Augmented Automatic Choosing Control of Filter Type Using ABC Algorithm and Its Application to Electric Power Systems

Tomohiro Hachino and Hitoshi Takata

***Abstract*—This paper presents a state feedback control using automatic choosing control and nonlinear filter for nonlinear systems with noise measurement. The unknown state variables are estimated by the nonlinear filter. A given nonlinear system is linearized piecewise, so that the theory of linear optimal control can be applied to each divided subsystem. The resulting controls on the subsystems are smoothly united into a single nonlinear feedback control by automatic choosing functions. Since the formula of the proposed control is of a structure-specified type, the design parameters included in the controller and filter are appropriately determined using artificial bee colony algorithm. This control is applied to the transient stability problem of a single-machine power system, whose simulation results show that the proposed controller can expand the stable region considerably.

***Keywords*—Artificial bee colony algorithm, augmented automatic choosing control, electric power system, filter, nonlinear control.

I. Introduction

THE problem of transient stability has been one of the most important themes in electric power systems. If the expansion of the stable region of generators is ensured, we can operate the power systems under severer conditions to increase the power output of generators. This problem becomes a control design for nonlinear systems with nonlinear noise measurements by appropriate selection of state variables and output variables.

In general, most controllers are synthesized by linearizing a given nonlinear system so that the linear estimation and control theory are applicable when some of the state variables of the system are not measurable. One of them is based on a truncation at the first order of the Taylor expansion [1]–[4]. This linear optimal control (LOC) is easy to implement to many practical nonlinear systems. As an application of this LOC, the transient stability problem of electric power systems with excitation control has been reported [1], [2]. The LOC is quite useful for this kind of nonlinear control problem owing to its simplicity, but it is generally only useful in a small region or in almost linear ones. Controllers based on a change of coordinates in differential geometry [5], [6] are effective in wider region, but not easy to implement to practical systems. Controllers based on fuzzy reasoning [7]–[10] are more practical, but usually need a lot of divisions which make up a complicated control formula.

This paper is concerned with a nonlinear feedback controller using the automatic choosing functions and the linear control theory for nonlinear systems with noisy measurement. The control is designed by piecewise linear controls which are smoothly united into a single nonlinear feedback control by the automatic choosing function. The state estimation mechanism by a nonlinear filter is added to this augmented automatic choosing control. This is called an augmented automatic choosing control of filter type (AACCF). The AACCF formula is of a structure-specified type and includes some parameters such as the adjusting parameters of the automatic choosing function, Taylor expansion points and so forth. Since the stable region for this controller greatly depends on these parameters, in this paper, the use of artificial bee colony (ABC) algorithm is proposed to determine these parameters properly. ABC algorithm is an optimization algorithm inspired by an intelligent behavior of honeybee swarms and has high potential for both global and local optimizations [11]. Many applications of this algorithm have been also reported for vehicle routing problem [12] and prediction of electric power damage by typhoons [13]. ABC algorithm finds the best solution through search by the three types of bees; the employed bees, the onlooker bees, and the scout bees. This algorithm consists of only the basic arithmetic operations and does not require complicated coding and genetic operations such as crossovers and mutations of genetic algorithm. Moreover, the performance of ABC algorithm is better than or similar to those of other population-based algorithms in spite of a few setting parameters [11], [14], [15]. These advantages suggest that the use of ABC algorithm increases efficiency when the AACCF is synthesized.

This paper is organized as follows. In Sect. II, the problem is formulated. In Sect. III, the AACCF formula that consists of the designs of the controller and the filter is given. In Sect. IV, the determination of design parameters included in the AACCF formula is presented using ABC algorithm. In Sect. V the proposed controller is applied to the transient stability problem of a single-machine power system by simulation. Finally some

Manuscript received May 9, 2013.
Tomohiro Hachino is with the Department of Electrical and Electronics Engineering, Kagoshima University, Kagoshima, 890-0065 Japan (phone and fax: +81-99-285-8392; e-mail: hachino@eee.kagoshima-u.ac.jp).
Hitoshi Takata is with the Department of Electrical and Electronics Engineering, Kagoshima University, Kagoshima, 890-0065 Japan (e-mail: takata@eee.kagoshima-u.ac.jp).

conclusions are remarked in Sect. VI.

II. Statement of the Problem

Consider a plant described by a nonlinear dynamic equation and a nonlinear measurement equation:

$$\begin{cases} \dot{\boldsymbol{x}}(t) = \boldsymbol{f}(\boldsymbol{x}(t)) + \boldsymbol{B}\boldsymbol{u}(t), \quad \boldsymbol{x}(t) \in \boldsymbol{\mathcal{D}} \subset R^n \\ \boldsymbol{y}(t) = \boldsymbol{h}(\boldsymbol{x}(t)) + \boldsymbol{v}(t) \end{cases} \tag{1}$$

where $\boldsymbol{x}(t) = [x_1(t), \cdots, x_n(t)]^{\mathrm{T}}$ is an n-dimensional state vector, $\boldsymbol{u}(t) = [u_1(t), \cdots, u_r(t)]^{\mathrm{T}}$ is an r-dimensional control vector, $\boldsymbol{y}(t) = [y_1(t), \cdots, y_m(t)]^{\mathrm{T}}$ is an m-dimensional measurement vector, $\boldsymbol{f} : \boldsymbol{\mathcal{D}} \to R^n$ and $\boldsymbol{h} : \boldsymbol{\mathcal{D}} \to R^m$ are nonlinear vector-valued functions with $\boldsymbol{f}(\boldsymbol{0}) = \boldsymbol{0}$ and are continuously differentiable, $\boldsymbol{B}$ is an $n \times r$ constant driving matrix, and $\boldsymbol{v}(t) \in \mathcal{N}(\boldsymbol{v}(t) : \boldsymbol{0}, \boldsymbol{V})$ is a white Gaussian noise whose mean value vector is $\boldsymbol{0}$ and covariance matrix is $\boldsymbol{V}$. $\boldsymbol{\mathcal{D}} \subset R^n$ is a compact domain whose interior contains $\boldsymbol{0} \in R^n$.

The aim of the paper is to design a nonlinear feedback control $\boldsymbol{u}(t)$ for the given system (1) under the assumption that the measurement of the plant is not perfect and noisy.

III. Synthesis of AACCF

A. Design of Control

Considering the nonlinearity of $\boldsymbol{f}$, introduce a vector-valued function $\boldsymbol{C} : \boldsymbol{\mathcal{D}} \to R^L$ that defines the separative variables $\{C_j(\boldsymbol{x}(t))\}$, where $\boldsymbol{C} = [C_1 \cdots C_j \cdots C_L]^{\mathrm{T}}$ is continuously differentiable. Let $\boldsymbol{D}$ be a domain of $\boldsymbol{C}^{-1}$. For example, if $x_2(t)$ is the element that has the highest nonlinearity of system (1), then

$\boldsymbol{C}(\boldsymbol{x}(t)) = x_2(t) \in D \subset R \quad (L = 1)$.

The domain $\boldsymbol{D}$ is divided into some subdomains: $\boldsymbol{D} = \cup_{i=0}^{M} \boldsymbol{D}_i$, where $\boldsymbol{D}_M = \boldsymbol{D} - \cup_{i=0}^{M-1} \boldsymbol{D}_i$ and $\boldsymbol{C}^{-1}(\boldsymbol{D}_0) \ni \boldsymbol{0}$. $\boldsymbol{D}_i$ $(i = 0, 1, \cdots M-1)$ endowed with a lexicographic order is the Cartesian product $\boldsymbol{D}_i = \Pi_{j=1}^{L} [a_{ij}, b_{ij}]$, where $a_{ij} < b_{ij}$.

We here introduce the following automatic choosing function of sigmoid type. This function has excellent properties: it is analytic, it has a formula with a few parameters and only uses $\{a_{ij}, b_{ij}, N\}$ on each subdomain, and it is an extension of trapezoid type [16]. This is approximation of the function taking values 1 on $\boldsymbol{D}_i$ and 0 on $\boldsymbol{D} - \boldsymbol{D}_i$ $(i = 0, 1, \cdots M)$, namely, of a partition of unity, as shown in Fig. 1. This function is described by

$$\begin{cases} I_i(\boldsymbol{x}(t)) = \displaystyle\prod_{j=1}^{L} I_i(\boldsymbol{x}(t); j) \quad \text{on} \quad \boldsymbol{D}_i \quad (i \neq M) \\ I_M(\boldsymbol{x}(t)) = 1 - \displaystyle\sum_{i=0}^{M-1} I_i(\boldsymbol{x}(t)) \quad \text{on} \quad \boldsymbol{D}_M \end{cases} \tag{2}$$

where

$$\begin{aligned} I_i(\boldsymbol{x}(t); j) = 1 &- \frac{1}{1 + \exp\{2N(C_j(\boldsymbol{x}(t)) - a_{ij})\}} \\ &- \frac{1}{1 + \exp\{-2N(C_j(\boldsymbol{x}(t)) - b_{ij})\}} \end{aligned} \tag{3}$$

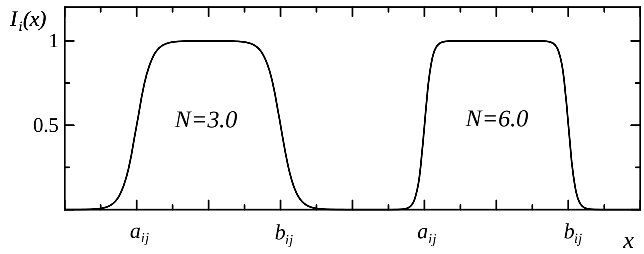

Fig. 1 Automatic choosing function ($N = 3.0, 6.0$)

in which N is of positive real value, $-\infty \leq a_{ij} < b_{ij} \leq \infty$.

The nonlinear function $\boldsymbol{f}$ of (1) is linearized by the Taylor expansion truncated at the first order about a point $\hat{\boldsymbol{\chi}}_i \in \boldsymbol{C}^{-1}(\boldsymbol{D}_i)$ and $\hat{\boldsymbol{\chi}}_0 = \boldsymbol{0}$ on each subdomain $\boldsymbol{D}_i$ (see Fig. 2):

$$\begin{aligned} \boldsymbol{f}(\boldsymbol{x}(t)) &\simeq \boldsymbol{f}(\hat{\boldsymbol{\chi}}_i) + \boldsymbol{A}_i(\boldsymbol{x}(t) - \hat{\boldsymbol{\chi}}_i) \\ &= \boldsymbol{A}_i \boldsymbol{x}(t) + \boldsymbol{w}_i \end{aligned} \tag{4}$$

where $\boldsymbol{A}_i = \partial \boldsymbol{f}(\boldsymbol{x}(t)) / \partial \boldsymbol{x}^{\mathrm{T}}(t)|_{\boldsymbol{x}(t)=\hat{\boldsymbol{\chi}}_i}$, and $\boldsymbol{w}_i = \boldsymbol{f}(\hat{\boldsymbol{\chi}}_i) - \boldsymbol{A}_i \hat{\boldsymbol{\chi}}_i$.

Introduce a stable zero dynamics [17]:

$$\begin{aligned} \dot{\hat{x}}_{n+1}(t) &= -\sigma \hat{x}_{n+1}(t) \\ &(\hat{x}_{n+1}(0) \simeq 1, \quad 0 < \sigma < 1) \end{aligned} \tag{5}$$

where the value of σ shall be selected so that $\sigma = -\dot{\hat{x}}_{n+1} / \hat{x}_{n+1} \leq -\dot{x}_k / x_k$ holds for all k $(k = 1, \cdots, n)$. This tries to keep $\hat{x}_{n+1}(t) \simeq 1$ for a good while when the system (1) is not on $\boldsymbol{C}^{-1}(\boldsymbol{D}_0)$. Then the nonlinear function $\boldsymbol{f}$ is approximated using (5) as follows:

$$\boldsymbol{f}(\boldsymbol{x}(t)) \simeq \boldsymbol{A}_i \boldsymbol{x}(t) + \boldsymbol{w}_i \simeq \boldsymbol{A}_i \boldsymbol{x}(t) + \boldsymbol{w}_i \hat{x}_{n+1}(t) \tag{6}$$

Assume that the control is designed using (2) as

$$\boldsymbol{u}(t) = \sum_{i=0}^{M} \boldsymbol{u}_i(t) I_i(\boldsymbol{x}(t)) \tag{7}$$

Substituting (6) and (7) into (1), the dynamic equation becomes

$$\begin{aligned} &\dot{\boldsymbol{x}}(t) \\ &\simeq \sum_{i=0}^{M} (\boldsymbol{A}_i \boldsymbol{x}(t) + \boldsymbol{w}_i \hat{x}_{n+1}(t) + \boldsymbol{B}\boldsymbol{u}_i(t)) I_i(\boldsymbol{x}(t)) \end{aligned} \tag{8}$$

because $\sum_{i=0}^{M} I_i(\boldsymbol{x}(t)) = 1$. Consider a special case of $I_i(\boldsymbol{x}(t)) = 1$ in which $N = -a_{ij} = b_{ij} \to \infty$ in (3).

The augmented system by (5) and (8) is written as

$$\dot{\boldsymbol{X}}(t) = \boldsymbol{\mathcal{A}}_i \boldsymbol{X}(t) + \boldsymbol{\mathcal{B}} \boldsymbol{u}_i(t) \tag{9}$$

where

$$\boldsymbol{X}(t) = [\boldsymbol{x}^{\mathrm{T}}(t), \hat{x}_{n+1}(t)]^{\mathrm{T}}$$

$$\boldsymbol{\mathcal{A}}_i = \begin{bmatrix} \boldsymbol{A}_i & \boldsymbol{w}_i \\ \boldsymbol{0} & -\sigma \end{bmatrix}, \quad \boldsymbol{\mathcal{B}} = \begin{bmatrix} \boldsymbol{B} \\ 0 \end{bmatrix}$$

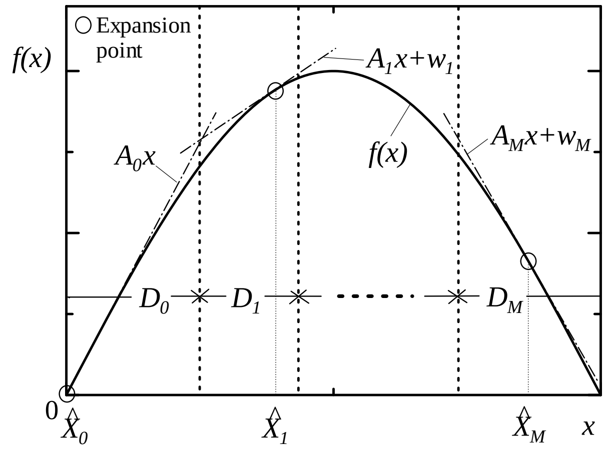

Fig. 2 Sectionwize linearization

To get the feedback gain matrix $\boldsymbol{F}_i$, we apply the LQ control theory. When the following cost function:

$$J_i = \frac{1}{2}\int_0^{\infty} \left(\boldsymbol{X}^{\mathrm{T}}(t)\boldsymbol{Q}\boldsymbol{X}(t) + \boldsymbol{u}_i^{\mathrm{T}}(t)\boldsymbol{R}\boldsymbol{u}_i(t)\right)dt \tag{10}$$

is introduced and the linear optimal control theory [3] is applied to (9), the controller $\boldsymbol{u}_i(t)$ on each subdomain is calculated as follows:

$$\begin{aligned} \boldsymbol{u}_i(t) &= -\boldsymbol{F}_i\boldsymbol{X}(t) \\ \boldsymbol{F}_i &= \boldsymbol{R}^{-1}\boldsymbol{\mathcal{B}}^{\mathrm{T}}\boldsymbol{P}_i \end{aligned} \tag{11}$$

where the $(n+1)\times(n+1)$ matrix $\boldsymbol{P}_i$ satisfies the Riccati equation:

$$\boldsymbol{P}_i\boldsymbol{\mathcal{A}}_i + \boldsymbol{\mathcal{A}}_i^{\mathrm{T}}\boldsymbol{P}_i + \boldsymbol{Q} - \boldsymbol{P}_i\boldsymbol{\mathcal{B}}\boldsymbol{R}^{-1}\boldsymbol{\mathcal{B}}^{\mathrm{T}}\boldsymbol{P}_i = \boldsymbol{0} \tag{12}$$

Here, $\boldsymbol{Q} = \boldsymbol{Q}^{\mathrm{T}} > 0$ and $\boldsymbol{R} = \boldsymbol{R}^{\mathrm{T}} > 0$ which denote positive symmetric matrices. Then the augmented automatic choosing controller $\boldsymbol{u}(t)$ is synthesized by substituting (11) into (7).

B. Design of Filter

We here design a filter for state estimation by an approach of linearization around the estimate. The control $u(t)$ is assumed to be known. If the nonlinear equations of (1) are linearized by the Taylor expansion about an assumed known optimal estimate $\boldsymbol{x}(t) = \hat{\boldsymbol{x}}(t)$, then

$$\begin{cases} \dot{\boldsymbol{x}}(t) \simeq \boldsymbol{f}(\hat{\boldsymbol{x}}(t)) + \boldsymbol{F}(t)(\boldsymbol{x}(t) - \hat{\boldsymbol{x}}(t)) + \boldsymbol{B}\boldsymbol{u}(t) \\ \boldsymbol{y}(t) \simeq \boldsymbol{h}(\hat{\boldsymbol{x}}(t)) + \boldsymbol{H}(t)\left(\boldsymbol{x}(t) - \hat{\boldsymbol{x}}(t)\right) + \boldsymbol{v}(t) \end{cases} \tag{13}$$

where $\boldsymbol{F}(t) = \partial\boldsymbol{f}(\boldsymbol{x}(t))/\partial\boldsymbol{x}^{\mathrm{T}}(t)|_{\boldsymbol{x}(t)=\hat{\boldsymbol{x}}(t)}$, $\boldsymbol{H}(t) = \partial\boldsymbol{h}(\boldsymbol{x}(t))/\partial\boldsymbol{x}^{\mathrm{T}}(t)|_{\boldsymbol{x}(t)=\hat{\boldsymbol{x}}(t)}$. Let the filter equation be given by

$$\dot{\hat{\boldsymbol{x}}}(t) = \boldsymbol{f}(\hat{\boldsymbol{x}}(t)) + \boldsymbol{B}\boldsymbol{u}(t) + \boldsymbol{K}(t)(\boldsymbol{y}(t) - \boldsymbol{h}(\hat{\boldsymbol{x}}(t))) \tag{14}$$

with initial value $\hat{\boldsymbol{x}}(0) = \hat{\boldsymbol{x}}_0$. From (13) and (14), the difference equation $\boldsymbol{e}(t) = \boldsymbol{x}(t) - \hat{\boldsymbol{x}}(t)$ is derived as

$$\dot{\boldsymbol{e}}(t) = (\boldsymbol{F}(t) - \boldsymbol{K}(t)\boldsymbol{H}(t))\boldsymbol{e}(t) - \boldsymbol{K}(t)\boldsymbol{v}(t) \tag{15}$$

So the covariance $\boldsymbol{S}(t) = \mathrm{E}[\boldsymbol{e}(t)\boldsymbol{e}^{\mathrm{T}}(t)]$ with $\mathrm{E}[\boldsymbol{e}(t)] = \boldsymbol{0}$ becomes

$$\begin{aligned} \dot{\boldsymbol{S}}(t) &= (\boldsymbol{F}(t) - \boldsymbol{K}(t)\boldsymbol{H}(t))\boldsymbol{S}(t) \\ &\quad + \boldsymbol{S}(t)(\boldsymbol{F}(t) - \boldsymbol{K}(t)\boldsymbol{H}(t))^{\mathrm{T}} + \boldsymbol{K}(t)\boldsymbol{V}\boldsymbol{K}^{\mathrm{T}}(t) \end{aligned} \tag{16}$$

when supposed $\mathrm{E}[\boldsymbol{e}(t)\boldsymbol{v}^{\mathrm{T}}(t)] = \boldsymbol{0}$, with initial value $\boldsymbol{S}(0) = \boldsymbol{S}_0$. We find $\boldsymbol{K}(t)$ such as to minimize an index

$$J(t) = t_r(\boldsymbol{S}(t)) \tag{17}$$

where $t_r(\cdot)$ denotes the trace operator. Thus we have

$$\begin{aligned} \boldsymbol{K}(t) &= \boldsymbol{S}(t)\boldsymbol{H}^{\mathrm{T}}(t)\boldsymbol{V}^{-1} \\ \dot{\boldsymbol{S}}(t) &= \boldsymbol{F}(t)\boldsymbol{S}(t) + \boldsymbol{S}(t)\boldsymbol{F}^{\mathrm{T}}(t) \\ &\quad - \boldsymbol{S}(t)\boldsymbol{H}^{\mathrm{T}}(t)\boldsymbol{V}^{-1}\boldsymbol{H}(t)\boldsymbol{S}(t) \end{aligned} \tag{18}$$

as the minimum error variance. Therefore, the filter algorithm is obtained by (14) and (18).

C. AACCF Formula

On the basis of the formulations in the above sections III. *A* and III. *B*, we have the AACCF formula as follows.

[AACCF formula]

$$\begin{aligned} \dot{\hat{\boldsymbol{x}}}(t) &= \boldsymbol{f}(\hat{\boldsymbol{x}}(t)) + \boldsymbol{B}\boldsymbol{u}(t) + \boldsymbol{K}(t)(\boldsymbol{y}(t) - \boldsymbol{h}(\hat{\boldsymbol{x}}(t))) \\ \hat{\boldsymbol{x}}(0) &= \hat{\boldsymbol{x}}_0 \end{aligned} \tag{19}$$

$$\boldsymbol{u}(t) = \sum_{i=0}^{M} \boldsymbol{u}_i(t)I_i(\hat{\boldsymbol{x}}(t)) \tag{20}$$

$$\begin{aligned} \boldsymbol{u}_i(t) &= -\boldsymbol{F}_i\hat{\boldsymbol{X}}(t) \\ \hat{\boldsymbol{X}}(t) &= [\hat{\boldsymbol{x}}^{\mathrm{T}}(t), \hat{x}_{n+1}(t)]^{\mathrm{T}} \end{aligned} \tag{21}$$

$$\begin{aligned} &I_i(\hat{\boldsymbol{x}}(t)) \\ &= \prod_{j=1}^{L}\left[1 - \frac{1}{1+\exp\{2N\left(C_j(\hat{\boldsymbol{x}}(t)) - a_{ij}\right)\}}\right. \\ &\qquad \left. - \frac{1}{1+\exp\{-2N\left(C_j(\hat{\boldsymbol{x}}(t)) - b_{ij}\right)\}}\right] \end{aligned} \tag{22}$$

The new AACCF controller $\boldsymbol{u}(t)$ is rewritten in detail as

$$\begin{aligned} \boldsymbol{u}(\hat{\boldsymbol{X}}(t)) &= \sum_{i=0}^{M} \boldsymbol{u}_i(\hat{\boldsymbol{X}}(t))I_i(\hat{\boldsymbol{x}}(t)) \\ &= -\sum_{i=0}^{M} \boldsymbol{R}^{-1}\boldsymbol{\mathcal{B}}^{\mathrm{T}}\boldsymbol{P}_i\hat{\boldsymbol{X}}(t)I_i(\hat{\boldsymbol{x}}(t)) \end{aligned} \tag{23}$$

Note that this $u(\hat{\boldsymbol{X}}(t))$ is analytic or a smooth infinite-time differentiable function with respect to $\hat{\boldsymbol{X}}(t)$, because $I_i(\hat{\boldsymbol{x}}(t))$ is so by (2). Thus the total differential equation of $\boldsymbol{\mathcal{X}} = [\boldsymbol{x}^{\mathrm{T}}(t), \hat{\boldsymbol{x}}^{\mathrm{T}}(t), \hat{x}_{n+1}(t)]^{\mathrm{T}} \in R^{2n+1}$ is made by the nonlinear continuous differential functions from (1), (5), and (19).

IV. Determination of Parameters by ABC Algorithm

A. Outline of ABC Algorithm

ABC algorithm is an optimization algorithm inspired by the behavior of real honeybees [11]. In this algorithm, the colony of artificial bees consists of the three groups of bees; the employed bees, the onlooker bees, and the scout bees. The roles of these groups are as follows:

1) Employed bees

The employed bees determine a food source within the neighborhood of the food source in their memory. The size of the employed bees is half of the colony size. Every employed bee works on only one food source. Therefore, the number of the employed bees is equal to the number of the food sources. The employed bees evaluate the profitability of the food sources such as the nectar amount, and share their information with the onlooker bees in the hive. A employed bee that has worked on abandoned food source is differentiated into a scout bee.

2) Onlooker bees

The onlooker bees waiting in the hive select one food source through the information obtained from the employed bees' dances and search in the neighborhood of the selected food source. This selection is implemented by the "roulette-wheel" slots weighted in proportion to the profitability of the food source. Therefore the onlooker bees are likely to search around more profitable food sources. The size of the onlooker bees is also half of the colony size.

3) Scout bees

The scout bee differentiated from the employed bee searches a new food source randomly.

In the optimization problem, the positions of the food sources correspond to the candidates of the solution and the profitability of the food source shows the fitness value that represents the goodness of the solution. The suboptimal solution is obtained by repeating search by the employed, onlooker, and scout bees.

B. Determination Algorithm by ABC

Since the AACCF formula is of a structure-specified type, each parameter included in the above equations must be properly selected so that the feedback control system (1) by AACCF could stabilize globally. Some of a set of parameters such as $\bar{\boldsymbol{\Omega}} = \{M, N, a_{ij}, b_{ij}, \hat{\boldsymbol{\chi}}_i^{\mathrm{T}}, \sigma, \ \boldsymbol{Q}, \boldsymbol{R}, \hat{\boldsymbol{x}}_0, \boldsymbol{S}_0\}$ may be suboptimally chosen by optimizing a cost function or fitness value function with the aid of ABC algorithm. In this paper the fitness value function

$$PI = \big\{|\max\ x_2(0) - \min\ x_2(0)| \\ : x_1(0) = x_3(0) = 0, \boldsymbol{x}(\infty) = \boldsymbol{0}\big\} \tag{24}$$

is maximized so as to expand a stable region (see Sect. V). The proposed algorithm for parameter determination is as follows:

step 1: Parameter selection

Choose $\boldsymbol{\Omega} \subset \bar{\boldsymbol{\Omega}}$ to be optimized and rewrite $\boldsymbol{\Omega} = \{\Omega_j : j = 1, 2, \cdots, \ell\}$

step 2: Initialization

(2-1) Generate an initial population of N_s bees with random positions of the food sources $\boldsymbol{\Omega}_{[i]}$ $(i = 1, 2, \cdots, N_s)$ from (25):

$$\Omega_{ij} = \Omega_{min,j} + rand[0,1] \cdot (\Omega_{max,j} - \Omega_{min,j}) \\ (j = 1, 2, \cdots, \ell) \tag{25}$$

where N_s denotes the size of the employed bees or onlooker bees and Ω_{ij} is the jth element of the vector $\boldsymbol{\Omega}_{[i]}$. $\Omega_{min,j}$ and $\Omega_{max,j}$ are the minimum and maximum values for Ω_{ij}, respectively. $rand[0, 1]$ is uniformly distributed random number with amplitude in the range $[0, 1]$.

(2-2) Set the iteration counter l to 1.

(2-3) Set the counter for abandonment $trial_i$ to 0. The counter $trial_i$ shows the number of times that the solution $\boldsymbol{\Omega}_{[i]}$ is not improved by the employed and onlooker bees.

step 3: Synthesis of AACCF

Design $\hat{\boldsymbol{x}}(t)_{[i]}$ and $\boldsymbol{u}(t)_{[i]}$ for $\boldsymbol{\Omega}_{[i]}$ using (19) and (20) $(i = 1, 2, \cdots, N_s)$.

step 4: Fitness value calculation

Calculate the fitness value $F_i(\boldsymbol{\Omega}_{[i]})$ from (24) as $F_i(\boldsymbol{\Omega}_{[i]}) = PI(\boldsymbol{\Omega}_{[i]})$.

step 5: Search by the employed bees

(5-1) Determine the new positions of the food sources $\boldsymbol{V}_{[i]}$ around $\boldsymbol{\Omega}_{[i]}$ for the employed bees from (26):

$$V_{ij} = \Omega_{ij} + rand[-1, 1] \cdot (\Omega_{ij} - \Omega_{kj}) \\ (j = 1, 2, \cdots, \ell) \tag{26}$$

where V_{ij} is the jth element of the vector $\boldsymbol{V}_{[i]}$ and k is a random integer selected from $\{1, 2, \cdots, N_s\}$, where $k \neq i$.

(5-2) Design $\hat{\boldsymbol{x}}(t)_{[i]}$ and $\boldsymbol{u}(t)_{[i]}$ for $\boldsymbol{V}_{[i]}$ using (19) and (20) $(i = 1, 2, \cdots, N_s)$.

(5-3) Calculate the fitness value $F_i(\boldsymbol{V}_{[i]})$ from (24) as $F_i(\boldsymbol{V}_{[i]}) = PI(\boldsymbol{V}_{[i]})$.

(5-4) If $F_i(\boldsymbol{\Omega}_{[i]}) < F_i(\boldsymbol{V}_{[i]})$, update $\boldsymbol{\Omega}_{[i]}$ and $F_i(\boldsymbol{\Omega}_{[i]})$ by $\boldsymbol{V}_{[i]}$ and $F_i(\boldsymbol{V}_{[i]})$, respectively, and set $trial_i = 0$. Otherwise set $trial_i = trial_i + 1$. This procedure is called "greedy selection".

The search by the employed bees is depicted in Fig. 3.

step 6: Search by the onlooker bees

(6-1) Choose one position of the food source for each onlooker bee from $\boldsymbol{\Omega}_{[i]}$ $(i = 1, 2, \cdots, N_s)$ through "roulette-wheel" slots weighted in proportion to the fitness value of the employed bee. Namely each onlooker bee selects one position of the food source with probability of $F_i(\boldsymbol{\Omega}_{[i]}) / \sum_{p=1}^{N_s} F_p(\boldsymbol{\Omega}_{[p]})$.

(6-2) Calculate the new positions of the food sources $\boldsymbol{V}_{[i]}$ corresponding to the selected positions $\boldsymbol{\Omega}_{[i]}$ from (26).

(6-3) Design $\hat{\boldsymbol{x}}(t)_{[i]}$ and $\boldsymbol{u}(t)_{[i]}$ for $\boldsymbol{V}_{[i]}$ using (19) and (20) $(i = 1, 2, \cdots, N_s)$.

(6-4) Calculate the fitness value $F_i(\boldsymbol{V}_{[i]})$ from (24) as $F_i(\boldsymbol{V}_{[i]}) = PI(\boldsymbol{V}_{[i]})$.

(6-5) Carry out the greedy selection with the same way of *step 5 (5-4)*.

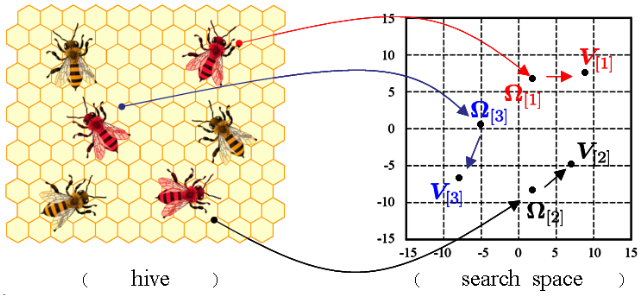

Fig. 3 Search by the employed bees

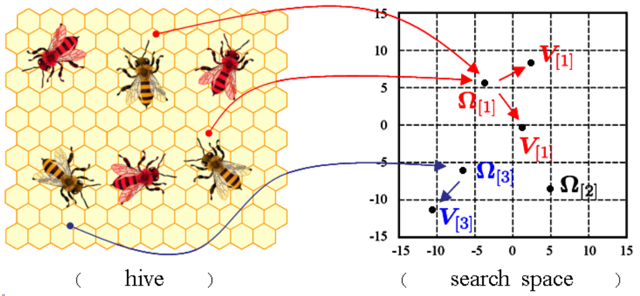

Fig. 4 Search by the onlooker bees

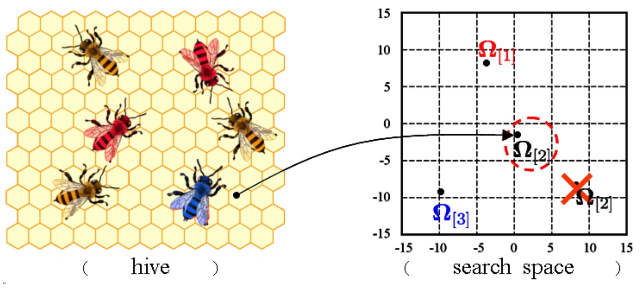

Fig. 5 Search by the scout bees

The search by the onlooker bees is depicted in Fig. 4.

step 7: Search by the scout bees

If the counter for abandonment $trial_i$ is greater or equal to the prespecified number *limit*, carry out the following procedure.

(7-1) Differentiate the corresponding employed bee into the scout bee and generate the new position of the food source $\boldsymbol{\Omega}_{[i]}$ for the scout bee randomly from (25).

(7-2) Design $\hat{\boldsymbol{x}}(t)_{[i]}$ and $\boldsymbol{u}(t)_{[i]}$ for corresponding $\boldsymbol{\Omega}_{[i]}$ using (19) and (20).

(7-3) Calculate the fitness value $F_i(\boldsymbol{\Omega}_{[i]})$ from (24) as $F_i(\boldsymbol{\Omega}_{[i]}) = PI(\boldsymbol{\Omega}_{[i]})$.

This step means that if the solution is not improved *limit* times through search by the employed and onlooker bees, the corresponding employed bee gives up to search around his food source and transforms himself to the scout bee to search around randomly selected food source. Since the number *limit* is usually set to be the product of the employed bee size and the dimension of the search space [11], this number is taken to be $limit = N_s \times \ell$ in this paper.

The search by the scout bees is depicted in Fig. 5.

step 8: Repetition

Set the iteration counter to $l = l + 1$ and go to *step 5* until the prespecified iteration number l_{max}.

Finally, at the termination of this algorithm when $l = l_{max}$, the suboptimal parameter vector $\hat{\boldsymbol{\Omega}}$ is determined by the best position of the food source.

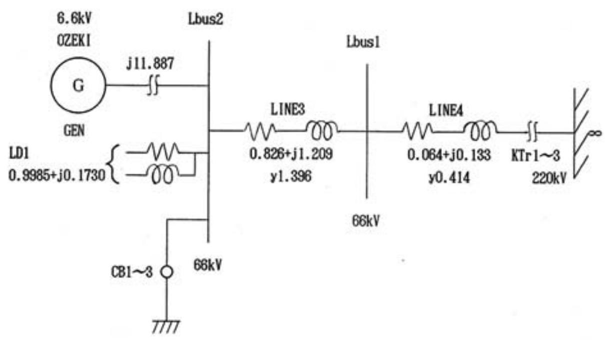

Fig. 6 Diagram of Ozeki-Power-Plant

V. Numerical Example

Consider a field excitation control problem of single machine power system, which is the Ozeki-Power-Plant of Kyushu Electric Power Company in Japan as shown in Fig. 6. This system is assumed to be described by

$$\left\{\begin{array}{l} \widetilde{M}\ddot{\delta} + \widetilde{D}(\delta)\dot{\delta} + P_e(\delta) = P_{in} \\ P_e(\delta) = E_I^2 Y_{11}\cos\theta_{11} + E_I\widetilde{V}Y_{12}\cos(\theta_{12}-\delta) \\ E_I + T_{d0}\dot{E}_q' = E_{fd} \\ E_I = E_q' + (X_d - X_d')I_d(\delta) \\ I_d(\delta) = -E_I Y_{11}\sin\theta_{11} - \widetilde{V}Y_{12}\sin(\theta_{12}-\delta) \\ \widetilde{D}(\delta) = \widetilde{V}^2\left\{\dfrac{T_{d0}''(X_d'-X_d'')}{(X_d'+X_e)^2}\sin^2\delta \right. \\ \qquad\qquad \left. + \dfrac{T_{q0}''(X_q - X_q'')}{(X_q+X_e)^2}\cos^2\delta\right\} \end{array}\right. \tag{27}$$

The output is supposed to be given by $P_e(\delta)$ and $\dot{\delta}$ which are easily measurable. E_{fd} is a control variable. Here, δ is phase angle, $\dot{\delta}$ the rotor speed, $\widetilde{M}$ the inertia coefficient, $\widetilde{D}(\delta)$ the damping coefficient, P_{in} the mechanical input power, $P_e(\delta)$ the generator output power, $\widetilde{V}$ the reference bus voltage, E_I the open circuit voltage, E_{fd} the field excitation voltage, X_d the direct axis synchronous reactance, X_d' the direct axis transient reactance, X_e the external impedance, $Y_{11}\angle\theta_{11}$ the self-admittance of the network, $Y_{12}\angle\theta_{12}$ the mutual admittance of the network, and $I_d(\delta)$ the direct axis current of the machine.

Put $\boldsymbol{x}$=$[x_1, x_2, x_3]^{\mathrm{T}}$=$[E_I - \hat{E}_I, \delta - \hat{\delta}_0, \dot{\delta}]^{\mathrm{T}}$ and $u = E_{fd} - \hat{E}_{fd}$, so that

$$\dot{\boldsymbol{x}} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} f_1(\boldsymbol{x}) \\ f_2(\boldsymbol{x}) \\ f_3(\boldsymbol{x}) \end{bmatrix} + \begin{bmatrix} b_1 \\ 0 \\ 0 \end{bmatrix} u \quad (28)$$

$$\boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} h_1(\boldsymbol{x}) \\ h_2(\boldsymbol{x}) \end{bmatrix} + \boldsymbol{v} \quad (29)$$

where

$$n = 3,\ r = 1,\ m = 2$$

$$\begin{aligned} f_1(\boldsymbol{x}) &= -\frac{1}{kT'_{d0}}\left(x_1 + \hat{E}_I - \hat{E}_{fd}\right) \\ &\quad + \frac{(X_d - X'_d)\widetilde{V}Y_{12}}{k} x_3 \cos\left(\theta_{12} - x_2 - \hat{\delta}_0\right) \\ f_2(\boldsymbol{x}) &= x_3 \\ f_3(\boldsymbol{x}) &= -\frac{\widetilde{V}Y_{12}}{\widetilde{M}}\left(x_1 + \hat{E}_I\right)\cos\left(\theta_{12} - x_2 - \hat{\delta}_0\right) \\ &\quad -\frac{Y_{11}\cos\theta_{11}}{\widetilde{M}}\left(x_1 + \hat{E}_I\right)^2 - \frac{\widetilde{D}(\boldsymbol{x})}{\widetilde{M}}x_3 + \frac{P_{in}}{\widetilde{M}} \\ h_1(\boldsymbol{x}) &= Y_{11}\cos\theta_{11}(x_1 + \hat{E}_I)^2 \\ &\quad + \widetilde{V}Y_{12}(x_1 + \hat{E}_I)\cos(\theta_{12} - x_2 - \hat{\delta}_0) \\ h_2(\boldsymbol{x}) &= x_3 \\ \widetilde{D}(\boldsymbol{x}) &= \widetilde{V}^2\left\{\frac{T''_{d0}(X'_d - X''_d)}{(X'_d + X_e)^2}\sin^2\left(x_2 + \hat{\delta}_0\right)\right. \\ &\quad \left. + \frac{T''_{q0}(X_q - X''_q)}{(X_q + X_e)^2}\cos^2\left(x_2 + \hat{\delta}_0\right)\right\} \\ b_1 &= \frac{1}{kT'_{d0}},\ \ k = 1 + (X_d - X'_d)\, Y_{11}\sin\theta_{11} \end{aligned}$$

The system parameters are given as follows:

$\widetilde{M} =$	$0.016095[pu]$	$T'_{d0} =$	$5.09907[sec]$
$\widetilde{V} =$	$1.0[pu]$	$P_{in} =$	$1.2[pu]$
$X_d =$	$0.875[pu]$	$X'_d =$	$0.422[pu]$
$Y_{11} =$	$1.04276[pu]$	$Y_{12} =$	$1.03084[pu]$
$\theta_{11} =$	$-1.56495[pu]$	$\theta_{12} =$	$1.56189[pu]$
$X_e =$	$1.15[pu]$	$X''_d =$	$0.238[pu]$
$X_q =$	$0.6[pu]$	$X''_q =$	$0.3[pu]$
$T''_{d0} =$	$0.0299[pu]$	$T''_{q0} =$	$0.02616[pu]$

The steady-state values are as follows:

$\hat{E}_I =$	$1.52243[pu]$	$\hat{\delta}_0 =$	$48.57°$
$\hat{\dot{\delta}}_0 =$	$0.0[deg/sec]$	$\hat{E}_{fd} =$	$1.52243[pu]$

Set $\boldsymbol{X} = [\boldsymbol{x}^{\mathrm{T}}, \hat{x}_4]^{\mathrm{T}} = [x_1, x_2, x_3, \hat{x}_4]^{\mathrm{T}}$, $\boldsymbol{C}(\boldsymbol{x}) = x_2$, $L = 1$, $M = 1$, $\hat{\chi}_0 = 0$, $R = 1$, $\boldsymbol{Q} = diag(1,1,1,1)$, $\boldsymbol{X}(0) = [0, x_2(0), x_3(0), 1]^{\mathrm{T}}$, $\hat{\boldsymbol{X}}(0) = [0, \hat{x}_2(0), 0, 1]^{\mathrm{T}}$, $\boldsymbol{S}(0) = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 5 & 10 \\ 0 & 10 & 50 \end{bmatrix}$, and $\boldsymbol{V} = diag(0.1, 0.1)$.

In this simulation, the performance (24) is maximized so as to expand a stable region of phase angle δ. We suboptimally select the parameters $\boldsymbol{\Omega} = \{N, a_1, \hat{\chi}_1, \sigma\} \subset \bar{\boldsymbol{\Omega}}$, which are N and a_1 of the automatic choosing function, Taylor expansion point $\hat{\chi}_1$ and zero dynamics coefficient σ, by ABC algorithm. The setting parameters of ABC algorithm are chosen as follows:

(i) employed bee size $N_s = 50$

(ii) maximum iteration number $l_{max} = 100$

By computation, the parameters are chosen as $N = 28.53$, $a_1 = 66.30°$, $\hat{\chi}_1 = [0, 89.04° - \hat{\delta}_0, 0]^{\mathrm{T}}$ and $\sigma = 0.5253$. Simulations are carried out for the proposed AACCF and the ordinary linear optimal control (LOC) under the same condition and the same noise as to be compared with each other. In the LOC, note that $\boldsymbol{w}_0 = 0$ and $M = 0$. So the augmentation $\boldsymbol{x} \to \boldsymbol{X}$ is not necessary, and $\hat{x}_{n+1}$ and σ are nothing. We set $\boldsymbol{x} = [x_1, x_2, x_3]^{\mathrm{T}}$, $\boldsymbol{C}(\boldsymbol{x}) = x_2$, $L = 1$, $\hat{\chi}_0 = 0$, $R = 1$, $\boldsymbol{Q} = diag(1,1,1)$, $\boldsymbol{x}(0) = [0, x_2(0), x_3(0)]^{\mathrm{T}}$, $\hat{\boldsymbol{x}}(0) = [0, \hat{x}_2(0), 0]^{\mathrm{T}}$, and $\boldsymbol{S}(0) = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 5 & 10 \\ 0 & 10 & 50 \end{bmatrix}$.

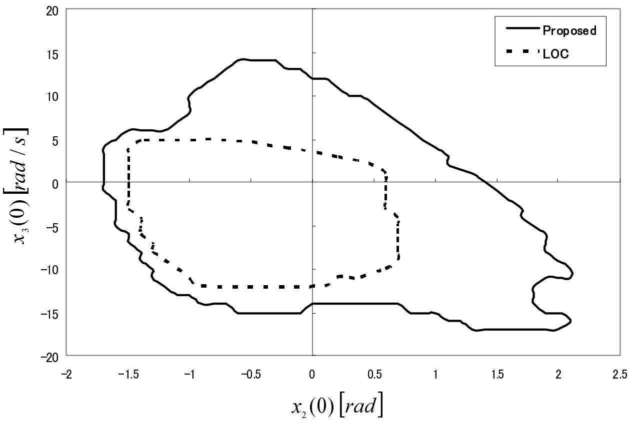

Fig. 7 Stable region

Fig. 7 shows the cross section $x_2(0) - x_3(0)$ of the stable regions for the proposed AACCF and LOC when $\hat{x}_2(0) = 0$. This indicates that the stable region, which is enclosed by the solid line for the AACCF, is considerably wider than for the LOC, shown by the dotted line. Figs. 8-13 show the time responses of $\boldsymbol{x}$, $\hat{\boldsymbol{x}}$, $P_e(\delta)$, and u, respectively, when $x_2(0) = 1.2$, $\hat{x}_2(0) = 0$, and $x_3(0) = 0$. These results indicate that the stable region and trajectories obtained by the proposed AACCF are much better than those obtained by the LOC.

VI. Conclusions

In this paper an AACCF has been presented for nonlinear systems with noisy measurement. The design parameters included in both controller and filter are appropriately determined using ABC algorithm. The use of ABC algorithm makes it easier to design the AACCF, because ABC algorithm has a few setting parameters. The proposed controller has been applied to the field excitation control problem of single-machine power system. Simulation results have shown that the new controller can expand the stable region and improve the time responses considerably.

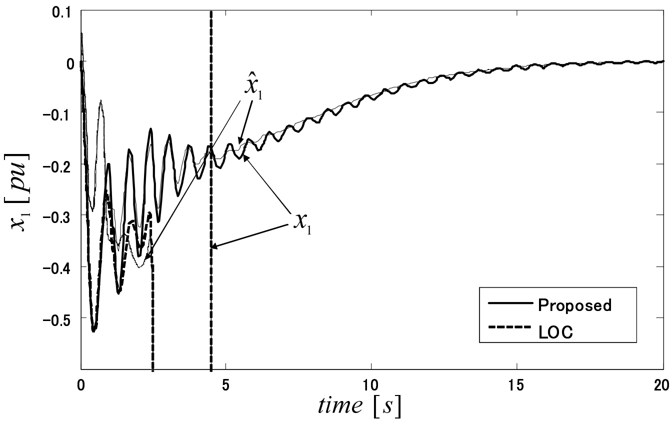

Fig. 8 Time responses x_1 and $\hat{x}_1$

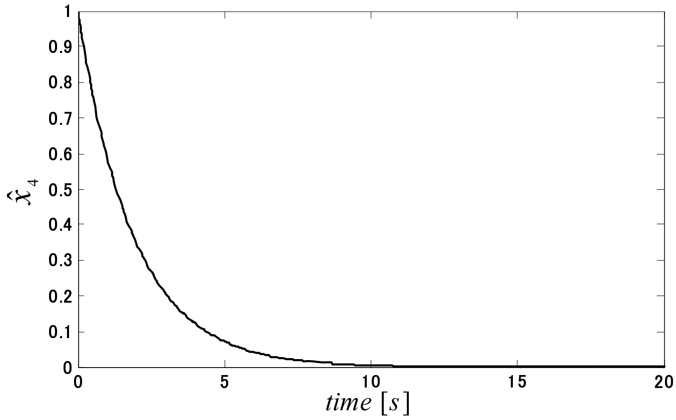

Fig. 11 Time response $\hat{x}_4$

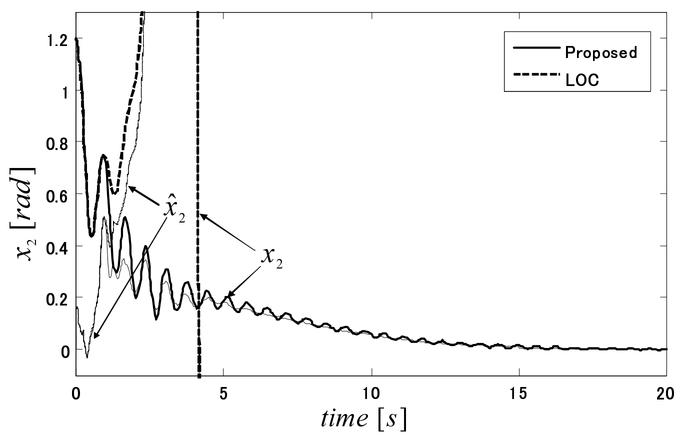

Fig. 9 Time responses x_2 and $\hat{x}_2$

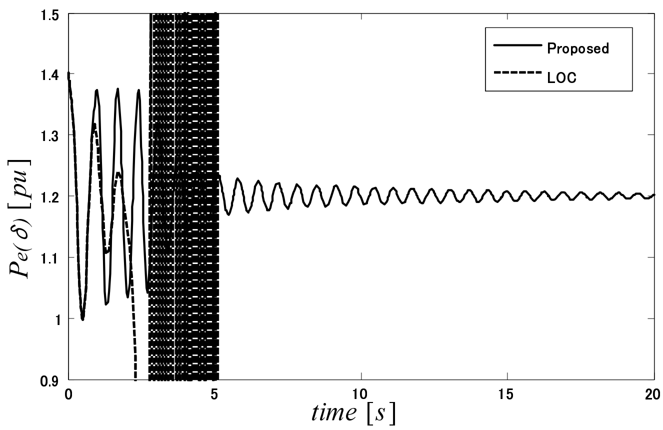

Fig. 12 Time response $P_e(\delta)$

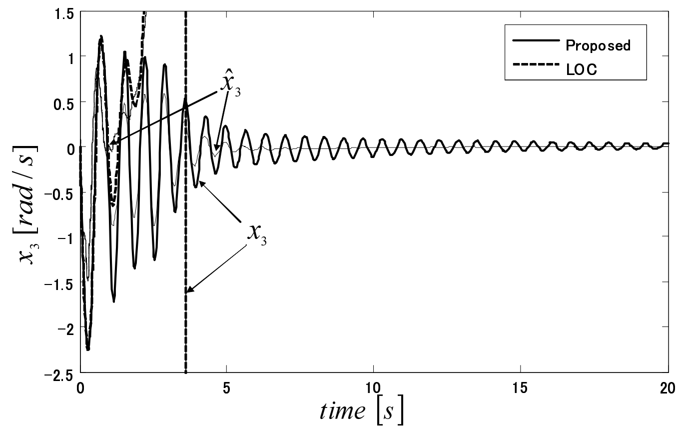

Fig. 10 Time responses x_3 and $\hat{x}_3$

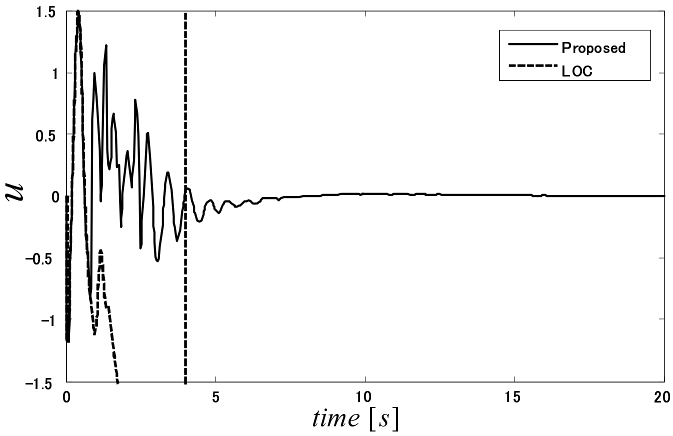

Fig. 13 Time response u

REFERENCES

[1] Y. N. Yu, K. Vongsuriya, and L. N. Wedman, Application of an optimal control theory to a power system, *IEEE Trans. Power Apparatus and Systems*, Vol. PAS-89, No. 1, pp. 55–62, 1970.

[2] J. H. Anderson, The control of a synchronous machine using optimal control theory, *Proc. IEEE*, Vol. 59, No. 1, pp. 25–35, 1971.

[3] A. P. Sage and C. C. White III, *Optimum Systems Control, (2nd edition)*, Prentice-Hall, Inc., 1977.

[4] M. Vidyasagar, *Nonlinear Systems Analysis*, Prentice-Hall, Inc., 1978.

[5] A. Isidori, *Nonlinear Control Systems: An Introduction*, Springer-Verlag, 1985.

[6] Y. Takagi and T. Shigemasa, An application of state-space linearization to a power system stabilizer, *Proc. 29th CDC*, pp. 1553–1558, 1990.

[7] K. Tanaka and M. Sugeno, Stability analysis and design of fuzzy control systems, *Fuzzy Sets and Systems*, Vol. 45, No. 2, pp. 135–156, 1992.

[8] J. Yaochu, Z. Jing, and J. Jingping, Fuzzy linearization for nonlinear systems, *Proc. 3rd IEEE Int. Conference Fuzzy Systems*, Vol. 3, pp. 1688–1693, 1994.

[9] J. Garus, Fuzzy control of motion of underwater robotic vehicle, *Proc. of the 6th WSEAS Int. Conference on Computational Intelligence, Man-Machine Systems and Cybernetics*, pp. 192–197, 2007.

[10] S. Javadi and A. Gohari, A novel design on fuzzy controller to obtain optimum response of boilers, *Latest Trends in Circuits, Automatic Control and Signal Processing, WSEAS Press*, pp. 220–225, 2012.

[11] D. Karaboga and B. Basturk, On the performance of artificial bee colony (ABC) algorithm, *Applied Soft Computing*, Vol. 8, No. 1, pp. 687–697, 2008.

[12] I. Brajevic, Artificial bee colony algorithm for the capacitated vehicle routing problem, *Proc. of the European Computing Conference, WSEAS Press*, pp. 239–244, 2011.

[13] T. Hachino, H. Takata, S. Fukushima, and Y. Igarashi, Prediction of electric power damage by typhoons in Japan using Gaussian process model trained by artificial bee colony algorithm, *Recent Advances in Automatic Control, Modelling and Simulation, WSEAS Press*, pp. 55–60, 2013.

[14] D. Karaboga and B. Akay, A comparative study of artificial bee colony algorithm, *Applied Mathematics and Computation*, Vol. 214, No. 1, pp. 108–132, 2009.

[15] I. Iimura and S. Nakayama, Search performance evaluation of artificial bee colony algorithm on high-dimensional function optimization (in Japanese), *Trans. of the ISCIE*, Vol. 24, No. 4, pp. 97–99, 2011.

[16] H. Takata, An automatic choosing control for nonlinear systems, *Proc. IEEE 35th CDC*, pp. 3453–3458, 1996.

[17] H. Takata and T. Nawata, Design of an augmented automatic choosing control by zero dynamics and GA for nonlinear systems (in Japanese), *Trans. IEE of Japan*, Vol. 122-C, No. 7, pp. 1172–1178, 2002.

Tomohiro Hachino received the B.S., M.S. and Dr. Eng. degrees in electrical engineering from Kyushu Institute of Technology in 1991, 1993, and 1996, respectively. He is currently an Associate Professor at the Department of Electrical and Electronics Engineering, Kagoshima University. His research interests include nonlinear control and identification, signal processing, and evolutionary computation. Dr. Hachino is a member of IEEJ, SICE, and ISCIE.

Hitoshi Takata received the B.S. degree in electrical engineering from Kyushu Institute of Technology in 1968 and the M.S. and Dr. Eng. degrees in electrical engineering from Kyushu University in 1970 and 1974, respectively. He is currently a Professor Emeritus and a part-time lecturer at Kagoshima University. His research interests include the control, linearization, and identification of nonlinear systems. Dr. Takata is a member of IEEJ and RISP.