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DECENTRALIZED INTERACTION ESTIMATORS FOR LOAD FREQUENCY CONTROL IN MULTI–AREA POWER SYSTEMS USING MODEL REDUCTION TECHNIQUE

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Load Frequency Control (LFC) has received considerable attention during last decades. This paper proposes a new method for designing decentralized interaction estimators for interconnected large-scale systems and utilizes it to multi-area power systems. For each area, a local estimator is designed to estimate the interactions of this area using only the local output measurements. In fact, these interactions are the information of other area. In each local station the overall large-scale power system is split into two related subsystems: the i-th area and the residue system (aggregation of other areas), then a low order dynamic model, closed to the dynamics of the main system, is considered for the interaction estimator. Hankel-norm model reduction technique is used to construct an approximate model for the interaction dynamics provided that the residue system is stable. The proposed method is implemented to a three-area power system to illustrate the effectiveness of the proposed method.

K e y w o r d s: Multi-area power systems

1 INTRODUCTION

In Power systems, one of the most important issues is load frequency control (LFC), which deals with the problem of how to deliver the demanded power at the desired frequency with minimum transient oscillations [20]. This problem has received considerable attentions during the last three decades led to development of many different approaches [21-23].

Load frequency control in a multi-area power system is an example of large-scale systems, which is important in electrical-power-system design and operation. Many control strategies for load frequency control have been proposed since the 1970s [1, 9, 10]. A local load frequency controller uses only its area's state measurements. It does not use any feedback from other area. Therefore the interactions of the other area are unknown for each local controller. In the most control strategies the interactions are considered as an external disturbances [6, 12]. While this paper addresses a method to reconstruct the interactions which can be used in control design strategies to yields the better results.

The classical scheme for decentralized state feedback control is based on the assumption that all states of the subsystems are available. In large-scale systems, especially multi-area power systems, however, this assumption is not usually realistic. Therefore, a state estimator has to be designed. This estimator exploits the model of each subsystem and its actual inputs and outputs to produce a good estimation of unknown states of the system. Interactions between subsystems are another uncertainties that make the complexity of controller design in large-scale systems. In the classical scheme for decentralized control, the interactions are unknown for the local observer or controller. Therefore the reconstruction of interactions, plays an important role in the local observers and controllers to achieve less conservative performance.

The main idea of this paper is to introduce a scheme to estimate the interactions in a decentralized approach. The decentralized observation problem was first considered in [2]. Necessary and sufficient conditions on the subsystems were derived in [8] under which the observers could be designed. In [18] an output-decentralization and stabilization scheme were proposed, which could be directly used to construct asymptotic state estimators for linear large- scale systems. The problem of robustness of a Luenberger observer applied to a given large- scale system was addressed in [7].

In [3] a decentralized filter was obtained by identifying the dynamics of the interaction variables, and estimating the local states and interactions using local information. An indirect method for decentralized estimation of interconnected large-scale systems was presented in [4]. In [4], the estimators were obtained in two steps. In the first step, an approximate model for the desired local variables, in an indirect method, was derived. In the second step a local filter was derived using the obtained model and the local measurements.

In the previously published papers, such as [19], [3], and [5], either the local state vector and the interaction variables are assumed to be available or the interactions have been treated as disturbances. However in the practical problems, as considered in this paper, there is no

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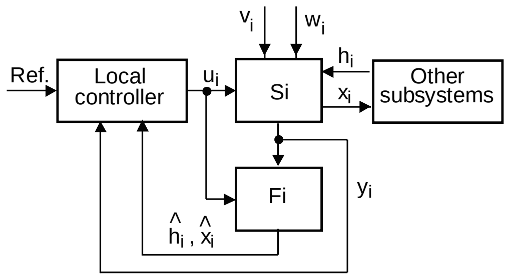

Fig. 1. State and interaction estimation diagram at ith subsystem

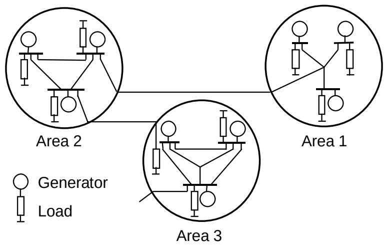

Fig. 2. Multi-area power system

measurement on the interaction variables. Our main objective, in this paper, is to introduce a method for designing decentralized estimators to estimate the states and interactions, using only local output feedback.

In a decentralized control problem, such as decentralized state estimation or the interaction estimation problem, the overall large-scale system is split into the two systems, the related subsystem (ith subsystem) and the residue system (aggregation of other subsystems). It should be noted that, the interactions to the ith subsystem are generated by the dynamics of the residue system. Therefore, by incorporating the dynamics of the residue system one can expect to reduce the error of the estimation. But if the dynamics of the residue system is added to the estimator dynamics, the order of the designed filter becomes very high, while, the aim of decentralized estimation is to use low order estimator for each subsystem.

This paper is organized as follows: Section 2 formulates the problem. The system under study is described in Section 3. Section 4 introduces the main contribution of this paper, which is to use the Hankel-norm model reduction technique to obtain some dynamics for the interactions. In Section 5, the simulation results for a three-area power system show the effectiveness of the proposed algorithm.

2 PROBLEM STATEMENT

Consider the large-scale LTI system S, composed of N subsystems S_i $(i = 1, 2 \dots, N)$ described by

$$\begin{aligned} \dot{x}_i &= A_{ii}x_i + h_i + B_i u_i + G_i w_i \\ y_i &= C_i x_i + v_i \end{aligned} \tag{1}$$

where, h_i is the interaction from other subsystems,

$$h_i = \sum_{j=1,\, j\neq i}^{N} A_{ij} x_j \tag{2}$$

where $x_i \in R^{n_i}$ is the state vector of ith subsystem and $u_i \in R^{p_i}$ is its control function. Furthermore $w_i \in R^{g_i}$ is the disturbance and $v_i \in R^{q_i}$ is the measurement noise, which are assumed be bounded. A_{ii}, B_i, C_i, and G_i describe the dynamics of the isolated ith subsystem, A_{ij} describes the interaction matrix from the jth subsystem, which are assumed to have appropriate dimensions. It is assumed that (C_i, A_{ii}) is observable and (A_{ii}, B_i) is controllable.

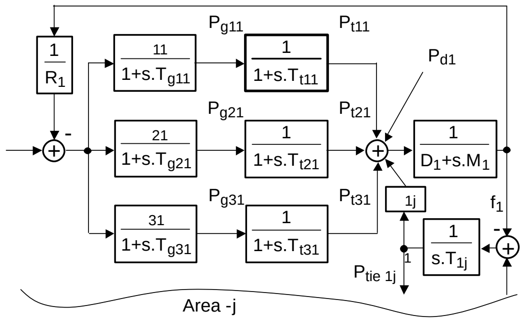

Fig. 3. Block diagram of area-1

The goal of this paper is to design an estimator F_i for each subsystem to estimate the interactions from other subsystems, h_i, and the states of ith subsystem. As seen in Fig. 1, the estimator F_i constructs the estimate of interaction, $\hat{h}_i$, and state estimation $\hat{x}_i$ from the input and output of S_i. The local controller uses these estimations to control the ith subsystem.

3 THE SYSTEM UNDER STUDY

A three-area power system shown in Fig. 2 is taken as an example system [16]. Figure 3 shows the block diagram of area 1. Referring to Fig. 3, state vector x, control vector u, and disturbance vector d can be defined as follows:

$$x=\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}, \; u=\begin{bmatrix} \Delta P_{c1} \\ \Delta P_{c2} \\ \Delta P_{c3} \end{bmatrix}, \; d=\begin{bmatrix} \Delta P_{d1} \\ \Delta P_{d2} \\ \Delta P_{d3} \end{bmatrix}, \; y=\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$$y_1=[\Delta f_1 \;\; \Delta P_{tie12}]', y_2=[\Delta f_2 \;\; \Delta P_{tie23}]', y_3=[\Delta f_3]'$$

$$x_1=\left[\, \Delta f_1 \; \Delta P_{t11} \; \Delta P_{t21} \; \Delta P_{t31} \; \Delta P_{g11} \; \Delta P_{g21} \; \Delta P_{g31} \; \Delta P_{tie12} \,\right]'$$

$$x_2=\left[\, \Delta f_2 \; \Delta P_{t12} \; \Delta P_{t22} \; \Delta P_{t32} \; \Delta P_{g12} \; \Delta P_{g22} \; \Delta P_{g32} \; \Delta P_{tie23} \,\right]'$$

$$x_3=\left[\, \Delta f_3 \; \Delta P_{t13} \; \Delta P_{t23} \; \Delta P_{t33} \; \Delta P_{g13} \; \Delta P_{g23} \; \Delta P_{g33} \,\right]'$$

Table 1. System parameters

Area 1	Area 2	Area 3
$D_1 = 0.006$	$D_2 = 0.0083$	$D_3 = 0.008$ (p.u.Mw/Hz)
$M_1 = 0.2$	$M_2 = 0.167$	$M_3 = 0.15$ (p.u.Mw)
$T_{t11} = 0.2$	$T_{t21} = 0.3$	$T_{t31} = 0.21$ (s)
$T_{t12} = 0.24$	$T_{t22} = 0.35$	$T_{t32} = 0.22$
$T_{t13} = 0.25$	$T_{t23} = 0.32$	$T_{t33} = 0.23$
$T_{g1i} = 2.22$	$T_{g2i} = 0.08$	$T_{g3i} = 0.1$ (s)
$R_{11} = 2.2$	$R_{21} = 2.45$	$R_{31} = 2.23$ (Hz/p.u.Mw)
$R_{12} = 2.23$	$R_{22} = 2.5$	$R_{32} = 2.21$
$R_{13} = 2.21$	$R_{23} = 2.48$	$R_{33} = 2.22$
$\alpha_{1i} = 0.25$	$\alpha_{2i} = 0.5$	$\alpha_{3i} = 0.5$
$\alpha_{12} = 0.2$		$\alpha_{23} = 5.0$
$T_{12} = 0.272$		$T_{23} = 0.109$ (p.u.Mw/Hz)

where are: Δf_i - incremental frequency deviation of area i, ΔP_{gki} - incremental governor valve position change of generator k of area i, ΔP_{ci} - control input of area i, ΔP_{tki} - incremental output of generator k in area i, $\Delta P_{tie\,ij}$ - incremental change in tie-line power between areas i and j, ΔP_{di} - disturbance of area i, M_i - equivalent inertia constant for area i, D_i - equivalent damping coefficient for area i, T_{gki} - governor time constant of generator k for area i, T_{tki} - turbine time constant of generator k for area i, T_{ij} -synchronizing coefficient in normal operating conditions between areas i and j, a_{ij} - ratio between the rated MW capacity of areas i and j, α_{ki} - distribution factor for generator k, R_i - drooping characteristic for area I.

The system parameters are listed in Table 1.

4 REDUCED ORDER MODEL TECHNIQUE

In this section, a low order dynamic model (closed to the dynamic of the main system) is considered for the interaction estimator. It is clear that the closer the order of the approximate model is to the order of the residue system, the error of the estimation is less. The proposed method in this section is to use the Hankel-norm model reduction technique to reduce the order of the dynamics of the residue system to a low order "approximate" model. This method is only applicable when the residue system is stable.

In model reduction techniques [14, 15, 17], the state-space description of a stable system is transformed to balanced coordinates, where the observability and controllability Gramians are equal and diagonal ("balanced"). The diagonal elements of the balanced Gramian in fact form a set of closed-loop input-output invariant (the Hankel singular values) which quantify the contribution of each state to the input-output map of the system. States that contribute weakly to the input-output map, are deleted. The method has some appealing properties: it generically leads to a stable reduced-order model and an error bound exist in terms of the truncated Hankel singular values.

Now the dynamics of large-scale system (1) is rewritten as

$$\begin{aligned} \dot{x}_i &= A_{ii}x_i + h_i + B_iu_i + G_iw_i \\ y_i &= C_ix_i + v_i\,, \end{aligned} \tag{3}$$

$$\begin{aligned} \dot{\tilde{x}}_i &= \tilde{A}_i\tilde{x}_i + A_{hi}x_i + \tilde{B}_i\tilde{u}_i + \tilde{G}_i\tilde{w}_i \\ h_i &= \tilde{C}_i\tilde{x}_i\,, \end{aligned} \tag{4}$$

where,

$$\tilde{C}_i = [A_{1i}\ A_{2i}\ \dots\ A_{i(i-1)}\ A_{i(i+1)}\ \dots\ A_{iN}]\,,$$
$$\tilde{B}_i = diag-block\{B_1\ B_2\ \dots\ B_{i-1}\ B_{i+1}\ \dots\ B_N\}\,,$$
$$\tilde{G}_i = diag-block\{G_1\ G_2\ \dots\ G_{i-1}\ G_{i+1}\ \dots\ G_N\}\,,$$

$$\tilde{u}_i = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{i-1} \\ u_{i+1} \\ \vdots \\ u_N \end{bmatrix}, \tilde{w}_i = \begin{bmatrix} w_1 \\ u_2 \\ \vdots \\ w_{i-1} \\ w_{i+1} \\ \vdots \\ w_N \end{bmatrix}, \tilde{x}_i = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{i-1} \\ x_{i+1} \\ \vdots \\ x_N \end{bmatrix}, A_{hi} = \begin{bmatrix} A_{1i} \\ A_{2i} \\ \vdots \\ A_{(i-1)i} \\ A_{(i+1)i} \\ \vdots \\ A_{Ni} \end{bmatrix}.$$

$$\tilde{A}_i = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1(i-1)} & A_{1(i+1)} & \dots & A_{1N} \\ A_{21} & A_{22} & \dots & A_{2(i-1)} & A_{2(i+1)} & \dots & A_{2N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{(i-1)1} & A_{(i-1)2} & \dots & A_{(i-1)(i-1)} & A_{(i-1)(i+1)} & \dots & A_{(i-1)N} \\ A_{(i+1)1} & A_{(i+1)2} & \dots & A_{(i+1)(i-1)} & A_{(i+1)(i+1)} & \dots & A_{(i+1)N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{N1} & A_{N2} & \dots & A_{N(i-1)} & A_{N(i+1)} & \dots & A_{NN} \end{bmatrix}$$

Equation (4) shows the dynamics of the residue system (interaction dynamics). By applying the model reduction technique on equation (4), the reduced order model interaction is obtained namely "*approximate model*". There is one main question: what is the appropriate order of the approximate model? If the order of approximate model is selected to be much less than $n - n_i$, the order of estimator becomes low which implies simplicity of the estimator but in this case the error of estimation is increased. One can choose the order of approximate model as the order of ith subsystem, *ie*, n_i. Note that, it is assumed that $n_i < n - n_i$ otherwise, the model reduction technique is not necessary and the dynamics of the residue system can be used as a model for the interactions.

There exists a similarity transformation T, which transforms both the observability and the controllability Gramians of the residue system (4) to the form $\Sigma := diag(\sigma_1,\ \sigma_2, \dots, \sigma_{n-ni})$ and the balance realization to the form

$$\begin{aligned} \dot{z} &= A_bz + B_bx_i + w_z \\ h_i &= C_bz \end{aligned}\,, \tag{5}$$

where,

$z = T\tilde{x}_i$, $A_b = T\tilde{A}_iT^{-1}$, $B_b = TA_{hi}$, $C_b = \tilde{C}_iT^{-1}$, $w_z = T\tilde{B}_i\tilde{u}_i + T\tilde{G}_i\tilde{w}_i$.

Partition the balance realization (5) according to n_i variables into

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{bmatrix} = \begin{bmatrix} A_{b11}\ A_{b12} \\ A_{b21}\ A_{b22} \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} + \begin{bmatrix} B_{b1} \\ B_{b2} \end{bmatrix} x_i + \begin{bmatrix} w_{z1} \\ w_{z2} \end{bmatrix},$$

$$h_i = [C_{b1}\ \ C_{b2}] \begin{bmatrix} z_1 \\ z_2 \end{bmatrix},$$

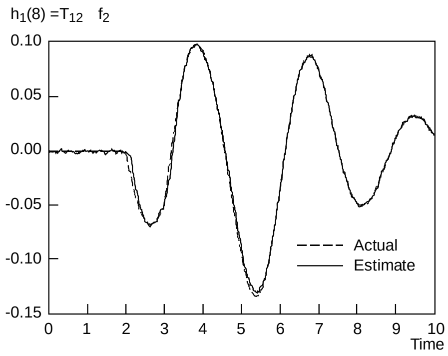

Fig. 4. Estimated interaction of area 1

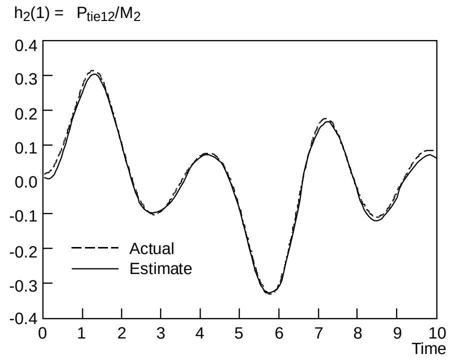

Fig. 5. First estimated interaction of area 2

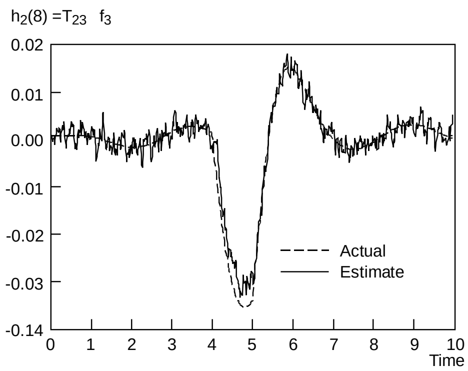

Fig. 6. Second estimated interaction of area 1

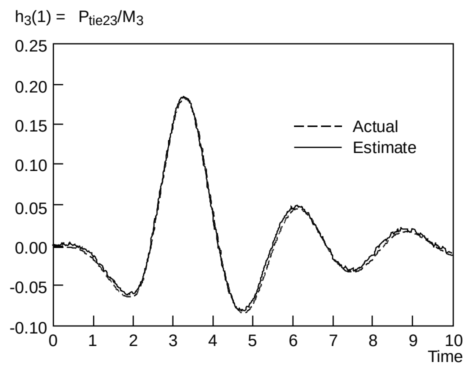

Fig. 7. Estimated interaction of area 3

and partition accordingly to

$$\Sigma = \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix}.$$

The n_i-state reduced-order model is then obtained as:

$$\begin{aligned} \dot{z}_1 &= A_{b11} z_1 + B_{b1} x_i + w_{z1} \\ h_i &= C_{b1} z_1 \,. \end{aligned} \tag{6}$$

LEMMA 1 ([11]). *Let $G_h := (\tilde{A}_i, A_{hi}, \tilde{C}_i)$, the transfer function matrix of the residue system, be asymptotically stable and minimal with $n - n_i$ states. Assume $n_i < n - n_i$ and $G_{hr} := (A_{b11}, B_{b1}, C_{b1})$ be an n_i-state reduced-order model obtained by balanced truncation. Then*

1) *G_{hr} is in balanced coordinates with balanced Gramian Σ_1.*
2) *If $\sigma_{ni} > \sigma_{ni+1}$ then G_{hr} is asymptotically stable and minimal.*
3) $\|G_h - G_{hr}\|_\infty \le 2\,\mathrm{trace}\,[\Sigma_2]$.

Note carefully that item 3) gives an error bound in terms of the truncated Hankel singular values.

The augmentation of the dynamic model of ith subsystem (3) and reduced-order interaction model (6) result in:

$$\begin{gathered} \begin{bmatrix} \dot{x}_i \\ \dot{z}_1 \end{bmatrix} = \begin{bmatrix} A_{ii} & C_{b1} \\ B_{b1} & A_{b11} \end{bmatrix} \begin{bmatrix} x_i \\ z_1 \end{bmatrix} + \begin{bmatrix} B_i \\ 0 \end{bmatrix} u_i + \begin{bmatrix} G_i w_i \\ w_{z1} \end{bmatrix} \\ y_i = C_i x_i + v_i \qquad h_i = C_{b1} z_1 \,. \end{gathered} \tag{7}$$

Assuming $\left(\begin{bmatrix} A_{ii} & C_{b1} \\ B_{b1} & A_{b11} \end{bmatrix}, [C_i, 0] \right)$ is observable, then we can use the measurement signal y_i and introduce a Kalman filter to estimate x_i and h_i as follows:

$$\begin{gathered} \begin{bmatrix} \dot{\hat{x}}_i \\ \dot{\hat{z}}_1 \end{bmatrix} = \begin{bmatrix} A_{ii} & C_{b1} \\ B_{b1} & A_{b11} \end{bmatrix} \begin{bmatrix} \hat{x}_i \\ \hat{z}_1 \end{bmatrix} + \begin{bmatrix} B_i \\ 0 \end{bmatrix} u_i + K_i (y_i - C_i \hat{x}_i), \\ \hat{x}_i(0) = 0, \;\; \hat{z}_i(0) = 0, \\ K_i = P \begin{bmatrix} C_i^\top \\ 0 \end{bmatrix} R^{-1}, \\ \dot{P} = \begin{bmatrix} A_{ii} & C_{b1} \\ B_{b1} & A_{b11} \end{bmatrix} P + P \begin{bmatrix} A_{ii} & C_{b1} \\ B_{b1} & A_{b11} \end{bmatrix}^\top \\ -P \begin{bmatrix} C_i^\top \\ 0 \end{bmatrix} R^{-1} [C_i \;\; 0] P + Q \,, \;\; P(0) = P_0 \,. \end{gathered} \tag{8}$$

5 SIMULATION RESULTS

In order to demonstrate the effectiveness of the proposed decentralized interaction estimation, numerical simulations have been carried out. Now the proposed interaction estimation method is implemented to a multi-area power system, which is described in Section 3. For each area, it is assumed that there occurs 0.1 puMW step disturbance in other two area. A local estimator is design for each area and the estimated interactions are shown in Figures 4 to 7.

It should be noted that, since the estimation of interactions is the main goal of this paper, no control input signals, ΔP_{ci}, are considered for each area. In fact they have no effect on the estimation results.

In area 1 there exist one interaction signal, $T_{12}\Delta f_2$, which is the frequency deviation of area 2 and in area 2 there exist two interaction signals, $T_{23}\Delta f_3$ and $\Delta P_{tie12}IM_2$, and in area 3 the interaction signal is $\Delta P_{tie23}IM_3$.

The simulation results show the effectiveness of the proposed algorithm even in the presence of measurement noise and disturbances.

6 CONCLUSION

In this paper, the design of decentralized estimators for interconnected large-scale systems was investigated. Local estimators were designed to estimate the interactions and states of each subsystem using only the local output measurement. We outlined the model reduction technique to construct an approximated model for the interaction dynamics. Numerical simulations were presented for a multi-area power system. These simulation results demonstrated the effectiveness of the proposed method.

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