Research Paper

Optimization of combustion process in coal-fired power plant with utilization of acoustic system for in-furnace temperature measurement

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HIGHLIGHTS

- Novel approach in combustion modelling and optimization in coal-fired boiler.
- R&D and implementation project that was carried on on real boiler.
- Artificial immune optimization system integrated with temperature profile measurement.
- Proper control of the fireball shape resulted in 0.27% boiler efficiency increase.

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ABSTRACT

This paper presents methodology and results of a research project on software optimization of combustion process efficiency in coal-fired power plant.

The general goal of this project was to increase boiler efficiency by proper control of the combustion process using optimization software, integrated with Distributed Control System and in-furnace temperature profile measurement system. The research goal relays on new approach in combustion modelling based on in-furnace temperature distribution and utilization of this model in on-line boiler control. It is assumed that this approach allows for more precise control of the combustion process, what finally has a positive influence on boiler performance – the efficiency in specific.

The solution has been designed, installed and tested on existing, utility plant – 225 MW (650 t/h of nominal steam generation). Final analysis has shown positive results – the boiler efficiency increased over 0.25%.

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1. Introduction

The electricity sector worldwide faces still-increasing demand for cost efficient power generation and stricter environmental regulations. These two factors motivate operators, especially in coal-fired generating stations, to search new solutions for process optimization. Nowadays, coal still plays an important role in electricity production – over 40% of global electricity production comes from coal [1]. That is why optimization of combustion process in terms of boiler efficiency and emission of air pollutants is the key in minimizing operational and maintenance costs. There are many methods for such optimization, which range from modernization of boiler equipment e.g. new measurement technologies, to on-line software optimization systems.

During last few years contactless temperature measurement technologies have become more popular in the industry. There are two main technologies, which are used in coal fired boilers to measure temperature distribution – acoustic technology [2–4] and laser technology [5,6]. In [7] authors present advantages of acoustic system in evaluation of combustion quality in pulverized coal-fired boiler. On the other hand, in [8] the meaning of laser technology in combustion optimization projects is presented. Temperature distribution in horizontal cross-section of a boiler is a great indicator of quality of combustion process. This indicator could be used in boiler control to optimize the combustion process. The research key of this work is to develop new modelling approach of the combustion process which is based on in-furnace temperature distribution. This new model will be used by combustion optimization software for on-line control of the combustion.

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Regarding software optimization systems for advanced combustion control there is number of different solutions. The main difference between those solutions relay on difference in approach in process modelling and difference in algorithms used to search for optimal solution. MPC is the main group of advanced process control algorithms for MIMO processes e.g. combustion process. Detailed description of different MPC solutions are provided in [9,10] and their advantages in combustion optimization were described in [11–14]. MPC as well as steady-state optimization solutions utilize often algorithms, which are inspired by processes that could be observed in the nature. One of most popular solutions combines artificial neural network algorithms for process modelling and genetic algorithm as the method for searching for the optimal solution. General idea of this solution could be found in [15]. Additionally, examples of implementation of artificial neural network and genetic algorithm for combustion process control are described in [16–19]. Effective combustion optimization could be also performed by solutions, which combine artificial neural network models and quadratic programming [20], artificial bee colony [21] or particle swarm [22] algorithms. Moreover, in [22] authors provide a comparative analysis of artificial neural network and support vector machine models of the combustion process. The support vector machine algorithm [23] have found also its application in combustion process optimization with genetic algorithm [24,25], ant colony [26,27], particle swarm, strength pareto evolutionary or archive-based hybrid scatter search [28] algorithms. Computational fluid dynamics is another method for combustion process modelling, which has been used for on-line combustion optimization. In [29,30] authors presented positive effect of implementation of computational fluid dynamics model.
with genetic algorithm and particle swarm optimization methods. All of the presented algorithms succeeded in combustion optimization projects – improved boiler efficiency, reduction of NOx emission, but also improved controllability of the process. All of the solutions have also meaningful disadvantages, which are described in chapter 4.

Other type of nature inspired optimization solutions are algorithms inspired by immune system. In [31] authors described architecture and combustion optimization results of SILO solution – the optimization algorithm, inspired by operation of immune system.

In many projects, combustion optimization solutions rely on standard DCS measurements. On the other hand, in [32–35] authors proved a great meaning of in-furnace temperature distribution in combustion process control. The [32,33] publication describes acoustic technology and the [34,35] publication – laser technology. In publications, authors presented positive influence of balanced temperature distribution on combustion process parameters, such as: excess air, CO and NOx emission, steam temperatures but especially – the boiler efficiency. Other examples, where in-furnace temperature distribution and flame quality are subjects of combustion optimization are described in [29,36,35], in [29] the temperature distribution in the furnace is obtained from CFD simulation. The flame quality in [36] is quantified by analysis of high resolution flame images.

Advantages of SILO system and acoustic temperature measurement technology – AGAM, motivated authors of this paper to carry on a research on novel method in combustion process modelling and control based on in-furnace temperature distribution. In comparison to commercial and research projects described in [32–34], the innovative approach in this project relays on the on-line optimization of fire-ball shape. By analyzing AGAM temperatures, SILO calculates current shape parameters of the fireball and compares them with a reference fire-ball shape. The goal for SILO is to control the combustion process to minimize the difference between reference and current shape. This will positively influence the process parameters, related to boiler efficiency e.g. flue gas temperature, excess air or CO emission.

2. Coal combustion modelling

In most optimization projects of the combustion process there are two main types of models – CFD and empirical models. CFD models are very complex and are used for deep investigation of the process. Information provided from CFD analysis could be used for manual tuning of a boiler. The process of model creation, definition of initial and boundary condition as well as calculations are time consuming. That is why CFD could not be efficiently used for closed-loop control of the combustion process.

For the purpose of standard combustion optimization empirical models are used. The model consists of, but it is not limited to the following input, output and disturbance signals:

- Inputs:
  - Secondary air dampers,
  - OFA dampers,
  - OFA tilts,
  - Coal feeders,
  - Burner tilts,
  - Oxygen setpoint bias,
  - ID and FB bias,

- Outputs:
  - Steam temperatures,
  - NOX emission,
  - CO emission,

- Oxygen content in flue gasses,
- Flue gas temperatures,
- Loss of ignition,

- Disturbances:
  - Boiler load,
  - Configuration of operating mills,
  - Fuel quality.

Combustion is a non-linear process. One of well-known modelling methods of non-linear processes is NARMAX (non-linear autoregressive moving average with exogenous input) [37]. The NORMAX relation between inputs and outputs of the non-linear process presents the following equation. All the parameters are defined basing on parametric tests that are performed on running unit.

$$y_k = \sum_{p=1}^{P} w_{(p)} \left( \sum_{i=1}^{N} a_{(p)}^i y_{k-i} + \sum_{i=1}^{K} \sum_{j=1}^{M} b_{(p)}^i u_{k-j} + c_{(p)} \right)$$

To increase the accuracy of the NORMAX model a neural network work is introduced to minimize the error between model and process outputs.

Artificial immune system could be considered as an alternative to the NORMAX method for combustion modelling. The artificial immune system is the principle that was used in SILO [39] – the system implemented in this research project. In this method there are the same input, output and disturbance signals represented by vectors.

$$u = [u^1, u^2, \ldots, u^K]^T$$
$$y = [y^1, y^2, \ldots, y^K]^T$$
$$z = [z^1, z^2, \ldots, z^K]^T$$


$$\mu(L_k, A) = \left( \prod_{i=1}^{K} g_{(i)}^e (\tilde{u}_{i}^k, \tilde{u}_i^k) \right) \cdot \left( \prod_{i=1}^{K} g_{(i)}^r (\tilde{u}_{i}^k, \tilde{u}_i^k) \right) \cdot \left( \prod_{j=1}^{R} g_{(j)}^o (\tilde{y}_j^k, \tilde{y}_j^k) \right) \cdot \left( \prod_{j=1}^{R} g_{(j)}^p (\tilde{y}_j^k, \tilde{y}_j^k) \right) \cdot \left( \prod_{l=1}^{D} g_{(l)}^f (\tilde{z}_l^k, \tilde{z}_l^k) \right)$$

The g functions are condition functions and examples of these are presented below:

$$g_l^f (\tilde{z}_l^k, \tilde{z}_l^k) = \begin{cases} 
0 & \text{if } |\tilde{z}_l^k - \tilde{z}_l^k| > 0.01 \\
1 & \text{if } |\tilde{z}_l^k - \tilde{z}_l^k| \leq 0.01
\end{cases}$$
calculated for average temperature is at the level of 2.5–3%.

that for the same boundary and initial conditions CFD simulation of the furnace. AGAM technology is described in details in [2–4,32,33]. In [32,33] authors provide a brief description and focus on system’s features, which are important from combustion optimization point of view.

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

\[
g_{ij}^{\text{ac}}(y_{ij}^k, y_{ij}^l) = \begin{cases} 
0 & \text{if } y_{ij}^k > 10 \text{ or } y_{ij}^l > 10 \\
1 & \text{if } y_{ij}^k \leq 10 \text{ or } y_{ij}^l \leq 10
\end{cases}
\]

\[
g_{ij}^{\text{ac}}(u_{ij}^k, u_{ij}^l) = 1
\]

Once the lymphocytes has been selected the algorithm calculates static gains that finally represent the relations in the process. The model is created every optimization step basing on information about current process operating point as well as using newest lymphocytes. During the operation, the artificial immune algorithm constantly records new lymphocytes that are utilized in next optimization steps.

The new approach in combustion process modelling and optimization to which this work refers, relays on artificial immune system method, but the difference is that the process output in furnace temperature distribution. This temperature distribution is aggregated in three fire-ball shape categories:

- Left-right hot spot position,
- intensity,
- dispersion.

It is assumed and proved within this work that controlling the shape of fireball, combustion optimization is much more precisely and, finally, achieve better results than standard approach. Moreover, the fireball shape model in this idea is a compromise between CFD analysis and empirical models. From one hand the relation between process inputs and shape categories has been defined with empirical methods – artificial immune system. From the other hand the temperature distribution is strongly related with CFD results, what has been proved in [38]. The analysis has shown that for the same boundary and initial conditions CFD simulation and AGAM system provide close temperature profiles and error calculated for average temperature is at the level of 2.5–3%.

3. Acoustic temperature measurement system – AGAM

AGAM is the acoustic system for in-furnace temperature distribution measuring is one of these. The system measures temperature distribution of combustion gases on horizontal cross-section of the furnace. AGAM technology is described in details in [2–4,32,33]. In [32,33] authors provide a brief description and focus on system’s features, which are important from combustion optimization point of view.

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

\[
C = \sqrt{\frac{\kappa \cdot B}{M} - T}
\]

In industrial applications, the system consists of transmitters and receivers placed at the same level of the furnace. A distance between transmitter and receiver is a single measuring path. Set of transmitters and receivers creates a measuring mesh (combination of multiple paths).

Fig. 1 presents an example configuration of transmitters/receivers and corresponding measuring mesh of the AGAM system installed in Rybnik power plant. It consists of 8 transmitters/receivers, which creates 21 measuring paths. The system measures temperature through each path basing on “travel-time” of sound impulse. A single transmitter generates specific sound’s impulse; all other receivers are “listening”. After receiving the impulse, system calculates the travel time. The temperature is calculated basing on the following equation:

\[
T = \frac{I^2}{k \cdot B - \frac{1}{\gamma}}
\]

It was analyzed in [32], that the precision of temperature measurement due to changes in combustion gas composition stays below 1.4% and the general error does not exceed 2%. Additionally, due to the fact that AGAM technology relay on contactless temperature measurement, radiation does not play a role on measurement results – AGAM measures row gas temperature.

4. SILO – System for on-line optimization of the combustion process

SILO is one of representatives of software solutions, which in control theory are called AC [9]. AC is a general name for group of solutions, mainly software. As the goal of base control systems is to facilitate basic operation by automation of the process, AC is aimed to optimize this process to meet particular performance and economic objectives of unit operation.

SILO is an AC-class software solution, which is aimed to perform automatic, on-line optimization of industrial processes – combustion in power boilers in particular. The SILO’s inspiration is an immune system of living creatures. This method is described in [31,39–42] but here will be briefly reminded. Additionally, the comparison between SILO and MPC approach can be found in [42].

In general, SILO consists of two main, independent modules: Knowledge Gathering and Optimization. The Knowledge Gathering module is aimed to collect information about the process characteristic. It monitors process signals and identifies static relations between process controlled inputs – MV and outputs – CV at certain operating point – constant DV. Each static input-output relation, for certain process operating point is stored in SILO’s database. Using this knowledge for optimization purposes, SILO is able to calculate ad-hoc static characteristic of the process for different operating points.

Functionality of the Optimization module relay on constant calculating and updating MV signals. Calculated MV values are transferred to base control layer as new setpoints or corrections to setpoints for boiler controlled devices. When optimizing the process, SILO’s Optimization module monitors one internal parameter – quality indicator. Formula of the quality indicator represents all optimization goals and their priorities. The formula for calculating quality indicator in SILO is presented below.

\[
J = \sum_{k=1}^{n_{x}} \left[ \alpha_k (|m_x - \tilde{m}_k| - \tau_{x}^m)^2 + \beta_k (|m_x - \tilde{m}_k| - \tau_{x}^m)^2 \right] + \sum_{k=1}^{n_{y}} \left[ \gamma_k (|y_x - \tilde{y}_k| - \tau_{y}^l)^2 + \delta_k (|y_x - \tilde{y}_k| - \tau_{y}^l)^2 \right]
\]

Finally, the main goal of the Optimization module is the minimization of the quality indicator. The module searches for such MV change ($\Delta m^{opt}$), which minimize the following formula:
The reheated steam temperature is 540.4 tons of steam generation per hour. The designed superheated and drum and natural circulation. Maximum continuous rating is 650 MW turbine. The boiler is a pulverized coal fired boiler with steam eight, bituminous coal fired units – OP-650 type boiler and 225 Rybnik Power Plant, unit 4. The Rybnik power station consists of plant rows (Fig. 2). Depending on load demand some pulverizers are turned off. This is a wall (front wall) fired boiler with three burners’ and twenty-four burners – each pulverizer supplies coal to four burners supplied from pulverizer 5, F1, F2, F3 and F4 are the burners supplied from pulverizer 6.

Regarding combustion control as well as optimization the boiler efficiency is the main subject. Efficiency of power boilers could be calculated using two methods: input-output or heat loss [46]. The heat loss method is mainly used for coal fired boilers and the efficiency is calculated by the following formula:

$$\eta_b = 1 - \frac{Q_{\text{loss}}}{Q_{\text{in}}} = 1 - \frac{Q_{\text{loss}}}{(Q_{\text{out}} + Q_{\text{loss}})}$$

To optimize the efficiency of combustion process, it is necessary to minimize heat losses and maximize useful heat outputs. Both components are defined by combustion parameters, which are measured on-line and listed in Table 1. In standard combustion optimization projects signals from the table are controlled directly by the optimization software. In the new approach the SILO system controls the in-furnace temperature distribution. Proper temperature distribution means proper combustion, what finally has a positive effect on combustion parameters and boiler efficiency.

In order to perform on-line control of the temperature distribution in the combustion optimization configuration the following signals must be identified.

- **MV (Manipulated Variables)** – 29 signals
  - Oxygen stepoint (combustion air demand) – 1 signal;
  - Secondary air dampers – 12 signals;
  - OFA II – 6 signals;
  - OFA III – 2 signals;
  - Protective air dampers – 2 signals;
  - Coal feeders – 6 signals.
- **CV (Controlled Variables)** – 12 signals
  - AGAM temperatures
- **DV (Disturbance Variables)** – 3 signals
  - Unit load;
  - Configuration of operating coal pulverizers;
  - Estimated coal quality (coal quality value is estimates by dividing currently generated MWs by currently coal flow, represented by sum of coal feeders speed)

Details of the fireball method as well as results of the project are presented in two following chapters.

5. New method in combustion optimization in existing power plant

The integrated SILO-AGAM solution has been implemented in Rybnik Power Plant, unit 4. The Rybnik power station consists of eight, bituminous coal fired units – OP-650 type boiler and 225 MW turbine. The boiler is a pulverized coal fired boiler with steam drum and natural circulation. Maximum continuous rating is 650 tons of steam generation per hour. The designed superheated and reheated steam temperature is 540 °C and pressure respectively 13.5 MPa and 2.3 MPa.

The boiler is equipped with six pulverizers (A, B, C, D, E and F) and twenty-four burners – each pulverizer supplies coal to four burners. This is a wall (front wall) fired boiler with three burners’ rows (Fig. 2). Depending on load demand some pulverizers are turned off.

The air/flue gas system consists of three FD fans and three ID fans. Two FD fans supplies primary air to the pulverizers and one FD fan – secondary air to the windbox. The secondary air is distributed through twelve secondary air dampers and sixteen OFAs. Each burner, in two lower rows has a dedicated secondary air damper. OFAs are arranged in two rows, OFA II installed on front wall and OFA III installed on rear wall. OFA I has been removed but the names remained unchanged. The boiler is equipped also with two protection air fans to protect the boiler’s evaporator against corrosion. The AGAM system has been installed at furnace exit at 30.2 m level.

Regarding combustion control as well as optimization the boiler efficiency is the main subject. Efficiency of power boilers could be calculated by the following formula:

$$\eta_b = 1 - \frac{Q_{\text{loss}}}{Q_{\text{in}}} = 1 - \frac{Q_{\text{loss}}}{(Q_{\text{out}} + Q_{\text{loss}})}$$

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- **DV (Disturbance Variables)** – 3 signals
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  - Estimated coal quality (coal quality value is estimates by dividing currently generated MWs by currently coal flow, represented by sum of coal feeders speed)

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6. The fireball control algorithm

The main research goal for this project was to integrate and utilize in SILO the information about temperature distribution provided by AGAM. In this chapter the research method and effects are described.

Initially special test were performed to investigate whether temperature distribution is controllable with boiler devices. Once it had been confirmed further research has been carried on to examine how a change in temperature distribution influences process outputs e.g. steam temperatures, NOx, CO, O2, etc. Detailed description of AGAM tests could be found in [47].

![Fig. 2. Fuel and air supply system in Rybnik's unit 4 boiler, where A1, A2, A3 and A4 are the burners supplied from pulverizer 1, B1, B2, B3 and B4 are the burners supplied from pulverizer 2, C1, C2, C3 and C4 are the burners supplied from pulverizer 3, D1, D2, D3 and D4 are the burners supplied from pulverizer 4, E1, E2, E3 and E4 are the burners supplied from pulverizer 5, F1, F2, F3 and F4 are the burners supplied from pulverizer 6.](image-url)
Once relation between setpoints of MV signals, temperature distribution and process outputs has been examined, the categories of fireball shape were defined:

- Left-right hot spot position,
- intensity,
- dispersion.

The fire-ball shape is calculated on a basis of twelve AGAM temperatures. Position of temperatures hot spot indicates, whether the fire-ball is shifted to left or right side of the furnace. Intensity, is calculated as average temperature for a given temperature profile and dispersion is a parameter calculated as standard deviation of AGAM temperatures. After defining shape categories, historical values of AGAM temperatures as well as process parameters have been analyzed to find the best values of the fire-ball categories (reference shape), which represent most efficient combustion.

To control the fireball shape in on-line mode it is necessary to calculate adjustments to current shape. For this purpose gradient optimization algorithm was developed. This algorithm monitors difference between current and reference shape, and calculate optimal setpoints for twelve AGAM temperatures to minimize this difference. The algorithm searches for such minimal change of current AGAM temperatures that finally gives reduced difference between current and reference shapes.

The method used in gradient optimization is the unconstrained gradient decent method. The objective function of this optimization task consists of differences between values of current and reference shape categories. The following formula represents this objective function:

\[
J = |\bar{s}_p (T_{AGAM}) - \bar{s}_p| + |\bar{s}_i (T_{AGAM}) - \bar{s}_i| + |\bar{s}_d (T_{AGAM}) - \bar{s}_d|
\]

The result of the gradient optimization is a vector of twelve optimized setpoints. It is calculated by minimization of the objective function, by the following optimization task:

\[
\text{min}_{\Delta T}|\bar{s}_p (T_{AGAM} + \Delta T) - \bar{s}_p| + |\bar{s}_i (T_{AGAM} + \Delta T) - \bar{s}_i| + |\bar{s}_d (T_{AGAM} + \Delta T) - \bar{s}_d|
\]

AGAM temperatures are defined in SILO as regular CV signals, so SILO collects the knowledge about relation between boiler controlled devices – MV and each single AGAM temperature. When, as a result of gradient optimization, setpoints of AGAM temperatures are changed, standard SILO algorithm utilize this knowledge to calculate such change of MV signals, which minimize difference between the measured temperature and its new setpoint.

Dynamically calculated setpoints for CV signals is a novel approach among all SILO implementations and refers to the definition of SILO’s objective function. Fig. 3 presents an example definition of standard penalty function for single AGAM temperature and Fig. 4 presents new method – the penalty function for dynamically calculated setpoints.

For this particular example i.e. AGAM temperature – \(T_{AGAM1}\), the setpoint is 1350 °C, the linear insensibility zone (linear tolerance) equals ± 20 °C and the square insensibility zone (square tolerance) is ± 50 °C. The measured value – \(T_{AGAM1}\), in this example, stays within linear tolerance, so penalty function returns zero – \(P_{AGAM1} = 0\) (green dashed line).

The result of gradient optimization is twelve optimized setpoints of AGAM temperatures. Each single setpoint is uploaded to SILO as setpoint in SILO’s penalty function. Fig. 4 presents how SILO interprets this setpoint’s change. As a result of gradient optimization, setpoint for this temperature changed – previously it was 1350 °C – Setpoint 1, the new equals 1380 °C – Setpoint 2. Linear and square insensibility zones stay unchanged and equal respectively ±20 °C and ±50 °C. After setpoint change, the \(T_{AGAM1}\) temperature is now beyond linear tolerance range and, consequently, a penalty is applied – \(P_{AGAM1} > 0\) (blue dashed line). In this case, in next optimization step, SILO calculates change of MV signals, which reduce this penalty and consequently, increase the temperature.

The following plots represent single step of the fireball optimization algorithm.

The first plot (Fig. 5) presents twelve AGAM temperatures monitored by SILO – before optimization. In this case the fireball is shifted to the right, rear side of the furnace. This shape differs from the reference significantly. Basing on difference between current and reference shape, the fire-ball optimization algorithm calculates
Fig. 5. AGAM temperatures measured before SILO optimization.

Fig. 6. AGAM temperatures’ setpoints, calculated by SILO optimization.

Fig. 7. AGAM temperatures measured after SILO optimization.

Fig. 8. SILO effect on boiler efficiency.
setpoints of AGAM temperatures. It gives twelve optimal setpoints of AGAM temperatures, presented on the second plot (Fig. 6). Then, those setpoints are transferred to SILO algorithm for further combustion optimization. The final result of this example, after SILO optimization step, is presented in the third plot (Fig. 7).

7. Optimization results

Evaluation of optimization results was done by analyzing historical data of the combustion process parameters. The method of this evaluation relays on simple comparing, how SILO operation

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![Fig. 9. SILO effect on left and right SH steam temperatures.](image)

![Fig. 10. SILO effect on left and right RH steam temperatures.](image)

![Fig. 11. SILO effect on difference of RH steam temperature.](image)
influences individual CV signals and efficiency of the process. In other words, the difference in process parameters and efficiency between SILO ON and SILO OFF states will be presented. The dataset represents the period of August 1st – December 31st 2014.

Before calculating final results, two statistical analyses must be performed – Kolmogorov-Smirnov [48] as well as Mann-Whitney-Wilcoxon [49] tests. Those tests help to evaluate, whether a change of particular parameter is caused by certain, intended impulse e.g. the gain in boiler efficiency was the effect of SILO operation.

Detailed information of optimization results are presented on Figs. 8–11.

Fig. 8 presents positive influence of SILO on the boiler efficiency for the whole load range. The highest increase was recorded for higher load range and the lowest for low load.

Result of SILO operation on superheated and reheated steam temperatures represents highest optimization priority on those signals. Steam temperatures influence boiler efficiency significantly, because they influence useful heat output of the boiler [46].

Regarding reheat steam temperature, the optimization effect is mostly seen on the left-side temperature at low and medium unit load. For high load level this temperature stays within the tolerance – ±5 °C around 540 °C.

Fig. 11 presents an improvement on left-right difference of reheated steam temperatures. This parameter was significantly reduced for low load range. For other operating points this problem did not occur – the parameter stayed within tolerance range.

8. Conclusions

The Rybnik’s project has a positive influence on the combustion process. The goal of this project was to increase the process efficiency over 0.2%. As it is presented below, final average efficiency increase is 0.27% (see Fig. 12).

By monitoring temperature distribution, SILO is able to control the combustion process to be more balanced. Balanced temperature distribution means balanced O2 distribution and, consequently, homogeneous combustion. This, finally, results in lower CO emission – due to reduction of local under-stoichiometric combustion. This opens for SILO a potential of further decreasing demand for combustion air.

A homogeneous temperature distribution is a great indicator of properly controlled combustion process. Due to the characteristics of this process, distribution of fuel and air must be adjusted continuously, in order to keep it at high quality.

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