# DECENTRALIZED STOCHASTIC CONTROL OF POWER SYSTEMS USING GENETIC ALGORITHMS FOR INTERACTION ESTIMATION

**M. Dehghani , A. Afshar, S. K. Nikravesh**

*Amirkabir University of Technology*
*Tehran, Iran*

Abstract: A decentralized feedback control scheme is proposed for optimization of large-scale systems. First, local controllers are used to optimize each subsystem, ignoring the interconnections. Next, an additional compensating controller was applied to minimize the effect of interactions and improve the performance of the overall system. At the cost of the suboptimal performance, this optimization strategy ensures stability of the system. To account for the modeling uncertainties, both a local Kalman filter and a novel approach by the usage of genetic algorithm is used to estimate all local states and interactions for each subsystem. A sample three-bus system is given to illustrate the proposed methodologies. 

Keywords- large-scale systems, decentralized control, stochastic control, Kalman filter, genetic algorithms, power systems.

## 1. INTRODUCTION

Most large-scale systems are characterized by a great multiplicity of controllers. For example, an electric power system has several control substations, each being responsible for operation of a portion of the overall system. This situation arising in a control system is often referred to as decentralization.

The main motivation behind decentralized control is the failure of conventional methods of centralized control theory. Some fundamental techniques such as pole placement, state feedback, optimal control and state estimation require complete information from all system sensors to sake the feedback control. This scheme is clearly inadequate for feedback control of large-scale systems. Due to physical configuration and high dimensionality of such systems, a centralized control is neither economically feasible nor even necessary. Therefore, the basic characteristic of any decentralized system is that the transfer of information from one group of sensors to others is quite restricted. (Jamshidi, 1997).

The research in large-scale systems control has been so far directed to applications of decentralized control. Yang, *et al*. (1999) designed a decentralized controller according to the achievement of a sufficient interaction margin. Wang, *et al*. (2000) assumed the large scale power system as a nonlinear system and found an adaptive robust controller for it. Menniti, *et al*. (2000) modeled the power system as an interconnected system using direct feedback linearization technique and a decentralized model reference adaptive control was designed. The authors minimize the interaction effects and design local adaptive controller for each subsystem. A completely decentralized load frequency control scheme was proposed by Rerkpreedapong and Feliachi (2002), where decentralization was achieved by developing a model for the interaction variables.

In this paper, first a linearized dynamic model of large-scale power systems is obtained. Then an optimization procedure is proposed to design a decentralized controller. It is shown that the stability of the overall system is guaranteed. To account for modeling uncertainties, an estimator is designed to estimate all the system states. For estimation, a novel approach by the usage of genetic algorithm is used. The effectiveness of the proposed controller is demonstrated using a three-bus test system.

## 2. DYNAMIC MODEL

The actual dynamic response of a synchronous generator in the practical power system is very complex and is very difficult to be dealt with in the controller design, unless some simplifications are made. It has been pointed out in (Zhu, *et al.* ,1998) that the classical third-order single- axis dynamic generator model can be used when designing the excitation controller.

### *2.1 System equations:*

For an n-generator power system, the third- order single-axis dynamic model of the *i*th generator can be written as follows. (Note that the system has already been reduced into a network retaining only generator nodes) (Zhu, *et al.* , 1998; Xi, *et al.*, 2003).

$$\dot{\delta}_i(t) = \omega_i(t) \tag{1}$$

$$\dot{\omega}_i(t) = -\frac{D_i}{M_i}\omega_i(t) + \frac{1}{M_i}\left(P_{mi} - P_{ei}(t)\right) \tag{2}$$

$$\dot{E}'_{qi}(t) = \frac{1}{T'_{doi}}\left[E_{fdi} - E'_{qi}(t) - \left(x_{di} - x'_{di}\right)I_{di}(t)\right] \tag{3}$$

These equations can be written in the following format in general:

$$\dot{x} = f(x,u) \tag{4}$$

Where $x = \left[\delta_i \quad \omega_i \quad E'_{qi}\right]$ and $u = \left[P_{mi} \quad E_{fdi}\right]'$.

And the Algebraic equations are:

$$I_{di}(t) = \sum_{j=1}^{n} E'_{qj}(t)\left(G_{ij}\sin\delta_{ij}(t) - B_{ij}\cos\delta_{ij}(t)\right) \tag{5}$$

$$I_{qi}(t) = \sum_{j=1}^{n} E'_{qj}(t)\left(G_{ij}\cos\delta_{ij}(t) + B_{ij}\sin\delta_{ij}(t)\right) \tag{6}$$

$$P_{ei}(t) = E'_{qi}(t)I_{qi}(t) \tag{7}$$

See (Xi, et *al.* , 2003) for definition of the symbols used in the above equations.

### *2.2 Linearization*

It is clear that the utilization of a very detailed model in the design of controllers is impractical. For this reason, approximated models and in particular linearized models have been often used for power systems, See (Kundur, 1994). Here, equation (4) is linearized to give the following format for every subsystem around the operating point found by loadflow solution.

$$\frac{dx_i}{dt} = A_i x_i + B_i u_i + \sum_{j=1}^{n} G_{ij} x_j \qquad i = 1 \ldots n \tag{8}$$

Where $A_i$ , $B_i$, $G_{ij}$ will be as given below:

$$A_i = \begin{bmatrix} 0 & 1 & 0 \\ \sum_{j=1}^{n} E'_{qio}.E'_{qjo}\begin{bmatrix}\cos(\delta_{io}-\delta_{jo}) \\ -\sin(\delta_{io}-\delta_{jo})\end{bmatrix} & -\frac{D_i}{M_i} & \sum_{j=1}^{n} -\frac{E'_{qjo}}{M_i}\begin{bmatrix}G_{ij}.\cos(\delta_{io}-\delta_{jo}) \\ +B_{ij}.\sin(\delta_{io}-\delta_{jo})\end{bmatrix} \\ \sum_{j=1}^{n} -\left(x_{di}-x'_{di}\right)E'_{qjo}\begin{bmatrix}G_{ij}.\cos(\delta_{io}-\delta_{jo}) \\ +B_{ij}.\sin(\delta_{io}-\delta_{jo})\end{bmatrix} & 0 & -\frac{1}{T'_{doi}} \end{bmatrix} \tag{9}$$

$$B_i = \begin{bmatrix} 0 & 0 \\ 1/M_i & 0 \\ 0 & 1/T'_{doi} \end{bmatrix} \tag{10}$$

$$G_{ij} = \begin{bmatrix} 0 & 0 & 0 \\ E'_{qio}.E'_{qjo}.\begin{bmatrix}-B_{ij}.\cos(\delta_{io}-\delta_{jo}) \\ +G_{ij}.\sin(\delta_{io}-\delta_{jo})\end{bmatrix} & 0 & E'_{qio}.\begin{bmatrix}B_{ij}.\sin(\delta_{io}-\delta_{jo}) \\ +G_{ij}.\cos(\delta_{io}-\delta_{jo})\end{bmatrix} \\ \left(x_{di}-x'_{di}\right)E'_{qjo}.\begin{bmatrix}B_{ij}.\sin(\delta_{io}-\delta_{jo}) \\ +G_{ij}.\cos(\delta_{io}-\delta_{jo})\end{bmatrix} & 0 & -\left(x_{di}-x'_{di}\right).\begin{bmatrix}-B_{ij}.\cos(\delta_{io}-\delta_{jo}) \\ +G_{ij}.\sin(\delta_{io}-\delta_{jo})\end{bmatrix} \end{bmatrix} \tag{11}$$

$x_i\left(i = 1\Lambda\ n\right)$ is used to show the main subsystem and $x_j\left(j = 1\Lambda\ n \quad except \quad i\right)$ for the subsystems attached to it.

## 3. CONTROL SYSTEM DESIGN

A useful approach in designing controllers for a given state space model, is LQR (linear quadratic regulator). It is known that the LQR has good gain and phase stability margins, but an accurate model is needed to enable its implementation. Here, first local state feedback gains ($K_i$) are designed using LQR and then an additional compensating gain ($K_{gi}$) is separately designed to cancel the effects of the interactions.

### *3.1 Control design with available states and Interaction variables*

Consider a large-scale linear time-invariant system described by n subsystems as in (8). Each subsystem has a goal of finding a “local” controller $u_i^l(t)$ which minimizes an associated cost while satisfying (8) with $G_{ij}$ ’s set to zero.

$$J_i = \int_0^\infty \left(x_i(t)^T Q_i x_i(t) + u_i(t)^T R_i u_i(t)\right)dt \qquad i = 1 \ldots n \tag{12}$$

$J_i$ is the performance index of the *i*th subsystem and $Q_i$ and $R_i$ are the corresponding system and input weighting matrix. Further, it is assumed that each subsystem pair $(A_i, B_i)$ is completely controllable. For the decoupled subsystem,

$$\dot{x}_i = A_i x_i + B_i u_i \qquad i = 1 \ldots n \tag{13}$$

the decentralized optimal control is given by :

$$u_i^l(t) = -R_i^{-1}B_i^T S_i x_i(t) = -K_i x_i(t) \tag{14}$$

Where $S_i$ is the symmetric positive-definite solution of the algebraic matrix Riccati equation.

By using the above controller, each closed-loop subsystem :

$$\dot{x}_i = \left(A_i - B_i R_i^{-1} B_i^T S_i\right)x_i \qquad i = 1 \ldots n \tag{15}$$

is globally exponentially stable with the degree π [9].

Then, the problem is to find a control law :

$$u_i^g(t) = K_{gi}(t,x) \tag{16}$$

to neutralize the interaction effects.

The complete system corresponding to (4) and (8) can be rewritten as:

$$\dot{x} = Ax + Bu + Gx \tag{17}$$

Where A=diag{$A_1$, $A_2$,.., $A_n$}, B=diag{$B_1$, $B_2$,…, $B_n$}, and

$$u(t) = u_l(t) + u_g(t) \tag{18}$$

The compensating control (16) can now be chosen as a linear law:

$$K_g(t,x) = -K_g x \tag{19}$$

The problem changes to choose the matrix gain $K_g$ so that $\inf_{Kg} \|(G - BK_g)x\|$ is achieved. As $\|(G - BK_g)x\| \le \|G - BK_g\|.\|x\|$ holds for all $x$, problem reduces to find $\min \|(G - BK_g)\|$. The solution to this latter problem is well known and $K_g = B^+G$, where $B^+$ is the Moore-Penrose generalized inverse of B, and

$$K_g = (B^T B)^{-1} B^T G \tag{20}$$

Finally, it is important to note that by using the local control (14), and the compensating control (19), the closed-loop system can be obtained as:

$$\dot{x}_i = \{(A - BR^{-1}B^T S) + [I - B(B^T B)^{-1} B^T]G\}x \tag{21}$$

This system is connectively exponentially stable with a prescribed degree $\pi$ (siljak and sundareshan, 1976).

### *3.2 Control design with estimation of state and interaction variables using genetic algorithm*

In an interconnected power system, not all the state variables are measurable, and the interaction variables cannot be obtained from local measurements. In (Sperry and Feliachi, 1988) the least square algorithm is used to solve this problem. Here, a new method is used to overcome this limitation.

In Fig. 1 , subsystem 1 is connected to subsystem 2 to n. They all have interaction on each other. Obviously, each subsystem has states which are shown by $X_1 \Lambda\ X_n$. $X_1$ shows all the states of subsystem 1 , $X_2$ shows the states of subsystem 2 and so on. From the viewpoint of subsystem 1, it can just measure the parameters of its own and calculate its states ( $X_1$ ) ignoring the interaction effects. It has no idea of the states in subsystem 2 to n. In the following, a method which can estimate the states of all subsystems is proposed. Here, the notation $x_i(i = 1\Lambda\ n)$ is used for the main subsystem which can measure its own parameter and $x_j(j = 1\Lambda\ n \quad except \quad i)$ for the subsystems attached to it.

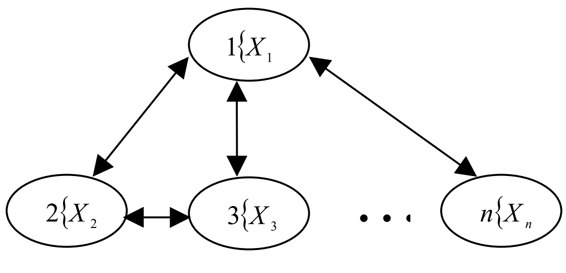


Fig. 1. Interconnection of subsystems and their states

For any of the *n* subsystems, assume that the local states ( $x_i$ ) in eq. (8) are known. So from (8):

$$\frac{dx_i}{dt} - A_i x_i - B_i u_i = \sum_{j=1}^{n} G_{ij} x_j \tag{22}$$

Since, the left side of the above equation is known and $G_{ij}$ for all i and j is known too, an estimation scheme can be used to estimate $x_j$. First, for any subsystem, assume that :

$$\frac{dx_i}{dt} - A_i x_i - B_i u_i = M \tag{23}$$

Then by the usage of (22):

$$M = G_{i1}x_1 + G_{i2}x_2 + \Lambda + G_{in}x_n \tag{24}$$

So, use the genetic algorithm to search for the best $x = [x_1 \quad x_2 \quad \Lambda \quad x_{i-1} \quad x_{i+1} \quad K \quad x_n]$ in order that the following optimization index is minimized:

$$f = \left\| M - \sum_{\substack{j=1 \\ j \ne i}}^{n} G_{ij} x_j \right\| \tag{25}$$

Applying the search techniques of genetic algorithm, all $x_j$'s for all subsystems can be estimated.

However, if $x_i$ is unknown,a local Kalman filter can be used in the following way, as given by the flowchart of Fig. 2:

$$\frac{d\hat{x}_i}{dt} = A_i \hat{x}_i + B_i u_i + K_i\left(z_i - C_i \hat{x}_i\right) + \sum_{\substack{j=1 \\ j \ne i}}^{n} G_{ij} \hat{x}_j \tag{26}$$

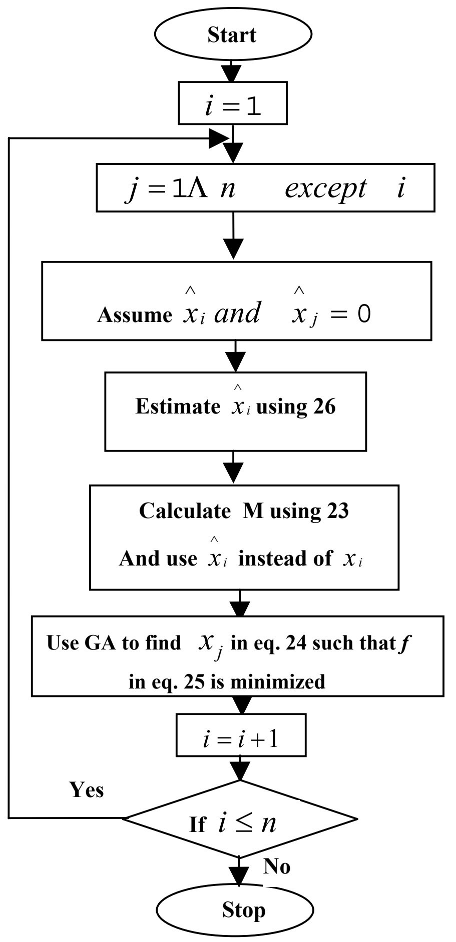


Fig. 2. Flowchart of state and interaction estimation using genetic algorithm

In each iteration, both the Kalman filter and the interaction estimator are used simultaneously. First, all the states are assumed to be zero. Then, by eq. (26) the local states of each subsystem are estimated. After that, by the help of eq. (22) and genetic algorithm, the interactions are estimated. Finally, go to the next iteration. Note that in each iteration the states estimated in the previous iteration are used as the initial seed for the genetic algorithm. The structure of the proposed controller is illustrated in Fig. 3:

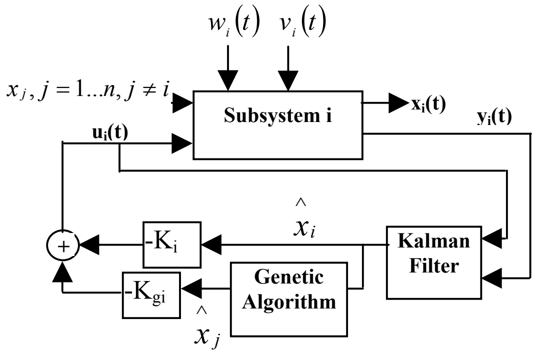


Fig. 3. Decentralized Control Structure for the *i*th subsystem

$w_i$ : Plant noise  $v_i$ : Measurement noise

$u_i$ : Control input  $y_i$ : Output

$x_i$: local state  $x_j$ : interaction state

*Decentralized stochastic control* Consider a large-scale linear system described by

$$\dot{x} = Ax + \sum_{i=1}^{n} B_i u_i + \xi(t) \tag{27}$$

$$y_i(t) = C_i x(t) + \eta_i(t) \tag{28}$$

Where each variable is defined as is common.
The problem is finding n decentralized controllers $u_i(t), \quad i = 1 \Lambda \ n$ such that (27) to (28) are satisfied, while the following cost functional is minimized:

$$J = E(\int_0^\infty \left( x(t)^T Q x(t) + \sum_{i=1}^{n} u_i(t)^T R_i u_i(t) \right) dt) \tag{29}$$

This stochastic linear regulator problem is interpreted by the separation principle, which states that the optimal control system consists of the optimal filter in cascade with the deterministic optimal controller derived in the previous section (Meditch, 1969; Brown, 1997). The result is indicated in Fig. 4.

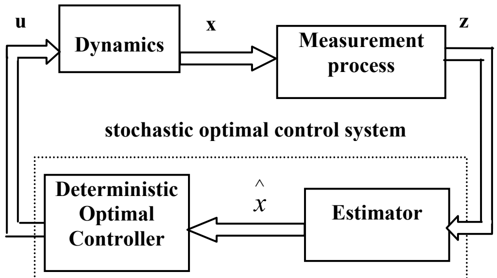


Fig. 4. Diagram illustrating separation principal

Due to (14), (16) and Fig. 4, the decentralized stochastic control can be written as:

$$u_i(t) = u_i^l(t) + u_i^g(t) = -(K_i + K_{gi})\hat{x}_i \tag{30}$$

## 4. SIMULATION RESULTS

A three- machine power system model, which is shown in Fig. 5, is chosen to demonstrate the efficiency of the proposed controller. The system parameters are given in Table 1.

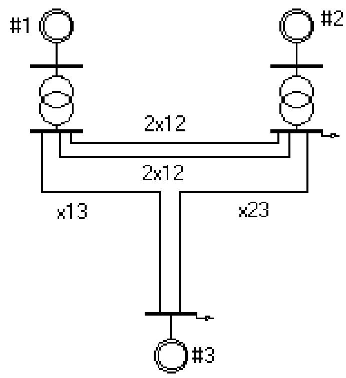


Fig. 5. Three-machine example system (Zhu, et al.,1998)

Table 1 Parameters of system in Fig. 5

| Parameters | | Generator 1 | Generator 2,3 |
|---|---|---|---|
| $x_d$ | P.U | 1.863 | 2.36 |
| $x_d'$ | P.U | .657 | .719 |
| $x_T$ | P.U | .129 | .127 |
| $D$ | P.U | 5.0 | 3.0 |
| $T_{do}'$ | sec | 6.9 | 7.96 |
| $H$ | sec | 4.0 | 5.1 |
| $x_{ad}$ | P.U | 1.712 | 1.712 |
| $k_c$ | P.U | 1.0 | 1.0 |
| $\omega_0$ | rad/s | 314.159 | |
| $x_{12}$ | P.U | .7 | |
| $x_{13}$ | P.U | .93 | |
| $x_{23}$ | P.U | .9 | |

This three-machine system has three subsystems, each including one generator and the related transformers and buses. Tielines can be considered as interactions. The system is modeled according to the formulation given in section 2. So, three subsystems each having three states, are obtained. For example, the numerical value of the parameters in equation (8) for subsystem 1 is:

$$A_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1.7514 & -1.25 & 0 \\ 0 & 0 & -.1449 \end{bmatrix} \tag{31}$$

$$B_1 = \begin{bmatrix} 0 & 0 \\ .25 & 0 \\ 0 & .1449 \end{bmatrix} \tag{32}$$

$$G_{12} = \begin{bmatrix} 0 & 0 & 0 \\ -.3947 & 0 & -.0181 \\ .0119 & 0 & -1.7226 \end{bmatrix} \tag{33}$$

$$G_{13} = \begin{bmatrix} 0 & 0 & 0 \\ -.7516 & 0 & -.2704 \\ .4801 & 0 & -1.2133 \end{bmatrix} \tag{34}$$

Here, only the results for one of the subsystems are shown. The same also applies to other subsystems.

### 4.1 Local controller design

Each subsystem is simulated separately and a local controller for every subsystem is designed. The responses of corresponding simulation results for subsystem 2 are shown in Fig. 6-8.

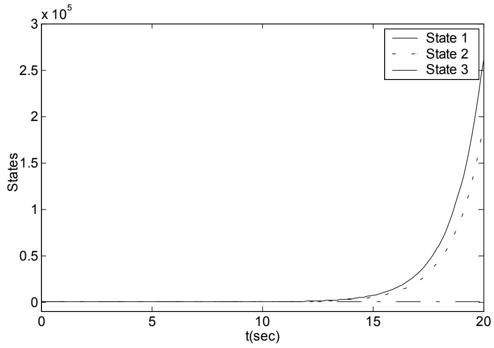


Fig. 6. Unit step response of system states without controller

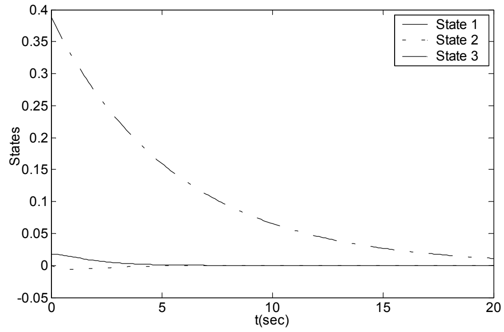


Fig. 7. Unit step response of system states with local controller

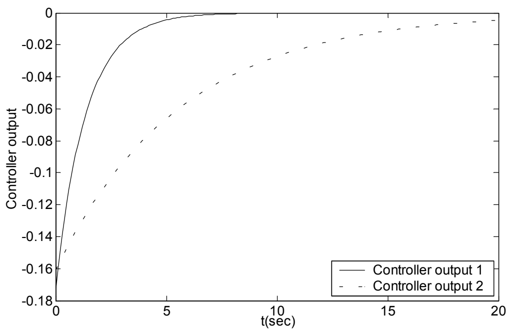


Fig. 8. deterministic local optimal control

Note that the performance index for every subsystem is given as the following:

$$J_i = \int_0^\infty \left( x_i(t)^T x_i(t) + u_i(t)^T u_i(t) \right) dt \qquad i = 1 \ldots n \qquad (35)$$

*4.2 Comparison of centralized and decentralized controllers*

In this part two cases are considered. First, a controller of the form $u = u_l + u_g$ which was discussed in part 3, is proposed (case 1). Second, a 9×9 optimal controller is designed and the system is considered globally (case 2). In both cases the behavior of system states is the same and is shown in Fig. 9. The curves of system states for both cases are the same and this indicates that the performance of decentralized system is almost the same as its centralized counterpart. In Fig. 10 the global control (Mechanical power) in eq. 18 is shown for subsystem 3 and is compared by the control needed in centralized case. Considering optimal controller output (Fig. 10), it is clear that in decentralized case, the amount of mechanical power is increased and it is necessary to have a larger controller output to minimize the interactions.

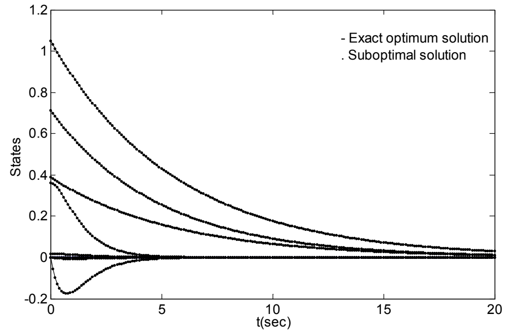


Fig. 9. states of the system in both cases

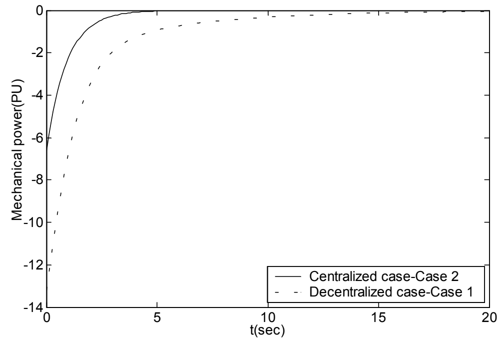


Fig. 10. Controller outputs of the system in both cases

*4.3 Performance due to addition of state estimator*

After designing the deterministic optimal controller, Kalman filter and genetic algorithm are used to estimate the states of all subsystems. In Fig. 11-12, the results of controlled system states for subsystem 3 are shown. The curves indicate that after a while, the estimated states converge to the actual ones and this proves the good performance of both algorithms in estimating the system states. This proves that the proposed decentralized stochastic control has an acceptable performance, compared to the centralized case.

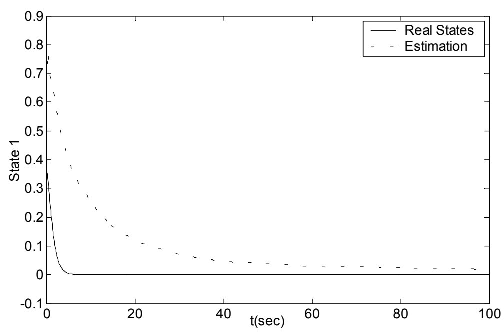


Fig. 11. The actual and estimated state 1

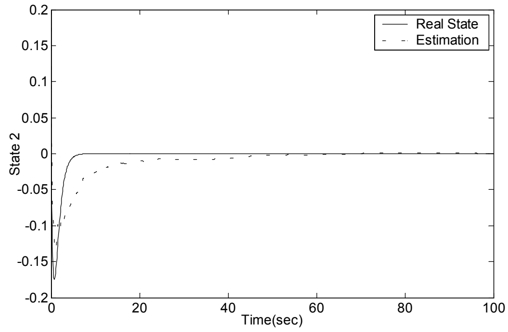


Fig. 12. The actual and estimated state 2

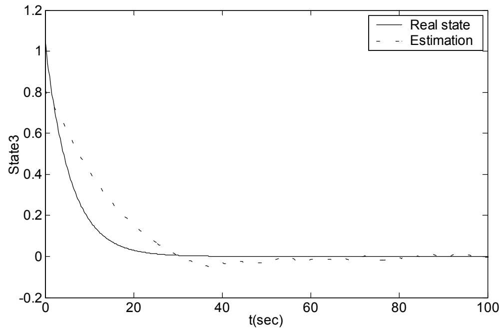


Fig. 13. The actual and estimated state 3

## 5. CONCLUSIONS

This paper proposes a decentralized stochastic controller for multimachine power systems. A decentralized feedback control scheme is proposed for optimization of the system. Local controllers are used to optimize each subsystem, ignoring the interactions. Then, a compensating controller is applied to minimize the effect of interconnections and improve the performance of the overall system. At the cost of the suboptimal performance, this optimization strategy ensures stability of the system. To account for the modeling uncertainties, a local Kalman filter and genetic algorithms are designed to estimate all local states and interactions for each subsystem. The controller uses these estimates, optimizes a given performance index and then regulates the system states. The performance of the proposed controller is assessed through simulation of a sample three-bus system. It is shown that the proposed methodology gives good results.

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