowledge items. If the monitored signals satisfy specific conditions, the knowledge item is saved in the database and used by the Optimization module in the next optimization steps.

The Knowledge Gathering module is tasked with identifying relations between process inputs m^c and outputs y—knowledge items, as well as updating averages of the control vector m^c for various process operating points—targets. The knowledge items are used by the Optimization module when operating in the Model Based layer, and the targets are used by the Optimization module when operating in the Transition State layer.

The Knowledge Gathering module analyzes short-term historical values in specific time windows. An example time window is presented in Fig. 4.

Each window must include a key change of at least one element of the mc vector while process disturbances d are constant. Process responses to a given mc change are automatically identified and stored in the knowledge database as a single knowledge item. Each knowledge item consists of: time stamp, change of control vector—m^c, change of process outputs—y and disturbance signals—d. SILO's knowledge is stored in thousands of knowledge items and is used by the Optimization module when it calculates the mathematical model of the process.

On the basis of the model, the Optimization module calculates a change in the control vector to minimize the performance indicator. In general, the performance indicator is a sum of penalty functions of each monitored process output signal and each decision signal. It is defined by the following formula:

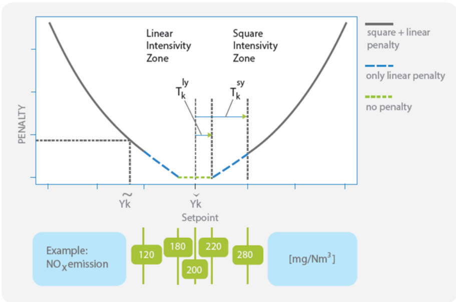

Figure 5: Example settings of penalty function for NO_X

$$J = \sum_{k=1}^{n_m}\left[\alpha_k\left(\left|\widehat{m}_k^c - \widetilde{m}_k^c\right|\right) - \tau_k^{lm})_+ + \beta_k(\left(\left|\widehat{m}_k^c - \widetilde{m}_k^c\right|\right) - \tau_k^{sm})_+)^2\right] + \\ + \sum_{k=1}^{n_y}\left[\gamma_k\left(\left|\widehat{y}_k - \widetilde{m}_k\right|\right) - \tau_k^{ly})_+ + \delta_k((\left|\widehat{y}_k - \widetilde{y}_k\right|) - \tau_k^{sy})_+)^2\right] \quad (2)$$

where: α_k—linear penalty coefficient for k-th control variable, β_k—square penalty coefficient for k-th control variable, γ_k—linear penalty coefficient for k-th monitored process output, δ_k—square penalty coefficient for k-th monitored process output, τ_k^{lm}—insensitivity zone for linear penalty for k-th control variable, τ_k^{sm}—insensitivity zone for square penalty for k-th control variable, τ_k^{ly}—insensitivity zone for linear penalty for k-th monitored process output, τ_k^{sy}—insensitivity zone for square penalty for k-th monitored process output, $(.)_+$—"positive" operator $(x)_+ = \frac{1}{2}(x + |x|)$, $\widetilde{m}_k^c$—current value for k-th control variable, $\widetilde{y}_k$—current value for k-th monitored process output, $\widehat{m}_k^c$—setpoint for k-th control variable, $\widehat{y}_k$—predicted value for k-th o monitored process output.|

An example of the penalty function of NO_X is presented in Fig. 5.

A penalty of a signal is calculated if the difference between the measured value and demand values is higher than the tolerance—insensitivity range. In the example above, the demand value of NO_X emission is 200 mg/Nm^3, the linear insensitivity zone is 20 mg/Nm^3 and square insensitivity zone is 80 mg/Nm^3. If the measured NO_X emission is within 180–220 mg/Nm^3 then the penalty equals 0—SILO focus on other parameters. If the NO_X is lower than 180 mg/Nm^3 or higher than 220 mg/Nm^3 then the linear penalty is calculated. The penalty is higher if the emission goes lower than 180 mg/Nm^3 and higher than 220 mg/Nm^3. Additional—square penalty is calculated if the NO_X emission is lower than 120 mg/Nm^3 or higher than 280 mg/Nm^3. This represents an automatic change of optimization priorities—the penalty increases rapidly.

Depending on process state and knowledge about the process, SILO can change the optimization strategy automatically [5].

At the very beginning of SILO implementation the knowledge database is empty and the system is unable to obtain the model of the process. In this case SILO operates in a Quasi Random Extremum Control layer. The goal for this layer is to collect new and improve existing knowledge. Operating in this layer, the optimizer manipulates the m^d vector in a specific way, as required by the Knowledge Gathering module. The process is also optimized, but in a long-time horizon.

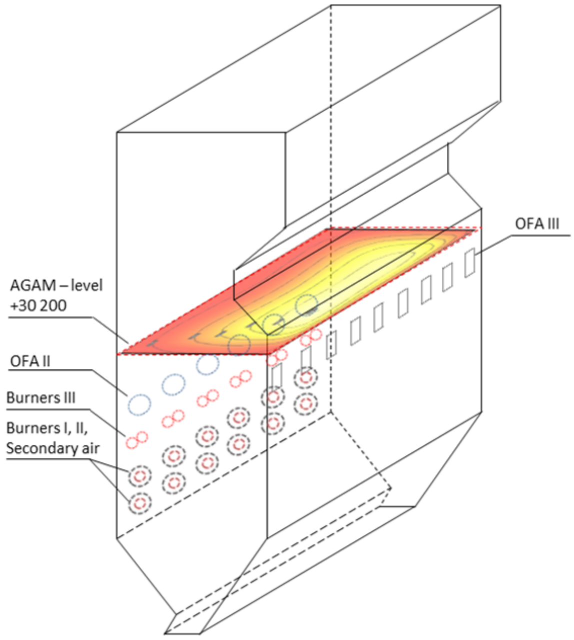

Figure 6: Fuel and air distribution system in K-4 boiler, in Rybnik Power Plant

If there are enough knowledge items in the database, SILO is able to obtain a mathematical model of the process and starts to operate in the Model Based Optimization layer. Operating in this layer SILO performs precise optimization, because setpoints are calculated based on the model. The model is created using the newest knowledge items, specific for the current operating point. At the beginning of each optimization step, the optimization algorithm selects the newest knowledge items, which represent process characteristics of the current operating point.

The two layers presented above are designed for steady state optimization. If operating point of the process is changing, SILO switches to the Transition State layer. In this case, the optimizer monitors the operating point continuously and applies adequate md vector targets to move it close to the optimum settings for the specific operating point [6, 7].

4. Details of AGAM-SILO-DCS integration

The approach of AGAM-SILO-DCS integration will be presented for an existing boiler in Rybnik Power Plant.

The Rybnik Power Plant is a baseload plant, which consists of 8 units with OP-650 type boilers. Boiler no 4 (K-4) is equipped with in-furnace sensing technology—AGAM, provided by Bonnenberg + Drescher Projektentwicklug GmbH. The integration of AGAM-SILO-DCS requires a special analysis of boiler construction, boiler control structures, operating regime and process parameters.

K-4 is a coal-fired boiler with 24 front-wall, low-NOX burners (3 levels). The fuel is supplied by 6 coal pulverizers. The combustion air is distributed by 12 secondary air dampers and 2 OFA levels (level II—6 dampers, level III—10 dampers). OFA dampers level II are installed on the front wall and OFA dampers level III are installed on the rear wall. The boiler is also equipped with protective air, supplied from the bottom, which protect the rear waterwall against corrosion. The fuel and air distribution system of this boiler is presented in Fig. 6.

Initially, the AGAM system was installed in this boiler to support SNCR control. The AGAM measurements are available in DCS system. 12 temperatures of each sub-area are defined as standard temperature measurements and the contour map plot is displayed on the operators' graphic. Initial analyses of AGAM data showed that for this boiler, temperature distribution is a good indicator of combustion process quality [8]. Additional analysis of process parameters revealed that some parameters could be improved:

- Process efficiency, calculated on-line, decreases with load increase.
- At low load range, superheat and reheat steam temperatures are permanently below the setpoints—540°C.
- At low load range, the difference between left and right reheat steam temperatures is relatively large.
- There is potential to reduce cooling spray flow.
- NO_X emission fluctuations are too high.
- Peaks of CO emissions are high and the emissions stay at an elevated level for a long time.

The AGAM-SILO-DCS integration starts with installation of SILO and communication with DCS (Distributed Control System). To optimize the process and solve the operating problems in this particular boiler, SILO will monitor the following process outputs:

- Superheat and reheat steam temperatures on the left and right side;
- Superheat and reheat spray flow on the left and right side;
- NO_X and CO emissions on the left and right side;
- O_2 content and temperature of flue gases;
- AGAM temperatures.

Those parameters will be maintained, by automatic SILO control of the following devices:

- Oxygen stepoint—1 signal;
- Secondary air dampers—12 signals;
- OFA II—6 signals;
- OFA III—2 signals;

Table 1: Optimization results on process symmetry

Parameter	Unit	Before OPT	Afer OPT	Change
Superheated steam temperature	℃	4.86	4.29	11.7%
Reheated steam temperature	℃	4.88	4.65	4.7%
O_2	%	1.23	1.15	6.5%
NO_X	mg/Nm^3	87.75	78.7	10.3%
CO	mg/Nm^3	-106.59	-89.63	15.9%

- Protective air dampers—2 signals;
- Coal feeders—6 signals.

SILO, thanks to its architecture, will learn the relation of the controlled devices to process parameters. Based on this knowledge SILO will calculate setpoints to perform balanced combustion, as indicated by AGAM temperatures. The optimizer will also monitor the other process signals. If, for some reason, AGAM temperatures are balanced but standard measurement not, SILO must have the knowledge and ability to reduce this imbalance, even if the AGAM temperatures subsequently become imbalanced.

Table 1 below presents the results of analysis of the process parameters after the first phase of the integration project. At this stage, the optimization was focused on process symmetry. All monitored parameters were improved, which is a good starting point for further optimization [9].

Table 1 presents the very first results of combustion optimization with the integrated AGAM-SILO-DCS solution. At this project stage it was assumed that balanced AGAM temperature distribution helps to balance combustion parameters. So, during this period the goal for SILO was to monitor AGAM temperature distribution and control the boiler to keep the AGAM temperatures balanced.

The results from Table 1 show that the goal for this stage of the project was achieved. The main output signals of the combustion process were balanced, which means the difference between the left and right side of the boiler was reduced. The main reason for imbalanced combustion was a huge imbalance in O_2. The temperature distribution is strictly related to O_2 content in combustion gases [1]. Balancing the temperature distribution affects the O_2 balance and, finally, other combustion parameters such as CO, NO_X and steam temperatures.

5. Conclusion

The advantage of software advanced control/optimization systems over manual operation relies on regularity. Even if operators are trained in how to use e.g. temperature distribution information for combustion process control, they will not beat a well-implemented advance control/optimization system. This is because process operators have many other duties and parameters to monitor, but those software systems are dedicated exclusively to combustion. Depending on the process requirements, they are able to collect information about the process every 5–10 second and calculate new setpoints every 3–5 minutes.

Integrating SILO-AGAM into the processes at Rybnik would increase combustion performance. The analyses conducted suggest that boiler efficiency could be increased by over 0.2% without violating any other process parameters or constraints. Higher boiler efficiency means lower coal consumption, as well as lower CO_2 and SO_X emission. Additionally, superheated and reheated steam temperatures will improve and CO emission reduced. NO_X will stay at the same, desired level—350 mg/Nm^3.

Acknowledgments

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Nomenclature

$(.)_+$ positive operator $(x)_+ = \frac{1}{2}(x+ \mid x \mid)$

α_k linear penalty coefficient for k-th control variable

α_k linear penalty coefficient for k-th control variable

β_k square penalty coefficient for k-th control variable

δ_k square penalty coefficient for k-th monitored process output

γ_k linear penalty coefficient for k-th monitored process output

κ adiabatic coefficient

τ_k^{lm} insensitivity zone for linear penalty for k-th control variable

τ_k^{ly} insensitivity zone for linear penalty for k-th monitored process output

τ_k^{sm} insensitivity zone for square penalty for k-th control variable

τ_k^{sy} insensitivity zone for square penalty for k-th monitored process output

$\tilde{m}_k^c$ current value for k-th control variable

$\tilde{y}_k$ current value for k-th monitored process output

$\widehat{m}_k^c$ setpoint for k-th control variable

$\widehat{y}_k$ predicted value for k-th o monitored process output

B universal gas constant

C speed of sound

d process disturbances vector (e.g.: unit load, mills configuration)

M molecular weight

m^c vector of controlled devices' feedback (e.g.: O2 content in combustion gasses feedback, OFA position feedback, etc.)

m^d decision vector (e.g.: O2 setpoint, auxiliary air and OFA dampers setpoint from SILO)

m^f optimization permissions vector of each controlled device

m^p operators' setpoints vector (e.g.: operator demand for oxygen, etc.)

m^t traced setpoints (e.g.: O2 setpoint, auxiliary air and OFA dampers setpoint from DCS)

T gas temperature

y optimized process outputs (e.g.: NOX and CO emission, steam temperatures, etc.)