SERBIAN JOURNAL OF ELECTRICAL ENGINEERING
Vol. 6, No. 3, December 2009, 373 - 387

UDK: 621.311.614.83]:512.614

An Application of Decentralized Estimation in a Fault Detection Problem*

Predrag R. Tadić[1,a], Miloš S. Stanković[2], Srdjan S. Stanković[1,b], Željko M. Djurović[1,c]

Abstract: This paper presents a design of a decentralized fault detection and isolation (FDI) filter by means of an overlapping decentralized estimation algorithm based on a consensus strategy. An efficient solution to the FDI problem can be obtained by an adequate system decomposition into overlapping subsystems and the construction of local FDI estimators aimed at achieving the desired performance. The general aspects and properties of a consensus based estimator are described in the first part of the paper. An applicability of such an estimator to an FDI problem in a large scale system is discussed next. Namely, a case study related to the detection of fire dissymmetry in a thermal power plant boiler is presented, including the process description and identification procedure, comparison between the results obtained by local and decentralized estimators and conclusions concerning their validity.

Keywords: Power plants, Fault detection, Consensus, Decentralized estimation.

1 Introduction

A great deal of attention has been paid to the problem of *decentralized state estimation* of complex large scale systems lately. The key requirement is that a large scale system be modeled as an interconnection of *subsystems*, and that each subsystem have a decision maker (intelligent *agent*) associated with it, having access to different local measurements, subsystem models, local estimators, and communication channels between the agents, see [26, 27, 28]. Unfortunately, most of the existing methodologies are not able to provide a systematic and general way of designing communication strategy between the agents without recurring to a strong fusion center [2, 34]. One of the recent ideas trying to circumvent this problem has been based on the application of a

[1]School of Electrical Engineering, University of Belgrade, Bulevar Kralja Aleksandra 73, 11120 Belgrade, Serbia
[2]University of Illinois at Urbana-Champaign, Illinois, USA; E-mail: mstanko3@uiuc.edu
E-mails: [a]tadicp@etf.rs; [b]stankovic@etf.rs; [c]zdjurovic@etf.rs
*Award for the best paper presented in Section *Automatic Control*, at Conference ETRAN 2009, June 15-19, Vrnjačka Banja, Serbia.

dynamic *consensus* strategy, where the consensus scheme ensures such communications between the agents which substantially improve the local state estimates when the subsystems are *overlapping* [30, 31, 32, 4, 3, 5, 12, 17, 18, 20, 22, 24, 25, 13, 6].

It seems reasonable to suppose that critical and unpredictable changes in system dynamics could be detected and isolated (localized) very efficiently and robustly utilizing low cost monitoring sensors connected by a network, provided efficient algorithms are constructed. However, most of the available FDI methods based on state estimation are centralized [7], so that connection between decentralized estimation and fault diagnosis is still lacking.

This paper presents the consensus-based overlapping decentralized state estimation algorithm with its most salient features, important for its application to the decentralized fault detection and isolation (FDI) problem. Following these general ideas, a case study is presented in which the problem of detection of fire dissymmetry in a thermal power plant boiler is analysed.

2 Decentralized Consensus-Based Kalman-Type Estimation

Let a finite-dimensional discrete-time stochastic system be represented by

$$\begin{aligned} S : \boldsymbol{x}(t+1) &= \boldsymbol{F}\boldsymbol{x}(t) + \boldsymbol{G}\boldsymbol{e}(t), \\ \boldsymbol{y}(t) &= \boldsymbol{H}\boldsymbol{x}(t) + \boldsymbol{v}(t), \end{aligned} \tag{1}$$

where t is the discrete-time instant, $\boldsymbol{x} = (x_1, \dots, x_n)^T$, $\boldsymbol{y} = (y_1, \dots, y_p)^T$, $\boldsymbol{e} = (e_1, \dots, e_m)^T$ and $\boldsymbol{v} = (v_1, \dots, v_p)^T$ are its state, output, input and measurement noise vectors, respectively, while $\boldsymbol{F}$, $\boldsymbol{G}$ and $\boldsymbol{H}$ are constant $n \times n$, $n \times m$ and $p \times n$ matrices, respectively. It is assumed that $\{\boldsymbol{e}(t)\}$ and $\{\boldsymbol{v}(t)\}$ are white zero-mean sequences of independent vector random variables with covariance matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$, respectively.

We shall consider in this section the general problem of *decentralized estimation* of the state $\boldsymbol{x}$ of S, based on the assumption that N *autonomous agents* generate their estimates of the state vector of S on the basis of: (1) locally available measurements; (2) specific *a priori* knowledge they possess about the system, and (3) real-time communication between the agents.

Formally, we shall assume that the i-th agent has a possibility to observe the p_i-dimensional vector $\boldsymbol{y}^{(i)} = \left(y_{l_1^i}, \dots, y_{l_{p_i}^i} \right)^T$, composed of the set of components of y with indices contained in the agent's *output index set*

$I_i^y = \left\{ l_1^i, \dots, l_{p_i}^i \right\}$, $l_1^i, \dots, l_{p_i}^i \in \{1, \dots, p\}$, $l_1^i < \cdots < l_{p_i}^i$, $p_i \le p$. We shall assume further that the i-th agent possesses the *local system model* S_i defined as

$$S_i: \; \boldsymbol{x}^{(i)}\left(t+1\right) = \boldsymbol{F}^{(i)} \boldsymbol{x}^{(i)}(t) + \boldsymbol{G}^{(i)} e(t), \\ \boldsymbol{y}^{(i)}(t) = \boldsymbol{H}^{(i)} \boldsymbol{x}^{(i)}(t) + \boldsymbol{v}^{(i)}(t), \tag{2}$$

$i = 1, \dots, N$, where $x^{(i)}$ is an n_i-dimensional vector composed of the components of x selected by the agent's *state index set* $I_i^x = \left\{ j_1^i, \dots, j_{n_i}^i \right\}$, $j_1^i, \dots, j_{n_i}^i \in \{1, \dots, n\}$, $j_1^i < \cdots < j_{n_i}^i$, $n_i \le n$, and $v^{(i)}$ is a measurement noise vector containing the components of v selected by I_i^y, having the covariance matrix $\boldsymbol{R}^{(i)}$ (which can be readily obtained from R); $\boldsymbol{F}^{(i)}$, $\boldsymbol{G}^{(i)}$ and $\boldsymbol{H}^{(i)}$ are $n_i \times n_i$, $n_i \times m$ and $p_i \times n_i$ and matrices, respectively. Local system models S_i can be obtained either by *overlapping decomposition* of the matrices $\boldsymbol{F}$, $\boldsymbol{G}$ and $\boldsymbol{H}$ in the global system model (1) starting from their sparsity, when $\boldsymbol{F}^{(i)}$, $\boldsymbol{G}^{(i)}$ and $\boldsymbol{H}^{(i)}$ can represent submatrices of $\boldsymbol{F}$, $\boldsymbol{G}$ and $\boldsymbol{H}$ [27, 29, 15, 16]. In general, local models can also be obtained on the basis of model reduction, local modeling and experimental parameter estimation, obeying the information structure constraints imposed by the whole multi-agent environment.

It is assumed that the *i*-th agent is able to generate autonomously the local estimate $\hat{x}^{(i)}$ of the local state $x^{(i)}$. The following Luenberger-type local estimators are assumed to be implementable by all the agents

$$\bar{E}_i: \; \hat{\boldsymbol{x}}^{(i)}\left(t+1 \mid t\right) = \boldsymbol{F}^{(i)} \hat{\boldsymbol{x}}^{(i)}\left(t \mid t-1\right) + \\ + \boldsymbol{F}^{(i)} \boldsymbol{L}^{(i)} \left[\boldsymbol{y}^{(i)}(t) - \boldsymbol{H}^{(i)} \hat{\boldsymbol{x}}^{(i)}\left(t \mid t-1\right) \right], \tag{3}$$

where $\boldsymbol{L}^{(i)}$ is a constant estimator gain.

Our task is to formulate an algorithm which would provide to all the agents in the network reliable estimates of the whole state vector $\boldsymbol{x}$ starting from the local estimation performed within each node and a decentralized communication strategy qualitatively uniform for all the nodes. We propose the following algorithm based on the introduction of a *consensus scheme:*

$$E_i: \; \xi_i\left(t \mid t\right) = \xi_i\left(t \mid t-1\right) + L_i \left[y^i(t) - H_i \xi_i\left(t \mid t-1\right) \right], \\ \xi_i\left(t+1 \mid t\right) = \sum_{j=1}^{N} C_{ij}(t) F_j \xi_j\left(t \mid t\right), \tag{4}$$

$i = 1,\ldots,N$, where ξ_i is an estimate of $\boldsymbol{x}$ generated by the i-th agent, $\boldsymbol{F}_i$ is an $n \times n$ matrix with $n_i \times n_i$ nonzero elements that are equal to those of $\boldsymbol{F}^{(i)}$, but are placed at the indices defined by $I_i^x \times I_i^x$, while $\boldsymbol{H}_i$ and $\boldsymbol{L}_i$ are $p_i \times n$ and $n \times p_i$ matrices, respectively, obtained from $\boldsymbol{H}^{(i)}$ and $\boldsymbol{L}^{(i)}$ in the same way as $\boldsymbol{F}_i$ is obtained from $\boldsymbol{F}^{(i)}$. We shall assume that $C_{ij}(t)$, $i, j = 1,\ldots,N,$ are $n \times n$ time-varying gain matrices defining communications between the nodes, given in the form $C_{ij}(t) = k_{ij}(t)K_{ij}(t)$, where $k_{ij}(t) = 1$ when the directed communication link from the node j to the node i exists, and $k_{ij}(t) = 0$ otherwise; $K_{ij}(t)$ are diagonal matrices with nonnegative elements, giving appropriate weights to the estimates communicated between the agents.

Define the $nN \times nN$ *consensus matrix* $\tilde{\boldsymbol{C}}(t) = [C_{ij}(t)]$, $i, j = 1,\ldots,N$, and assume that it is *row-stochastic* for all t, [15]. Having in mind the assumed time variability of $C_{ij}(t)$, this assumption practically implies recalculation or rescaling of the submatrices K_{ij} composing the consensus matrix $\tilde{\boldsymbol{C}}(t)$ for each new realization of $k_{ij}(t)$, $i, j = 1,\ldots,N$. This rescaling does not impose any difficulty and can be easily done locally by each agent in many different ways.

It is possible to observe that the proposed algorithm is based on a combination of: a) *decentralized overlapping estimators* represented by (3), and b) *a consensus scheme* tending to make the local estimates ξ_i as close as possible (see [33, 12, 17, 18, 20, 21, 24, 25]). The estimator is strictly scalable as far as the calculation of $\xi_i(t \mid t)$ in (4) is concerned, since it does not depend on the number of agents; on the other hand, calculation of $\xi_i(t+1 \mid t)$ remains scalable as long as each agent communicates with a fixed or bounded number of neighbors. Consequently, scalability of the algorithm can be violated only when the structure of the consensus matrix $\tilde{\boldsymbol{C}}(t)$ is such that the number of connections per node tends to infinity when N tends to infinity.

3 Detection of Fire Dissymmetry in a Thermal Power Plant Boiler

3.1 Process description and identification

Very complex physical models for the thermal power plants boilers may be found in the literature [9, 19] consisting of more than 10 differential equations and over 100 non-linear algebraic equations. Some simplifications of these models may be done for the purpose of control of one variable in particular [12] or taking into account only the most relevant variables [11] or achieving the balance between the simplicity and modelling details [1]. However, the dynamics of the main variables of the boiler process may be identified around their operating points using controlled auto-regressive integrating moving-average models. These models are appropriate for many industrial processes in which disturbance are non-stationary [8]. For the purpose of this analysis, this kind of models will be adopted.

For the sake of this example, let us consider the mainly used boilers with the burners located in the floor and fires upward. The burner tile is made of high temperature refractory and is where the flame is contained in. Air registers located below the burner and at the outlet of the air blower are devices with movable flaps or vanes that control the shape and pattern of the flame, whether it spreads out or even swirls around. Flames should not spread out too much, as this will cause flame impingement.

Geometry of the boiler with the locations of the mills around it, is designed in such a way to satisfy the strict thermo-dynamical conditions. One of these conditions is that the flame inside the burner has a regular circular shape. This condition is strongly related to the boiler energy efficiency and other control requirements that should be fulfilled. Unfortunately, the shape of the flame may not be monitored directly because of the high temperature and intensive concentration of waste gases. This example will demonstrate the way how to detect the flame asymmetry using by decentralized consensus based estimation approach.

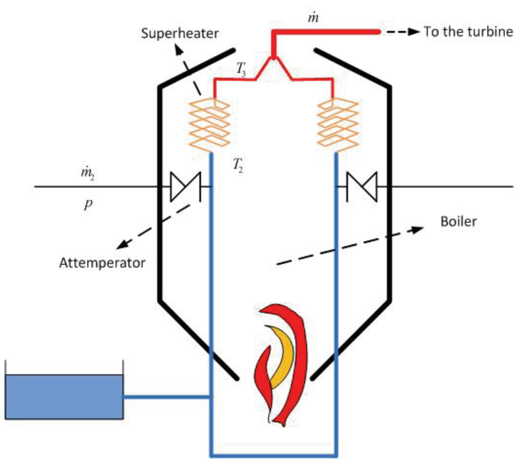

Fig. 1 – *A part of simplified water/steam cycle in thermal power plants.*

Fig. 1 shows a part of the simplified water/steam cycle in thermal power plants. Water at temperature T_0 is pumped at rate m_0 from the reservoir into pipes which lay along the walls of the furnace. The heat generated inside the furnace by burning coal raises the temperature of the water and eventually evaporates it. However, at that point the steam is saturated and may contain droplets of water. If these were to reach the turbine, they might cause significant damage to the turbine blades. In order to prevent this from happening, the steam is again circulated through the furnace via a series of pipes which are commonly known as superheaters – basically, heat exchangers which transfer thermal energy from the flames onto the steam.

Steam temperature at the output of each superheater needs to be regulated. This is achieved by injecting a stream of cold water into the steam, thus lowering its temperature – a process known as attemperation. Cooling water flow m_2, and thus the amount of cooling, is controlled by the valve position p. Since the steam must not contained water, the attemperation must be done prior to superheating.

Steam temperature is increased from boiling point to a final value of about 530ºC in several stages. Every stage may consist of two or more (usually an even number) attemperator/superheater groups. Fig. 1 represents two parallel lines of these groups, one on each side of the furnace (we will denote them as the left and the right attemperator/superheater). For the sake of simplicity, we will concentrate only on the final stage, which feeds the steam at temperature T_3 directly into the turbine.

The results presented in this article are based on measurements of steam flow and temperatures at the inputs and outputs of the superheaters at block A4 of the “TENT Nikola Tesla” thermal power plant in Obrenovac, Serbia. The temperatures are denoted $T_2^{(l)}$, $T_3^{(l)}$, $T_2^{(r)}$ and $T_3^{(r)}$, the superscript refereeing to the left (l) and the right (r) pipeline. The main objective is to estimate the influence of the furnace on each of the final stage superheaters, i.e. the amount of temperature increase due to the thermal energy being passed on from the flames to the steam inside the pipeline. We shall denote this time-varying immeasurable quantity as $P[k]$. Since the output temperature $T_3^{(s)}$, where $(s) \in \{(l),(r)\}$ denotes the left or the right side, depends on the input temperature $T_2^{(s)}$, steam flow m (measured in the common pipeline leading to the turbine), and the intensity of the flame *in the vicinity* of the superheater, it should be possible to estimate the local influence of the furnace on each side.

If these local influence differ for the left and the right superheater, we can conclude that a flame dissymmetry has occurred.

In order to implement the methodology presented in this paper, a state space model for each of the superheaters was derived. For the purpose of identification, the superheaters were treated as MISO systems, each with its own input and output temperatures, and with the common immeasurable furnace influence $P[k]$ and the measurable steam flow $f[k]$, as shown in Fig. 2 (although we consider $P[k]$ as being a common input, we will allow for differences in this quantity as seen locally by each superheater, as will be explained later on). All of the denoted quantities represent small signal values, i.e. deviations from their respective mean values.

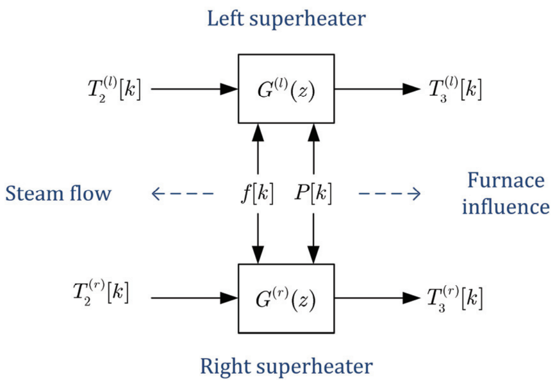

Fig. 2 –*Block diagram of the connection between the superheaters.*

The transfer function matrices $G^{(l)}$ and $G^{(r)}$ were adopted in the form:

$$G^{(s)}(z)=\begin{bmatrix} \dfrac{\sum_{n=1}^{2} b_T^{(s)}[n]z^{-n}}{1+\sum_{n=0}^{1} a^{(s)}[n]z^{-n}} & \dfrac{\sum_{n=1}^{2} b_f^{(s)}[n]z^{-n}}{1+\sum_{n=0}^{1} a^{(s)}[n]z^{-n}} & 1 \end{bmatrix} \tag{5}$$

with the input vector $[T_2^{(s)} \quad f \quad P]^T$. The coefficients $b_T^{(s)}[n]$, $b_f^{(s)}[n]$ and $a^{(s)}[n]$ were identified by neglecting the unknown input P, and applying a Nelder-Mead simplex minimization procedure which minimizes the criterion:

$$J=\sum_{n=1}^{N}\left(T_3[n]-\hat{T}_3[n]\right)^2 , \tag{6}$$

where N is the number of measurement samples, $T_3[n]$ represents the measured output and $\hat{T}_3[n]$ the model output with measured $T_2^{(s)}[k]$ and $f[k]$, and with $P[k]=0$. Based on the obtained polynomial coefficients, it is possible to form the corresponding state-space models by assuming that the furnace influence $P[k]$ remains roughly the same in the course of two sampling periods.

As mentioned in previous section, the estimation procedure may be performed in two ways. The first one is to design the local estimators adjoined to the left and to the right superheater, each of them using its local measurements to estimate the furnace influence in its own vicinity, without communicating in any way to the other agent. The other approach would be to apply a decentralized estimator with overlapping states and to use the consensus approach to generate the final estimate. Therefore, by using these two strategies simultaneously, we are able to estimate both the local furnace influence on each superheater, and also the overall furnace power. By comparing these estimates we are able to say if a flame dissymmetry has occurred; for example, if the overall furnace power remains the same, but the left superheater estimates an increase in $P[k]$ and at the same time the right superheater estimates a decrease in $P[k]$, than we can conclude that the flame has shifted from the centre of the furnace to the left side. The example that is described in this section with the following results points out clearly what kind of information is contained in each of these estimators and how to establish the mechanism for efficient fault detector. According to that, the following part of the section is showing the results obtained by local estimators, decentralized estimators and finally the analysis leading to fault detection algorithm.

3.2 Local estimators

As previously stated, in order to derive a state space model from the obtained transfer function, assumptions had to be made in regard to the dynamics of $P[n]$. Assuming that $P[n]\approx P[n-1]\approx P[n-2]$, we can obtain the following state space model:

$$\begin{aligned}\boldsymbol{X}^{(s)}[n+1]&=\boldsymbol{F}^{(s)}\boldsymbol{X}^{(s)}[n]+\boldsymbol{G}^{(s)}\boldsymbol{E}^{(s)}[n]+\boldsymbol{W}^{(s)}[n],\\ \boldsymbol{y}^{(s)}[n]&=\boldsymbol{H}\boldsymbol{X}^{(s)}[n]+\boldsymbol{r}^{(s)}[n];\quad s\in\{l,r\},\end{aligned}\tag{7}$$

where $\boldsymbol{y}^{(s)}[n]$ is simply the output temperature $\boldsymbol{T}_3^{(s)}[n]$, the state and input vectors $\boldsymbol{X}^{(s)}[n]$ and $\boldsymbol{E}^{(s)}[n]$ are given by:

$$\boldsymbol{X}^{(s)}[n]=\begin{bmatrix} T_3^{(s)}[n] \\ T_3^{(s)}[n-1] \\ P[n] \end{bmatrix}, \qquad \boldsymbol{E}^{(s)}[n]=\begin{bmatrix} T_2^{(s)}[n] \\ T_2^{(s)}[n-1] \\ f[n] \\ f[n-1] \end{bmatrix}, \tag{8}$$

the state, input and output matrices $\boldsymbol{F}^{(s)}$, $\boldsymbol{G}^{(s)}$ and $\boldsymbol{H}$ are:

$$\boldsymbol{F}^{(s)}=\begin{bmatrix} -a^{(s)}[1] & -a^{(s)}[2] & A^{(s)} \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad \boldsymbol{H}=\begin{bmatrix} 1 & 0 & 0 \end{bmatrix},$$
$$\boldsymbol{G}^{(s)}=\begin{bmatrix} b_T^{(s)}[1] & b_T^{(s)}[2] & b_f^{(s)}[1] & b_f^{(s)}[2] \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \tag{9}$$

with $A^{(s)}=1+a_1^{(s)}+a_2^{(s)}$, and $\boldsymbol{W}^{(s)}$ and $\boldsymbol{r}^{(s)}$ being the input and measurement noises for the left ($s=l$) and right ($s=r$) side.

Having the corresponding state space models, it is possible to design local estimators in order to estimate the local variables $T_3^{(s)}[n]$ and the joined state $P[n]$ (local influence of the furnace) as well. It is important to notice that, in the ideal case, the estimations of this state $P[n]$ obtained from the left and right estimator should be the same. Significant difference in the estimates indicates that the geometrical shape of the flame in the furnace is not circular, and consequently the equivalent thermal power seen from other sides are not equal.

Local estimators are implemented as standard Kalman filters, and Fig. 3 shows the obtained estimates of the immeasurable state $P[n]$, where $\hat{P}^{(l)}$ and $\hat{P}^{(r)}$ denote the estimates obtained by the observer assigned to the left and to the right branch, respectively (the estimate denoted as $\hat{P}$ shall be explained shortly).

The presented results are based on a sequence of 18000 samples (the sampling period is 1s) and they show a noticeable difference between the left and right estimate. This result is rather surprising, since the electrical power of the plant was almost constant during the first 12000 seconds (305 MW) and after that it was decreased to the level of (270 MW) with the decreasing rate of 3 MW/min. This would lead us to expect a constant estimate of $P[n]$ during the first two thirds of experiment and an increase in furnace influence in the last part of the sequence. This increase is indeed visible, and can be explained by the decrease of steam flow, which occurs since its set-point is determined by the current electric power. When the flow decreases, the steam takes longer to travel through the superheater, its exposure to the thermal power of the furnace is prolonged, and the increase of output temperature is greater. This causes the observer to produce a greater value for the furnace influence estimate.

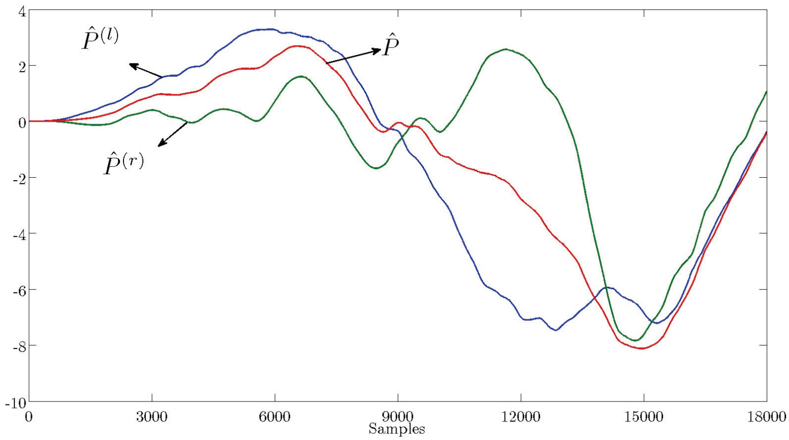

Fig. 3 – *The estimations of the joined state* $P[n]$ *obtained by the local estimators* ($\hat{P}^{(l)}$ *and* $\hat{P}^{(r)}$) *and the decentralized consensus-based estimator* ($\hat{P}$).

3.3 Consensus based decentralized estimators

Given a large scale system, as it is explained in the subsections 1 and 2, there are many advantageous and disadvantageous of constructing a decentralized state estimator. The key requirement is that a large scale system be modeled as an interconnection of subsystems, and that each subsystem has a decision maker (intelligent agent) associated with it. Depending on the available resources, an agent might have access to different local measurements, subsystems models and communication channels to other agents. In our case, the subsystems are the two superheaters, with the connections between them being the furnace power and steam flow. Intelligent agents are simply observers Kalman-type observers, each having its own superheater model, access to measurements of local input and output temperatures and the common steam flow.

The following approach is taken: (1) the system is decomposed into two parts (the left and the right superheater), with common quantities (the furnace power and steam flow) influencing both of them, thus providing the overlapping; (2) a *consensus strategy* is applied, enabling all agents in the network to obtain estimates of the whole state vector, based on some shared data. The local estimators are Kalman-type observers, with final estimates being generated by using local measurement residuals, but with prediction based on a consensus between the two observers.

Since each observer estimates all of the states, the state vector is expanded in the following manner:

$$\boldsymbol{X}^{(l)}[n] = \boldsymbol{X}^{(r)}[n] = \boldsymbol{X}[n] = \begin{bmatrix} T_3^{(l)}[n] \\ T_3^{(l)}[n-1] \\ P[n] \\ T_3^{(r)}[n] \\ T_3^{(r)}[n-1] \end{bmatrix}, \tag{10}$$

where $\boldsymbol{X}^{(l)}$ and $\boldsymbol{X}^{(r)}$ are state vectors for the left and right estimators, respectively. The state and input matrices have the following shapes:

$$\boldsymbol{F}^{(l)} = \begin{bmatrix} -a_1^{(l)} & -a_2^{(l)} & A^{(l)} & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \tag{11}$$

$$\boldsymbol{F}^{(r)} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & A^{(r)} & -a_1^{(r)} & -a_2^{(r)} \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \tag{12}$$

$$\boldsymbol{G}^{(l)} = \begin{bmatrix} b_T^{(l)}[1] \quad b_T^{(l)}[2] \quad b_f^{(l)}[1] \quad b_f^{(l)}[2] \\ \boldsymbol{0}_{4\times 4} \end{bmatrix}, \tag{13}$$

$$\boldsymbol{G}^{(r)} = \begin{bmatrix} \boldsymbol{0}_{3\times 4} \\ b_T^{(r)}[1] \quad b_T^{(r)}[2] \quad b_f^{(r)}[1] \quad b_f^{(r)}[2] \\ \boldsymbol{0}_{1\times 4} \end{bmatrix}. \tag{14}$$

The input vectors are the same as in (9), and the output matrices are given by:

$$\boldsymbol{H}^{(l)}[n] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad \boldsymbol{H}^{(r)}[n] = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \end{bmatrix}. \tag{15}$$

Let us denote the estimated state vectors of the left and right observers as $\boldsymbol{X}_e^{(l)}[n]$ and $\boldsymbol{X}_e^{(r)}[n]$, respectively, and let $\boldsymbol{X}_p^{(l)}[n]$ and $\boldsymbol{X}_p^{(r)}[n]$ be the corresponding predictions. These predictions should be generated based on the following consensus scheme:

$$\boldsymbol{X}_p^{(l)} = \boldsymbol{C}^{(l,l)}\left(\boldsymbol{F}\boldsymbol{X}_e^{(l)}[n] + \boldsymbol{G}^{(l)}\boldsymbol{E}^{(l)}[n]\right) + \boldsymbol{C}^{(l,r)}\left(\boldsymbol{F}\boldsymbol{X}_e^{(r)}[n] + \boldsymbol{G}^{(r)}\boldsymbol{E}^{(r)}[n]\right), \quad (16)$$

$$\boldsymbol{X}_p^{(r)} = \boldsymbol{C}^{(r,l)}\left(\boldsymbol{F}\boldsymbol{X}_e^{(l)}[n] + \boldsymbol{G}^{(l)}\boldsymbol{E}^{(l)}[n]\right) + \boldsymbol{C}^{(r,r)}\left(\boldsymbol{F}\boldsymbol{X}_e^{(r)}[n] + \boldsymbol{G}^{(r)}\boldsymbol{E}^{(r)}[n]\right). \quad (17)$$

As the initial guess for the consensus matrices $\boldsymbol{C}$, the following values were selected:

$$\boldsymbol{C}^{(l,r)} = \boldsymbol{C}^{(r,r)} = \begin{bmatrix} 0_{2\times2} & 0_{2\times1} & 0_{2\times2} \\ 0 & 0.5 & 0_{1\times2} \\ 0_{2\times2} & 0_{2\times1} & I_2 \end{bmatrix}, \quad (18)$$

$$\boldsymbol{C}^{(l,l)} = \boldsymbol{C}^{(r,l)} = \begin{bmatrix} I_2 & 0_{2\times1} & 0_{2\times2} \\ 0_{1\times2} & 0.5 & 0_{1\times2} \\ 0_{2\times2} & 0_{2\times1} & 0_{2\times2} \end{bmatrix}. \quad (19)$$

The results obtained by the described procedure were used as a measure of the overall furnace influence $\hat{P}[n]$. The trace denoted as $\hat{P}$ in Fig. 3 represents the corresponding estimate. Next, the residuals were formed by subtracting $\hat{P}[n]$ from the previous locally estimated values $\hat{P}^{(l)}$ and $\hat{P}^{(r)}$. These residuals were compared to a threshold, and an interval in which a flame dissymmetry has occurred was identified. The results are shown in Fig. 4.

4 Conclusion

An overlapping Kalman-type observation scheme with consensus based prediction was described in the first part of the paper. The stability and optimality of this strategy, as well as the possibility of applying it in the framework of FDI problems, were briefly discussed.

The second part of the paper describes an application of decentralized consensus based estimation to the problem of flame dissymmetry detection in a thermal power plant furnace. A combination of typical Kalman-type local observers on one hand, and the consensus based scheme on the other hand, was used to generate residuals which were compared to a threshold in order to detect the occurrence of flame dissymmetry.

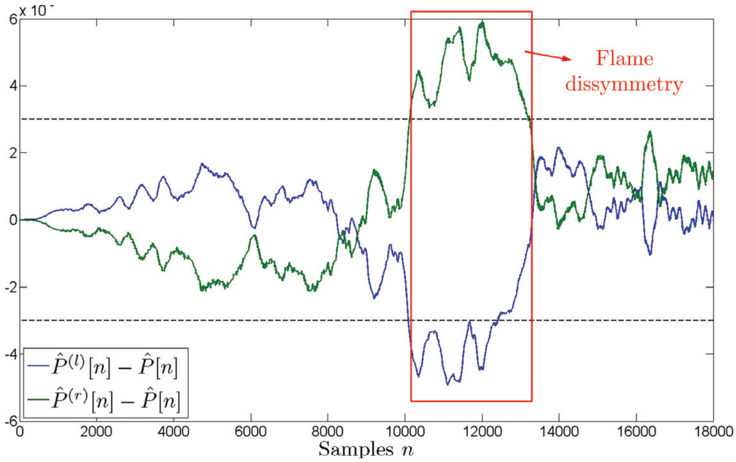

Fig. 4 – *Detection of flame dissymmetry by combining the estimates of local observers and the decentralized consensus-based observer.*

Experimental results show that the possibilities of applying decentralized estimation schemes in FDI problems are certainly worth investigating, especially so for large scale systems, where the use of centralized observers becomes an issue, due to the large dimensions of state vectors. Although the presented example uses only two local agents, the strategy could easily be expanded to include other superheaters in the system (there is a total of 3 superheating stages with 2 superheaters – one on each side of the furnace – in every stage), by a simple modification of the prediction equation in (4).

5 References

[1] K.J. Astrom, R.D. Bell: Drum-boiler Dynamics, Automatica, Vol. 36, No. 3, March 2000, pp. 363 – 378.

[2] Y. Bar-Shalom, X. Li: Multitarget-multisensor Tracking: Principles and Techniques, YBS Publishing, 1995.

[3] B. Baran, E. Kaszkurewicz, A. Bhaya: Parallel Asynchronous Team Algorithms: Convergence and Performance Analysis, IEEE Transaction on Parallel and Distributed Systems, Vol. 7, No. 7, Jul 1996, pp. 677 – 688.

[4] D.P. Bertsekas, J.N. Tsitsiklis: Comments on "Coordination of Groups of Mobile Autonomous Agents Using Nearest Neighbor Rules", IEEE Transaction on Automatic Control, Vol. 52, No. 5, May 2007, pp. 968 – 969.

[5] V.D. Blondel, J.M. Hendrickx, A. Olshevsky, J.N. Tsitsiklis: Convergence in Multiagent Coordination, Consensus and Flocking, IEEE Conf. Decision and Control, Dec. 2005, pp. 2996 – 3000.

[6] C.G. Cassandras, W. Li: Sensor Networks and Cooperative Control, European Journal of Control, Vol. 11, No. 4-5, pp. 436 – 463.

[7] W.H. Chung, J.L. Speyer: A Game Theoretic Fault Detection Filter, IEEE Transactions on Automatic Control, Vol. 43, No.2, Feb. 1998, pp. 143 – 161.

[8] D.W. Clarke, C. Mohtadi, P.S. Tuffs: Generalized Predictive Control – Part I. The Basic Algorithm, Automatica, Vol. 23, No. 2, Mar.1987, pp. 137 – 148.

[9] D.W. Clarke, C. Mohtadi, P.S. Tuffs: Generalized Predictive Control – Part II. The Extensions and Interpretations, Automatica, Vol. 23, No. 2, Mar.1987, pp. 149 – 160.

[10] R. Cori, T. Busi: Parameter Identification of a Drum Boiler Power Plant, 3rd Power Plant Dynamics, Control and Testing Symposium, Knoxville, Tennessee, Sept. 1977.

[11] B. De Jager, H. Anneveld, F. De Blok: Modeling, Simulation and Control of Multi-fuel Once-through Boilers, IFAC Conference on Control of Power Plants and Power Systems, Mexico, 1995, pp. 77 – 82.

[12] F.P. De Mello: Boiler Models for System Dynamic Performance Studies, IEEE Transactions on Power Systems, Vol. 6, No. 1, Feb. 1991, pp. 66 – 74.

[13] J.A. Fax, R.M. Murray: Information Flow and Cooperative Control of Vehicle Formations, IEEE Transactions on Automatic Control, Vol. 49, No. 9, Sept 2004, pp. 1465 – 1476.

[14] H. Gharavi, S.P Kumar: Special Issue on Sensor Networks and Applications, Proceedings of the IEEE, Vol. 91, No. 8, Aug. 2003, pp. 1151 – 1153.

[15] R.A. Horn, C.A. Johnson: Matrix Analysis, Cambridge University Press, 1985.

[16] A. Iftar: Decentralized Estimation and Control with Overlapping Input, State and Output Decomposition. Automatica, Vol. 29, No. 2, Mar. 1993, pp. 511 – 516.

[17] M. Ikeda, D.D. Siljak: Overlapping Decentralized Control with Input, State and Output Inclusion, Control Theory and Advanced Technology, Vol. 2, No. 2, 1986, pp. 155 – 172.

[18] A. Jadbabaie, J. Lin, A. Morse: Coordination of Groups of Mobile Autonomous Agents using Nearest Neighbor Rules, IEEE Transactions on Automatic Control, Vol. 48, No. 6, Jun 2003, pp. 988 – 1001.

[19] Z. Lin, B. Francis, M. Maggiore: Necessary and Sufficient Graphical Conditions for Formation Control of Unicycles, IEEE Transactions on Automatic Control, Vol. 50, No. 1, Jan. 2005, pp. 121 – 127.

[20] J. McDonald, H. Kwatny: A Mathematical Model for Reheat Boiler Turbine-generator Systems, IEEE PES Winter Power Meeting, New York, Jan. 1970, pp. 1 – 19.

[21] L. Moreau: Stability of Multiagent Systems with Time-dependent Communication Links, IEEE Transactions on Automatic Control, Vol. 50, No. 2, Feb. 2005, pp. 169 – 182.

[22] R. Olfati-Saber, R.M. Murray: Consensus Problems in Networks of Agents with Switching Topology and Time-delays, IEEE Transactions on Automatic Control, Vol. 49, No. 9, Sept. 2004, pp. 1520 – 1533.

[23] R. Olfati-Saber, J.A. Fax, R.M. Murray: Consensus and Cooperation in Networked Multiagent Systems, Proceedings of the IEEE, Vol. 95, No. 1, Jan. 2007, pp. 215 – 233.

[24] R. Olfati-Saber, E. Franco, E. Frazzoli, J.S. Shamma: Belief Consensus and Distributed Hypothesis Testing in Sensor Networks, Network Embedded Sensing and Control, Springer-Verlag, Berlin, 2006.

[25] W. Ren, R. Beard: Consensus Seeking in M ulti-agent Systems under Dynamically Changing Interaction Topologies, IEEE Transactions on Automatic Control, Vol. 50, No. 5, May 2005, pp. 655 – 661.

[26] W. Ren, R.W. Beard, D.B. Kingston: Multi-agent Kalman Consensus with Relative Uncertainty, American Control Conference, June 2005, Vol. 3, pp. 1865 – 1870.

[27] C. Sanders, E. Tacker, T. Linton, R. Ling: Specific Structures for Large Scale State Estimation Algorithms having Information Exchange, IEEE Transactions on Automatic Control, Vol. 23, No. 2, Apr. 1978, pp. 255 – 260.

[28] D.D. Siljak: Decentralized Control of Complex Systems. Academic Press, Boston, 1991.

[29] J. Speyer: Computation and Transmission Requirements for a Decentralized Linear Quadratic Gaussian Control Problem, IEEE Transactions on Automatic Control, Vol. 24, No. 2, Apr. 1979, pp. 266 – 269.

[30] S.S. Stankovic, D.D. Siljak: Contractibility of Overlapping Decentralized Control, Systems and Control Letters, Vol. 44, No. 3, Oct. 2003, pp. 189 – 200.

[31] S.S. Stankovic, M.S. Stankovic, D.M. Stipanovic: Consensus based Overlapping Decentralized Estimator, IEEE Transactions on Automatic Control, Vol. 54, No. 2, Feb. 2009, pp. 410 – 415.

[32] S.S. Stankovic, M.S. Stankovic, D.M. Stipanovic: Decentralized Parameter Estimation by Consensus based Stochastic Approximation, 46th IEEE Conference on Decision and Control, Dec. 2007, pp. 1535 – 1540.

[33] J. Tsitsiklis, D. Bertsekas, M. Athans: Distributed Asynchronous Deterministic and Stochastic Gradient Optimization Algorithms, IEEE Transactions on Automatic Control, Vol. 31, No. 9, Sept. 1986, pp. 803 – 812.

[34] Y. Zhu, Z. You, J. Zhao, K. Zhang, X.R. Li: The Optimality for the Distributed Kalman Filtering Fusion with Feedback, Automatica, Vol. 37, No. 9, Sept. 2001, pp. 1489 – 1493.