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Optimal Control for Combustion Process

Abstract. *This paper proposes a multi-dimensional optimal controller for the combustion process control. This approach provides the flexibility to migrate from many separate systems, based on the traditional multi-SISO control scheme. Discussed algorithm takes into account the additional information about the process, eg. on the basis of the flame image in the combustion proces. Paper presents selected results of simulation studies*

Streszczenie. *W artykule zaproponowano wielowymiarowy, optymalny kontroler do sterowania procesem spalania. Podejście to umożliwia elastyczną migrację z wielu odrębnych układów, opartych na tradycyjnym schemacie sterowania typu SISO. Omówiony algorytm, pozwala uwzględnić dodatkowe informacje o procesie, np. na podstawie obrazu płomienia w procesie spalania. W pracy przedstawiono wybrane rezultaty przeprowadzonych badań symulacyjnych. (**Sterowanie optymalne procesem spalania**).*

Keywords: combustion process, optimal control system, advanced control algorithms.
Słowa kluczowe: proces spalania, układ sterowania optymalnego, zaawansowane algorytmy sterowania.

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Introduction

Intensification of economic development increases the demand for electricity, mainly covered by fossil sources. Both diversification of energy sources and gradual independence of exhaustible energy resources stands the most important priorities of the global community.

Development of the smart power engineering networks opens possibilities for innovative management approaches, based on modern diagnosis and control methods.

Usually, traditional control systems of power plants are based on a number of regulation loops and feedforward compensators that contribute to maintain the main process variables within reasonable values. With a few modifications these structures can be adopted to the modern, demand-driven energy systems. Introduction of distributed generation and smart-grid systems require plants with enhanced load-following capability. Facing the occurrence of sudden load changes, control system emergency procedures or safety features ought to keep avoiding potentially dangerous behaviour. The dynamic performance can be improved significantly when using multivariable control techniques instead of the classic SISO loops.

A multivariable, multiple-input, multiple output (MIMO) control scheme would reduce potentially dangerous events and unnecessary (redundant, tentative) emergency procedures. Both the power reliability and plant efficiency would therefore be increased.

The transition to such approach have some obstacles, denoted in the table 1.

Table 1. The Aspects of classic and multivariable control

Cause	MIMO	SISO
Controls	Controls centralisation. Failure of the control algorithm may induce the failure of the several plants.	Controls decentralisation. Single SISO loop can be disconnected in case of emergency
Design	Complex design and implementation	Well known methods methods and tools
Maintaince	Needs additional training activities	Well assessed by staff

Therefore the conventional multi –SISO solutions cannot be completely abandoned because it is well assessed, reliable technology on the one hand, but opens new pole of potential on the other hand [4].

Power engineering background to optimal control

Optimal control is the process of determining control and state trajectories for a dynamic system over a period of time to minimize a performance index, which include a chosen quantity of importance for the control system. Optimal control and its modifications have found applications in many different fields and it is an active research area within control theory. The arrival of digital computer has enabled the application of optimal control theory and methods to many complex problems.

The solutions to the most practical optimal problems cannot be found by analytical means. Indirect methods involve iterating on the necessary procedures to seek their satisfaction. This usually involves attempting to solve nonlinear two-point boundary-value problems, through the forward integration of the plant equations and the backward integration of the costate equations.

With direct methods, optimal control problems are discretized and converted into nonlinear programming problems. These methods involve the approximation of the control and states using basis functions, such as splines or Lagrange polynomials. Direct collocation methods involve the discretization of the differential equations using, for example, trapezoidal, Hermite–Simpson [2], or pseudospectral approximations [2, 3]. In this way, the differential equations become a finite set of equality constraints of the nonlinear programming problem.

The nonlinear optimization problems that arise from direct collocation methods may be very large, having possibly hundreds to tens of thousands of variables and constraints.

However, some complex optimal control problems can be conveniently formulated as having multiple phases. These phases may be both inherent to the problem and also to allow for peculiarities in the solution of the problem such as discontinuities in the control variables. The multiphase optimal control problems arrange additional constraints are added to the problem to define the linkages between interconnected phases [2, 3].

The legal regulations and technological restrictions in energetics sector impose need for efficient control of pulverized coal combustion's complex process. Process control difficulties are the result of unavailable or incomplete information about the combustion process. The article analyze optimal control algorithm for combustion process using additional information signals (esp. optical information of changes in selected parameters of the flame). The authors discussed correlation between the selected process models and indicators of optical signals, that are used in the control algorithm.

As evidenced [4, 5-10], intelligent control algorithms, used in the combustion process offer the great potential due to the significant complexity of the physical and chemical phenomena occurring in the considered process

The authors objective was to develop adaptive process control system of pulverized coal combustion and biomass energy in the boiler using information from both traditional measurements and additional information about the process).

Multivariable optimal control strategies

Multi-SISO control systems based on frequency decoupling have satisfactory performance when load variations are smooth and small. This condition is satisfied in normal operation, where the load demand profile does not change suddenly, and when startup and shutdown are safety-compliant procedures.

Plant interactions are no longer compensated by the control system when sudden and significant changes of the power demand are observed. In order to avoid the overshoot of temperatures and pressures, and to improve the load-following characteristics of the control system, various control strategies were proposed, eg: model-based estimator of the load margin, H_{inf} techniques in coal-fired plant [5], fuzzy logic [11], hybrid supervision systems [12], genetic algorithms [13].

Optimal and robust control techniques (LQG, $H_{inf/\mu}$) have been adopted by [14, 15]. These techniques may stand the core of the improved supervisory systems.

The implementation of a MIMO control over an existing multi-SISO control configuration can be carried out by considering dynamic behaviour of an enlarged plant by the new, multivariable system. Such approach unites the plant components and the various feedback loops of the classic regulation system so the controlled variables of the enlarged plant are a subset of the outputs of the power generation unit [2, 15].

Two different possible configurations can be defined, depending on which control variables are chosen. The first possibility is to act on the set-points of the classical control, whereas an alternative is to inject a correction signal, added to the control input variables of the plant [2, 16]. The schemes of the two architectures, named from now on controlled reference value (CRV) and control action correction (CAC), are presented in the figure 1.

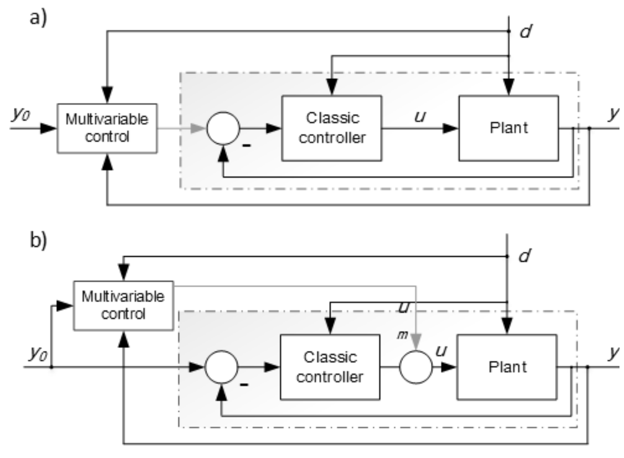

Fig.1. MIMO control architectures: (a) controlled reference value (b) control action correction

In the figure, y is the controlled output vector and y_0 the corresponding reference value. The control variables are denoted as u, while u_m is the control variable of the multivariable controller.

CRV approach based on a multivariable state space linear quadratic Gaussian (LQG) predictive controller has been adopted by [16] to optimise the control of a combined cycle turbine power plant, where the non-linear simulation model was used. [17] used such a structure to synthesise a MPC controller for a coal power plant.

Structures based on the CAC architecture have also been adopted. [2, 13, 14] have designed a CAC-based multivariable control system for the control of steam pressure and temperature of a 85 MW coal-fired power plant boiler. The results obtained show a significant improvement of the control system performance [2].

Identification of a model for control

In optimal control algorithms a reduced order model of the plant is usually applied. For the most implementations such models are in general linear. The choice of a specific control algorithm often imposes the model structure that needs to be implemented.

In general, physical-based models allow the designer to better understand the plant dynamics and their structure and parameterisation may be related to both geometric and physical characteristic of the plant. Physical based models expose process non-linearities and approach to their description. Their main purpose is to provide accurate simulation of plant behaviour over wide range of operating conditions. The simulation approach extremely simplifies the work of the control designer to avoid expensive and time-consuming in-field testing. The design cycle is reduced and various alternative configurations can be tested without impact on the plant.

In order to ensure rational, finite-time simulator behaviour, model order ought to be reduced also algorithm

In order to ensure both control algorithm and simulator convergence, the reduced order model ought to be used. It is usually achieved by linearization the non-linear equations to obtain a set of linear state-space. The procedure is complicated for multivariable system with a number of set variables with implicit relations.

For SISO feedback control loops inside system structure, the linearization is more complex. In such a case designers use black-box identification methods of multivariable model from available, acquired data sets.

Multivariable models contain large number of parameters whose estimation and selection are affected by excessive computational load and numerical errors.

Regarding to the MIMO systems, they are often presented in state-space form. It is caused by the access to the information on the dynamics in a limited number of parameters on one hand. But on the other hand, there are subspace model identification (SMI) methods, that lead to the reliable models when the number of states, inputs and outputs is high.

In general, the identification procedure consists of five stages: experiment design, data pre-processing, choice of model complexity, identification and validation [2,13-15].

Imaging method in the combustion process

Flame is a reflection of the combustion process occurring in chemical reactions and physical processes. Optical diagnostic methods allows for non-invasive way to obtain fast, spatially selective additional information about the ongoing combustion process. It is possible to determine the content of the air-fuel ratio, the quantity of heat release and temperature regarding to the spectrum of flames in the visible emission band. Flame stands the result of dynamic equilibrium between the local flame propagation speed and the speed of the incoming fuel mixture [18,19-23]. Changes of the flame front position in space, are seen as the flame shape fluctuations are disruption of this balance results. This allows to assume that the shape of a flame can be an indicator of the combustion process, occurring under certain conditions [20-25].

Radiation emitted by the flame is a reflection of the combustion process occurring in chemical reactions and physical processes. Optical diagnostic methods, in addition to acoustic [22-25] belongs to the most important methods, which allow the non-invasive way to obtain non delayed and spatially selective additional information about the ongoing combustion process. Regarding to the spectrum of flames in the visible emission, it is possible to include determine the content of the air-fuel ratio, the quantity of heat release and temperature [24, 25].

Among optical methods, image processing based approach seems to be particularly important.

Conducted, real combustion tests results of coal dust and biomass were used for simulation model elaboration. Therefore, combustion stoichiometric conditions were adjusted during the tests, by the secondary air flow adjustment. This resulted in fuel dust-air mixture changes exit velocity, bringing to the state of the close flame disappearance.

The area of the flame was isolated from the grayscale images, regarding to the amplitude of each pixel. It was assumed arbitrarily that the relevant pixel in the image belongs to the flame, if its amplitude is more or equal to the 64. The flame surface area was considered as the sum of all pixels belonging to the flame area and the length of the designated area contour.

Combustion process optimal controller

The unconstrained case of the MPC, CAC scheme based algorithm was chosen for simulation purposes. The control algorithm is based on a state space model of the enlarged plant with structure:

$$x(k+1) = A\,x(k) + B_m u_m(k) + B_w w_m(k) + B_z z(k) \qquad (1)$$
$$y(k) = C\,x(k)$$

where: $\boldsymbol{x}$ – state vector, $\boldsymbol{y}$ – output vector, $\boldsymbol{u_m}$ – input (or control) vector, $\boldsymbol{A}$ – state matrix, $\boldsymbol{B}$ – input matrix, $\boldsymbol{C}$ – output matrix.

The optimal controller represents solution of an optimisation problem with the following cost function minimisation:

$$J = \sum_{i=1}^{n} \left[r(k+i) - y'(k+i\,|\,k)\right]' \mu_y(k) \left[r(k+i) - y'(k+i\,|\,k)\right] + \sum_{i=1}^{c} \Delta u_m(k+i\,|\,k)' \mu_m(k) \Delta u_m(k+i\,|\,k), \qquad (2)$$

where: $r(k)$ – reference value, $y'(k+i|k)$ is the predictor based on the observations $y(k)$ and $v(k)$. The cost function is a weighted sum of the error between the reference and predicted value of the output upto n steps (prediction horizon) and the control effort upto c steps ahead (the control horizon), expressed in terms of the control increment Δu_m. The tuning of the controller was elaborated by choosing the prediction horizons n and c and the weights μ_y and μ_u. Their choice cannot be casual and ought to rely on process knowledge and observations. For example, the prediction horizon n incrementation results in better performance since a greater prediction of the future error is possible. Also, for some values control error must be high particularly when classical regulation is slow and largely responsible for overall performance. Control horizon c and the input weight μ_u influence the strength of the control action. To avoid the excessive penalisation of control action, μ_u should not be too high. Moreover, high values of the control horizon c affect undesired oscillations of the control variables. In case of lack of constraints on the control variables μ_u it is necessary to determine its valu high enough to avoid the saturation of the actuators.

The control system was evaluated by simulating a sudden step change of the load request. This test replicates the critical situation that occurs when an unexpected change of power and NOx radicals takes place (see Fig 2).

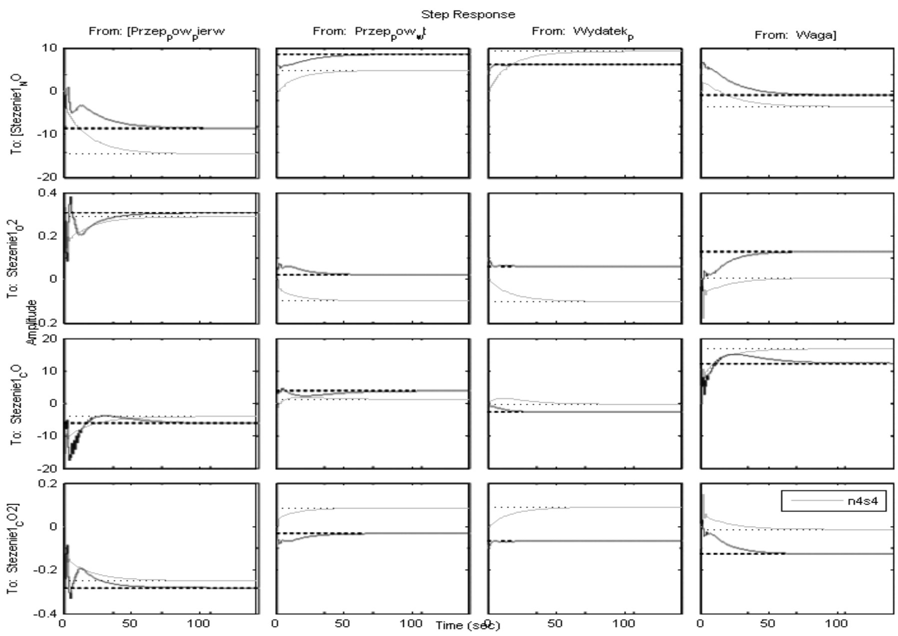

Fig.2. MIMO controller response to sudden change of power load regarding to the relationship between the concentrations of NO_x, CO, flue gas temperature in the combustion chamber

The correction signals introduced by the optimizing algorithm are indeed small. The introduced simulation of the MIMO controller results in better performance. The evaluation of the control signals indicate negligible change in magnitude of input signals.

Conclusions

The application of multivariable optimal control techniques to the fossil fuel power plants has been discussed. Article focused on solution that replace muti-SISO configuration with optimal MIMO approach. Regarding to the conducted simulation test the following results were achieved:

- The increment of the prediction horizon *n* allows better performance since a greater prediction of the future error is possible.
- While using temperature values, its error weight must be high regarding to the fact the classical temperature regulation is slow and responsible for overall performance.
- The μ_u value must not be too high to avoid radical penalisation of the control action.
- High control horizon values returns undesired oscillations.

Further works ought to be concentrated on the more precise robustness verification of the proposed controller.

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