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Procedia Engineering 100 (2015) 1539 – 1546

Procedia Engineering

www.elsevier.com/locate/procedia

25th DAAAM International Symposium on Intelligent Manufacturing and Automation, DAAAM 2014

Nonlinear State and Unmeasured Disturbance Estimation for Use in Power Plant Superheaters Control

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Abstract

This paper deals with the state and unmeasured disturbance estimation within the nonlinear model predictive control of the superheated steam temperature in a once-trough boiler of a fossil fuelled power plant. The nonlinear model of the once-trough boiler has very high order, it is significantly nonlinear and load dependent. Model is excited by several disturbances, but not all of them are measured. Particularly the heat of flue gas is unmeasured disturbance which has significant influence on the superheated steam temperature and its estimation could improve the control performances of the superheated steam temperature. The proposed nonlinear state and unmeasured disturbance observer is based on the nonlinear moving horizon estimation algorithm.

Peer-review under responsibility of DAAAM International Vienna

Keywords: nonlinear model predictive control; Estimation; Unmesuared disturbance; Once-through boiler; Fossil power plant

1. Introduction

Superheated steam temperature is very significant variable in a fossil fuelled power plant. It has influence on efficiency of the power plant, lifetime of the boiler components and the turbine and last but not least on the power plant safety. From this reason the tight control of the superheated steam temperature on a constant value with keeping its variations as small as possible is very important requirement.

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Peer-review under responsibility of DAAAM International Vienna
doi:10.1016/j.proeng.2015.01.526

In recent years the building of new power plants based on the renewable energy increases. The actual electric power of these power plants is very variable during the day. Therefore it is necessary to change the load of fossil power plants very often. Since the steam superheating process is significantly nonlinear and load changes are fast and quite high, the issue of the superheated steam temperature control is more complicated and very actual. Each improving of this control process has significant economic benefit.

The control systems for superheated steam temperature control based on the PID, or adaptive PID control [1] are still mostly used. The control performances of these systems are not tight enough for current requirements achievement. Therefore our research is focused on the advanced control algorithm design for superheated steam temperature control, in particular the nonlinear model predictive control (NMPC) is considered.

The first our research results with NMPC were published in [2]. In this case the simple nonlinear open loop state observer was used in NMPC feedback. This paper follows on this research and its objective is to propose the nonlinear close loop state and unmeasured disturbance observer. The unmeasured disturbance is the flue gas heat. This disturbance is not constant in real process even when the power plant is operated on the constant load. It is possible to assume that flue gas heat estimation could improve the control performances of the superheated steam temperature, especially in the situation when the temperature rapidly increases in very short time without any obvious reasons. This is caused by unexpected local changes of flue gas heat.

The number of NMPC applications in industry increases in last decade [3], but the NMPC is almost not used as a control strategy in power plants. Despite of this fact it is possible to find a few applications or simulation studies which use the NMPC for power plant boiler control. The examples of NMPC applications for power plant boiler control are in [4, 5]. In [4] the very simplified model is used, in [5] the nonlinear fuzzy model is used. In both cases the system states are estimated using the Kalman filter. Next the examples of pressure and water levels control in power plant drum-boiler are in [6, 7]. While in the first example the state dependent Kalman filter is used for system states estimation, in the second example the particle filter is used. In [8] the comparison of the linear and the nonlinear MPC of benchmark drum boiler is presented. Interesting application of MPC with real-time maintenance of the control model is in [9].

In almost all cases the very simplified dynamic model is used. The nonlinear state estimation is mostly based on the Kalman filtering or it is not solved at all due to the possibility of measurement of all state variables. In our case the verified and high order nonlinear model of once-through boiler is used. The model sufficiently accurately describes the dynamic of steam superheating process. The observer is based on the nonlinear moving horizon estimation (NMHE) algorithm which is suitable for the large scale problems and whose advantage is possibility of constraint implementation on particular variables (inputs, outputs and differential states).

Nomenclature

Nonlinear model nomenclature

ρ	density
$\dot{m}$	flow rate
T	temperature
c	heat capacity
$\dot{Q}$	input heat flow
L	tube length
V	volume of steam in the tube
S	tube heating area
Δz	the length of one cell
α	heat transfer coefficient (wall-steam)
p	pressure

Observer algorithm nomenclature

J	objective function
N	receding horizon
y	output variables (outlet superheater temperature)
u	manipulated variables (valve)
Q_y, Q_u, Q_d	penalization matrices
x	system differential states
d_m	measured disturbances
d_{unm}	unmeasured disturbances
f, g	functions of nonlinear discrete-time model

Subscripts

Fe	tube	*in*	inlet side	*min*	minimal value	*m*	measured (known) value
s	steam	*out*	outlet side	*max*	maximal value	^	estimated value

2. Nonlinear once-through boiler model – superheating part

The nonlinear model describes the dynamic of once-through boiler of real power plant at our country. The model works in the whole operating range of power plant load from 50 % to 100 %. The power plant produces electricity in this operating range. The model allows the technology process simulation, the actual situation analysis with respect of the actual control circuit based on the adaptive PID control and mainly it allows the possibility of new control algorithm application.

The technological node of superheating (see Fig. 1) is a part of the once-through boiler. The analysed boiler has except the superheating part the steam generator part and the steam reheating part. The connection between superheating and reheating parts is through the high pressure part of the turbine and counter-current steam to steam heater inside the boiler. The practical experiences and some simulation results lead to the conclusion that the most important part for the output superheated steam temperature is the output superheater. The technology of all heaters are very similar, the differences are mainly in the physical placement in the boiler which leads to different dynamic. Every superheater has the control valve on the inlet to inject the cooling water. The actual control strategy is to hold all outlet superheaters temperatures constant or at least in some narrow area.

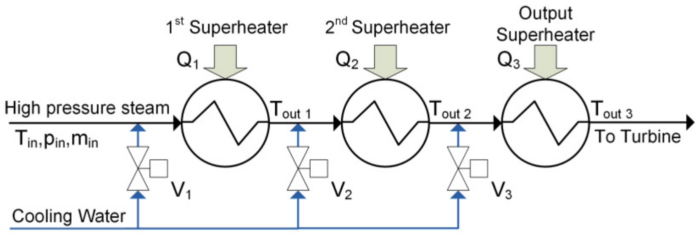

Fig. 1. Technological node of steam superheating in the high-pressure part of the once-through boiler.

The simulation model of the superheater can be constructed in many different forms according to the final application area. Two border approaches exist. The first one is based on the finite element method application and brings very precise description of the temperature inside the superheater, but the utilization in the process control area is weak and brings together problems with the computing demands and simulation speed. On the other end of the simulation model spectrum stays the global balances approach [10, 11]. In this case the model is very simple and the dynamic is usually described by one linear transfer function. The biggest disadvantage of this approach is in the nonlinearity of the steam superheating process, because the dynamic behaviour of this process cannot be described by linear transfer function in the whole power plant operating range. The simulation model used to the purpose discussed in this paper is a cell type nonlinear model. The main inspiration to create this model is in [12]. The main difference in this application is the work with the mass of tubes.

The simulation model is based on the standard Euler balances – the mass balance, energy balance and momentum equilibrium [13]. Some important presumptions together with simplification are made in [14]. At first the pressure dynamic is neglected, at the second the input flue gas heat to the heater is known in advance (in this study is under estimation as an unmeasured input) and parameters of the steam (the density, the heat capacity, etc.) inside the tube are computed as the mean from the value on the inlet and the value corresponding to the actual outlet. The final set of the equations is as follows.

$$\frac{d\,\mathbf{T}_s}{dt} = \frac{\dot{m}}{\Delta V \cdot \bar{\rho}} \cdot \mathbf{\Gamma}^* \cdot \mathbf{T}_s + \alpha \frac{L}{\Delta z \cdot \bar{\rho} \cdot \bar{c}_s}\left(\mathbf{T}_{Fe} - \mathbf{T}_s\right) + \mathbf{\Omega} \cdot \frac{\dot{m}}{\Delta V} \cdot \frac{T_{in}}{\rho_{in}} \tag{1}$$

$$\frac{d\,\mathbf{T}_{Fe}}{dt} = \frac{1}{m_{Fe} \cdot c_{Fe}} \cdot \left(\dot{\mathbf{Q}}_{\mathbf{in}} - \alpha \cdot S \cdot \left(\mathbf{T}_{\mathbf{Fe}} - \mathbf{T}_{\mathbf{s}}\right)\right) \tag{2}$$

where $\mathbf{T}_s = \left[\mathbf{T}_{s1}\ \mathbf{T}_{s2}\ ...\ \mathbf{T}_{s,out}\right]^T$; $\mathbf{\Omega} = \left[1\ 0\ ...\ 0\right]^T$; $\mathbf{\Gamma}^* = \begin{bmatrix} 1 & 0 & & 0 \\ -1 & 1 & & \vdots \\ 0 & \cdots & -1 & 1 \end{bmatrix}$; $\bar{\rho} = \dfrac{\rho_{in} + \rho_{out}}{2}$

The first equation describes the temperature dynamic of steam inside the tube – cell model and serves the information about the outlet temperature as the last index of the state vector. The second equation realizes the connection between the heat source and the steam through the tube. The tube dynamic is important part of a model and has significant influence to the outlet steam temperature dynamic. The flue gas is the source of heat in the boiler. In (2) it is realized as a general value which respects the total amount of heat transferred from the flue gas to the steam and the tube. This realization has the advantage for the disturbance realization and disturbance simulation. Since the heat exchanger tube of each superheater is separated into several parts (cells) the resulting nonlinear model has high order (1^{st} and 2^{nd} superheater are 10^{th} order, the output superheater is 20th order).

3. Nonlinear state and unmeasured disturbance estimation

3.1. Nonlinear moving horizon estimation (NMHE) algorithm

The proposed state and unmeasured disturbance observer is based on the NMHE algorithm [15]. The NMHE algorithm is very similar to the NMPC. In both cases the constrained nonlinear optimization control problem (OCP) with finite time horizon has to be solved for each sample of estimation (resp. control). The objective function of the OCP is in the form of quadratic criterion. The nonlinearity of OCP is given by the nonlinear dynamic model, which is included in the optimization constraints. The basic NMHE optimization problem can be formulated as follows:

$$\begin{aligned} & J(k) = \sum_{p=0}^{N-1} \left\| y_m(k-p|k) - \hat{y}(k-p|k) \right\|_{Q_y}^2 + \sum_{p=1}^{N} \left\| u_m(k-p|k) - \hat{u}(k-p|k) \right\|_{Q_u}^2 \\ & \text{Subject to: } \dot{\hat{x}}(n+1) = f\left(\hat{x}(n), \hat{u}(n), \hat{d}_m(n)\right) \qquad n \in \langle k-N; k \rangle \\ & \hat{y}(n) = g\left(\hat{x}(n), \hat{u}(n), \hat{d}_m(n)\right) \\ & \hat{x}(k-N) = x_0 \\ & \hat{d}_m(n) = d_m(n) \\ & u_{\min} \le \hat{u}(n) \le u_{\max};\ x_{\min} \le \hat{x}(n) \le x_{\max};\ y_{\min} \le \hat{y}(n) \le y_{\max} \end{aligned} \tag{3}$$

In the OCP (3) it is assumed that all disturbances are measured. Since our aim is to estimate except the system states also the value of unmeasured flue gas heat, it is necessary to modify the objective function of OCP (3) as follows:

$$J(k) = \sum_{p=0}^{N-1} \left\| y_m(k-p|k) - \hat{y}(k-p|k) \right\|_{Q_y}^2 + \sum_{p=1}^{N} \left\| \Delta\hat{d}_{unm}(k-p|k) \right\|_{Q_d}^2 \tag{4}$$

Within the modified objective function (4) the value of unmeasured disturbance, which minimize the difference between all samples of estimated and measured output variable, is computed. The increments of unmeasured disturbance are used in (4), because the unmeasured disturbance reference value is not known in advance. The advantage of this approach is the possibility of value and rate limits inclusion into the optimization constraints. The action values u, which are included in the original objective function of OCP (3), are fixed on theirs measured (known) values within the constraints (similarly as the measured disturbances in (3)) in this case.

Further modification of OCP (3) is connected with nonlinear model. The nonlinear once-through boiler model described in chapter 2 is continuous-time. When we substitute the discrete-time model in (3) by the continuous-time one it is necessary to discretize the OCP. The mostly used discretization algorithms are the single and the multiple shooting methods [16]. After the OCP discretization the nonlinear program in the standard form is obtained:

$$\begin{aligned} &\min F(X) \\ &\text{Subject to:} \quad G(X) = 0 \\ &\qquad\qquad\quad\; H(X) \leq 0 \end{aligned} \tag{5}$$

The nonlinear program (NLP) can be solved using the methods based on the sequential quadratic programming (SQP) or the methods based on the interior point methods (IPM) [17]. All numerical problems mentioned above (OCP discretization and NLP solving) were solved using the software ACADO toolkit [18]. It is a software environment written in C++ which contains collection of algorithms for automatic control and dynamic optimization. ACADO toolkit has implemented both of the discretization methods (single and multiple shooting). For the NLP solving the active set SQP algorithm is implemented.

3.2. Observer structure

One of the general advantages of NMPC is that it is a multivariable control strategy. It is easy possible to set a priority of particular control objective by appropriate setting of penalization matrices. However the multivariable structure of NMPC for superheating steam control is connected with several difficulties. The high order nonlinear model of three superheaters has influence on high dimension of optimization problem with slow-time solution and problematic real time performance. Therefore the distributed structure of NMPC is considered as the better choice. Each superheater is controlled by separate NMPC. The structure of one NMPC is on Fig. 2.

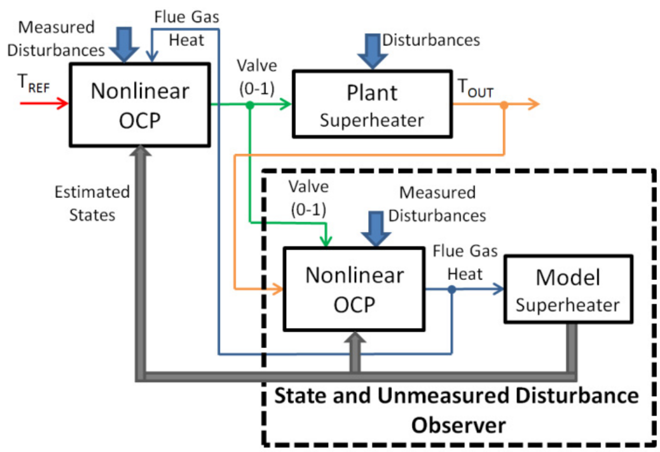

Fig. 2. Structure of NMPC with the close loop state and unmeasured flue gas heat observer.

This paper is focused only on the state and unmeasured disturbance observer (marked by dashed line on the Fig. 2). The structure clearly describes the NMHE algorithm mentioned in chapter 3.1. In the *Nonlinear OCP* block the NMHE optimization problem is solved for each sample of estimation. The resulting value of flue gas heat (resp. the increments of flue gas heat) and system states are subsequently used for close-loop NMPC.

3.3. Observer settings

Appropriate setting of the observer is very important. It has influence on estimation stability, estimation performance and computation demands. The sampling time was 10 s. The receding horizon has to respect the nonlinear model time constant. It was set to 100 s (10 samples). The outlet temperature was weighted in OCP (4) by penalization (Q_y = 100), the increments of the flue gas heat was weighted by (Q_d = 1). Both variables (temperature and flue gas heat) were scaled into the same order. For the OCP discretization the single shooting method was used and NLP was solved using the active set SQP method. Gauss-Newton method was used for the Hessian matrix approximation.

4. Simulation experiments

The functionality of proposed observer was verified by several simulation experiments. Three chosen experiments presented in this paper were made on the output superheater. As it was mentioned in chapter 2, the output superheater is the most important one. The output steam from the output superheater enters into the turbine. Further the difference of the inlet and the outlet steam temperature is significantly higher on the output superheater than on the 1st and on the 2nd superheater. Next the output superheater is more sensitive on the flue gas heat.

In the first experiment the power plant load was constant (70 %) and the output superheater worked in open loop (without control). The two minute long impulse on the flue gas heat is considered. The amplitude of pulse is 10 % from nominal value of flue gas heat. The aim of this experiment was to estimate the impulse on the flue gas heat (see Fig. 3a). The demonstration of the system state estimation is on Fig. 3b. The system states represent the steam temperatures and the heat exchanger tube temperatures in particular cells of the output superheater. The output superheater is separated into the ten parts and therefore the estimation of twenty temperatures is shown on Fig. 3b.

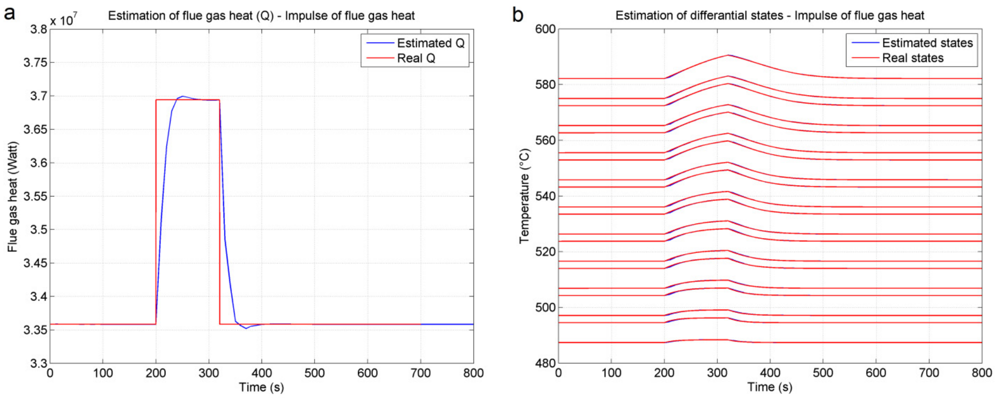

Fig. 3. Experiment 1: (a) Flue gas heat estimation; (b) System differential states estimation.

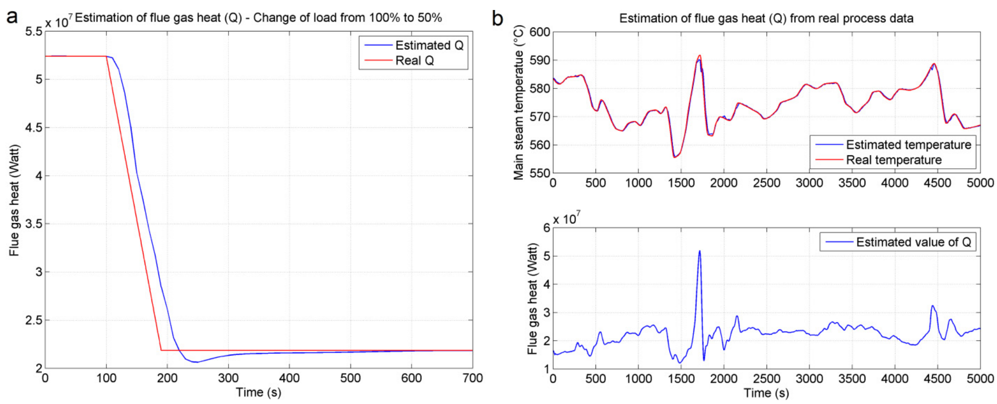

Fig. 4. Flue gas heat estimation: (a) during the ramp change of load (Experiment 2); (b) from process data of real power plant (Experiment 3).

In the second experiment (see Fig. 4a) the ramp change of power plant load from 100 % to 50 % is considered. This fast load change can be regarded as the worst scenario that can occur during the real power plant operation. During the load change the value of flue gas heat and many other variables (pressure, mass flow of steam) are also changing. The aim of experiment was to estimate the ramp change of flue gas heat during the control process.

The last experiment (see Fig. 4b) demonstrates the using of proposed nonlinear observer as an offline analyser of measured process data from real power plant. The aim was to estimate the unmeasured flue gas heat when the input and output steam temperature, cooling water valve position and all measured disturbances were known. The power plant load was almost constant (50 %). We can see that the flue gas heat is variable during the constant load.

Conclusion

The contribution of this paper is the proposal of nonlinear observer based on the nonlinear moving horizon algorithm. The observer allows the system differential states estimation and the unmeasured disturbance estimation. The observer functionality was verified by several simulation experiments.

From the 1st and the 2nd experiments it is obvious that the observer estimates the value of unmeasured flue gas heat with sufficient rate and accuracy and with small oscillations (Fig. 3a and 4a). It is possible to assume that the information about unmeasured disturbance will have significant influence for better NMPC control performance. The system states estimation performance was also satisfactory. All estimated temperatures were almost the same as the real ones (see Fig. 3b). The observer can be also used for the online or the offline identification of flue gas heat value from the real process data (see Fig. 4b).

It is important to mention that the computation time of observer optimization problem was about two times shorter than the sample time 10 s. The optimization problem has to be solved for each sample and it is necessary to consider that the sum of observer and controller computation times has to be shorter than 10 s for the real time performance. In further work the connection of proposed nonlinear state and unmeasured disturbance observer with NMPC is planned and especially the influence of unmeasured disturbance estimation will be examined.

Acknowledgements

This work has been supported by the Technology Agency of the Czech Republic under contract No. TA02020109 “Predictive Control System for Stability Improvement and Higher Efficiency of Power Plants”.

This work was supported by Student Grant Competition of Technical University of Liberec.

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