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An Augmented Automatic Choosing Control with Constrained Input Using Weighted Gradient Optimization Automatic Choosing Functions

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Abstract—In this paper we consider a nonlinear feedback control called augmented automatic choosing control (AACC) for nonlinear systems with constrained input using weighted gradient optimization automatic choosing functions. Constant term which arises from linearization of a given nonlinear system is treated as a coefficient of a stable zero dynamics. Parameters of the control are suboptimally selected by maximizing the stable region in the sense of Lyapunov with the aid of a genetic algorithm. This approach is applied to a field excitation control problem of power system to demonstrate the splendidness of the AACC. Simulation results show that the new controller can improve performance remarkably well.

Keywords—Augmented automatic choosing control, nonlinear control, genetic algorithm, zero dynamics.

I. Introduction

IT is generally easy to design the optimal control laws for linear systems, but it is not so for nonlinear systems, though they have been studied for many years[1]-[8]. One of the most popular and practical nonlinear control laws is synthesized by applying the linearization method by Taylor expansion and the linear optimal control method to a given nonlinear system. This is only effective in a small region around the steady state point or in almost linear systems[1]-[3].

Another nonlinear control called an automatic choosing control (ACC) has been studied [6]. This controller is effective in nonlinear systems with high nonlinearity and wider regions. But constant terms, which generally appear in equations when linearized by Taylor expansion, lead the controller to have bias at the origin, so the resulting ACC must be modified by bothersome unbiased nonlinear functions in view of stability.

Moreover, there exist various constraints in many physical systems, so a design of nonlinear control laws subject to constraints has been urgent but been studied a few[9].

In this paper we present an augmented automatic choosing control (AACC) for nonlinear systems with constrained input by using a genetic algorithm(GA)[10] and its design procedure is as follows. Assume that a system is given by a nonlinear differential equation. Choose a separative variable, which makes up nonlinearity of the given system. The domain of the variable is divided into some subdomains. On each subdomain, the system equation is linearized by Taylor expansion around a suitable point so that a constant term is included in it. This constant term is treated as a coefficient of a stable zero dynamics. The given nonlinear system approximately makes up a set of augmented linear systems, to which the optimal linear control theory is applied to get the linear quadratic (LQ) controls[2]. These LQ controls are smoothly united by weighted gradient optimization automatic choosing functions to synthesize a single nonlinear feedback controller. This controller is then limited so as to hold a specified constraint.

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This controller is of a structure-specified type which has some parameters, such as the number of division of the domain, regions of the subdomains, points of Taylor expansion, gradients of the automatic choosing function, and weights of the automatic choosing function. These parameters must be selected optimally so as to be just the controller's fit. Since they lead to a nonlinear optimization problem, we are able to solve it by using the GA suboptimally. In this paper the suboptimal values of these parameters are selected by maximizing a stable region in the sense of Lyapunov.

This approach is applied to a field excitation control problem of power system, which is Ozeki-Power-Plant of Kyushu Electric Power Company in Japan, to demonstrate the splendidness of the AACC. Simulation results show that the new controller using the GA is able to improve performance remarkably well.

II. Augmented Automatic Choosing Control Using Zero Dynamics

Assume that a nonlinear system is given by

$$\dot{x} = f(x) + g(x)u, \quad x \in \mathbf{D} \tag{1}$$

subject to

$$u_{j,min} \leq u[j] \leq u_{j,max} \quad (j = 1, \cdots, r) \tag{2}$$

where $\cdot = d/dt$, $x = [x[1], \cdots, x[n]]^T$ is an n-dimensional state vector, $u = [u[1], \cdots, u[j], \cdots, u[r]]^T$ is an r-dimensional bounded control vector, $u_{j,min}$: the minimum value of $u[j]$, $u_{j,max}$: the maximum value of $u[j]$, $f : \mathbf{D} \to R^n$ is a nonlinear vector-valued function with $f(0) = 0$ and is continuously differentiable, $g(x)$ is an $n \times r$ driving matrix with $g(0) \neq 0$ and is continuously differentiable, $\mathbf{D} \subset R^n$ is a domain , and T denotes transpose.

Considering the nonlinearity of f, introduce a vector-valued function $C : \mathbf{D} \to R^L$ which defines the separative variables $\{C_j(x)\}$, where $C = [C_1 \cdots C_j \cdots C_L]^T$ is continuously differentiable. Let D be a domain of C^{-1}. For example, if

$x[2]$ is the element which has the highest nonlinearity in f, then

$$C(x) = x[2] \in D \subset R \quad (L = 1)$$

(see Section IV). The domain D is divided into some subdomains: $D = \cup_{i=0}^{M} D_i$, where $D_M = D - \cup_{i=0}^{M-1} D_i$ and $C^{-1}(D_0) \ni 0$. $D_i (0 \le i \le M)$ endowed with a lexicographic order is the Cartesian product $D_i = \Pi_{j=1}^{L}[a_{ij}, b_{ij}]$, where $a_{ij} < b_{ij}$.

Introduce a stable zero dynamics :

$$\dot{x}[n+1] = -\sigma_i x[n+1] \tag{3}$$

$$(x[n+1](0) \simeq 1, \quad 0 < \sigma_i < 1).$$

Equation(1) combines with (3) to form an augmented system

$$\dot{\mathbf{X}} = \bar{f}(\mathbf{X}) + \bar{g}(\mathbf{X})u \tag{4}$$

where

$$\mathbf{X} = \begin{bmatrix} x \\ x[n+1] \end{bmatrix} \in \mathbf{D} \times R$$

$$\bar{f}(\mathbf{X}) = \begin{bmatrix} f(x) \\ -\sigma_i x[n+1] \end{bmatrix}, \bar{g}(\mathbf{X}) = \begin{bmatrix} g(x) \\ 0 \end{bmatrix}.$$

We assume a cost function being

$$J = \frac{1}{2}\int_0^\infty \left(\mathbf{X}^T\mathbf{Q}\mathbf{X} + u^T R u\right) dt \tag{5}$$

where $\mathbf{Q} = \mathbf{Q}^T > 0$, $R = R^T > 0$, and the values of these matrices are properly determined based on engineering experience.

On each D_i, the nonlinear system is linearized by the Taylor expansion truncated at the first order about a point $\hat{X}_i \in C^{-1}(D_i)$ and $\hat{X}_0 = 0$ (see Fig. 1):

$$f(x) + g(x)u \simeq A_i x + w_i + B_i u \quad \text{on} \quad C^{-1}(D_i) \tag{6}$$

where

$$A_i = \partial f(x)/\partial x^T|_{x=\hat{X}_i}, \; w_i = f(\hat{X}_i) - A_i\hat{X}_i,$$
$$B_i = g(\hat{X}_i).$$

Make an approximation of (4) by

$$\dot{\mathbf{X}} = \bar{A}_i\mathbf{X} + \bar{B}_i u \quad \text{on} \quad C^{-1}(D_i) \times R \tag{7}$$

where

$$\bar{A}_i = \begin{bmatrix} A_i & w_i \\ 0 & -\sigma_i \end{bmatrix}, \bar{B}_i = \begin{bmatrix} B_i \\ 0 \end{bmatrix}.$$

An application of the linear optimal control theory[2] to (5) and (7) yields

$$u_i(\mathbf{X}) = -R^{-1}\bar{B}_i^T\mathbf{P}_i\mathbf{X} \tag{8}$$

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

$$\mathbf{P}_i\bar{A}_i + \bar{A}_i^T\mathbf{P}_i + \mathbf{Q} - \mathbf{P}_i\bar{B}_i R^{-1}\bar{B}_i^T\mathbf{P}_i = 0. \tag{9}$$

Introduce a gradient optimization automatic choosing function of sigmoid type with weight d_i:

$$I_i(x) = d_i \prod_{j=1}^{L}\Big\{1 - \frac{1}{1+\exp\left(2N_{1i}\left(C_j(x) - a_{ij}\right)\right)} - \frac{1}{1+\exp\left(-2N_{1i}\left(C_j(x) - b_{ij}\right)\right)}\Big\} \tag{10}$$

where N_{1i}:positive real value, $-\infty \le a_{ij}$, $b_{ij} \le \infty$. $I_i(x)$ is analytic and almost unity on $C^{-1}(D_i)$, otherwise almost zero when $d_i = 1$ (see Fig. 2).

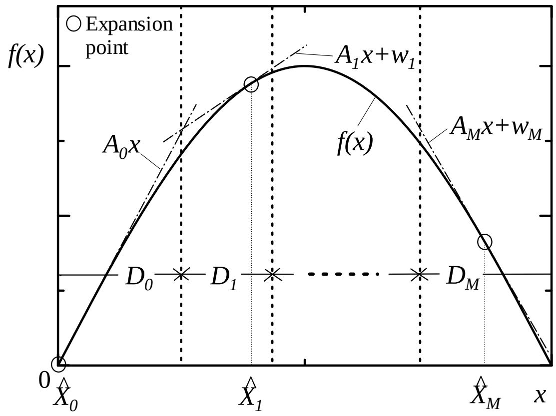

Fig. 1 Sectionwize linearization

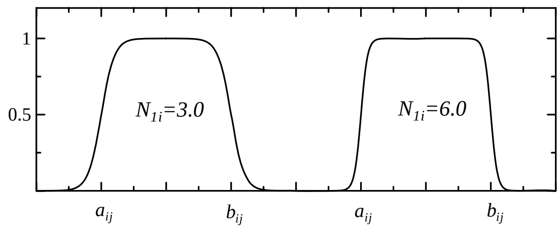

Fig. 2 Automatic Choosing Function(N_{1i}=$3.0, 6.0$)

Uniting $\{u_i(\mathbf{X})\}$ of (8) with $\{I_i(x)\}$ of (10) yields

$$\hat{u}(\mathbf{X}) = [\hat{u}(\mathbf{X})[1], \cdots, \hat{u}(\mathbf{X})[j], \cdots, \hat{u}(\mathbf{X})[r]]^T = \sum_{i=0}^{M} u_i(\mathbf{X}) I_i(x).$$

We finally have an augmented automatic choosing control which is satisfied with the constraint condition (2) by

$$u(\mathbf{X}) = [u(\mathbf{X})[1], \cdots, u(\mathbf{X})[j], \cdots, u(\mathbf{X})[r]]^T \tag{11}$$

where

$$u(\mathbf{X})[j] = \begin{cases} u_{j,max} & \text{if} \quad \hat{u}(\mathbf{X})[j] \ge u_{j,max} \\ u_{j,min} & \text{if} \quad \hat{u}(\mathbf{X})[j] \le u_{j,min} \\ \hat{u}(\mathbf{X})[j] & \text{otherwise} \end{cases}$$

$$(1 \le j \le r).$$

III. PARAMETER SELECTION BY GA

Introduce a Lyapunov function candidate:

$$V(\mathbf{X}) = \mathbf{X}^T \Pi(\mathbf{X}) \mathbf{X} \tag{12}$$

where

$$\Pi(\mathbf{X}) = \sum_{i=0}^{M} \mathbf{P}_i \Pi_i(x) \ ,$$

$$\Pi_i(x) = \eta_i \prod_{j=1}^{L} \left\{ 1 - \frac{1}{1+\exp\left(2N_2\left(C_j(x)-a_{ij}\right)\right)} - \frac{1}{1+\exp\left(-2N_2\left(C_j(x)-b_{ij}\right)\right)} \right\} \tag{13}$$

where $\mathbf{P}_i$ satisfies the Riccati equation (9). N_2 and η_i are positive real values. By the Lyapunov's direct method, the equilibrium point 0 is uniformly stable on a connected set:

$$\mathbf{D}_V = \left\{ x \in \mathbf{D} : V(\mathbf{X}) < \gamma, \, \dot{V}(\mathbf{X}) < 0 \right\}$$

where

$$\gamma = \inf \left\{ V(\mathbf{X}) : \mathbf{X} \neq 0, \, \dot{V}(\mathbf{X}) = 0 \right\}.$$

In order to make a stable region in the sense of Lyapunov as wide as possible, we define a performance

$$PI = -\gamma. \tag{14}$$

A set of parameters included in the control of (11) is

$$\bar{\Omega} = \{M, N_{1i}, d_i, a_{ij}, b_{ij}, \cdots\} \tag{15}$$

which is suboptimally selected by minimizing PI with the aid of GA[10] as follows.

<**ALGORITHM**>

step1:Apriori: Set values $\bar{\Omega}_{apriori}$ appropriately.

step2:Parameter: Choose $\Omega \subset \bar{\Omega}$ to be improved and rewrite

$$\Omega = \{N_{1i}, d_i, a_i, b_i, \cdots\} = \{\alpha_k : k = 1, \cdot\cdot, K\}.$$

step3:Coding: Represent each α_k with a binary bit string of $\widetilde{L}$ bits and then arrange them into one string of $\widetilde{L}K$ bits.

step4:Initialization: Randomly generate an initial population of $\widetilde{q}$ strings

$$\{\Omega_p : p = 1, \cdot\cdot, \widetilde{q}\}.$$

step5:Decoding: Decode each element α_k of Ω_p by

$$\alpha_k = (\alpha_{k,max} - \alpha_{k,min}) A_k / (2^{\widetilde{L}} - 1) + \alpha_{k,min}$$

where $\alpha_{k,max}$:maximum, $\alpha_{k,min}$:minimum, and A_k:decimal values of α_k.

step6:Lyapunov function: Make $\gamma = \gamma_p$ $(p = 1, \cdot\cdot, \widetilde{q})$ for Ω_p by using (12).

step7:Fitness value calculation: Calculate

$$PI_p = -\gamma_p$$

by (14), or fitness $F_p = -PI_p$.

step8:Reproduction: Reproduce each of individual strings with the probability of

$$F_p / \textstyle\sum_{j=1}^{\widetilde{q}} F_j.$$

step9:Crossover: Pick up two strings and exchange them at a crossing position by a crossover probability P_c.

step10:Mutation: Alter a bit of string (0 or1) by a mutation probability P_m.

step11:Repetition: Repeat step5$\sim$step10 until prespecified G-th generation. If unsatisfied, go to step2.

As a result, we have a suboptimal control $u(\mathbf{X})$ for the string with the best performance over all the past generations.

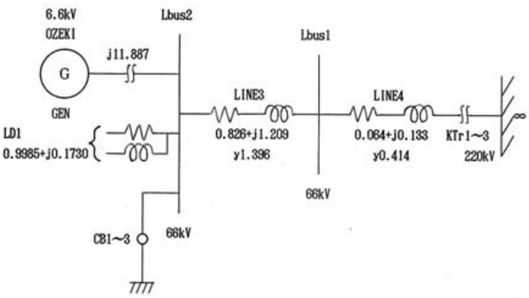

Fig. 3 Diagram of Ozeki-Power-Plant

IV. NUMERICAL EXAMPLE

Consider a field excitation control problem of power system. Fig. 3 is a diagram of Ozeki-Power-Plant of Kyushu Electric Power Company in Japan. This system is assumed to be described[7] by

$$\begin{aligned}
&\widetilde{M}\frac{d^2\delta}{dt^2} + \widetilde{D}\frac{d\delta}{dt} + P_e = P_{in} \\
&P_e = E_I^2 Y_{11}\cos\theta_{11} + E_I \widetilde{V} Y_{12}\cos(\theta_{12}-\delta) \\
&E_I + T'_{d0}\frac{dE'_q}{dt} = E_{fd} \\
&E_I = E'_q + (X_d - X'_d) I_d \\
&I_d = -E_I Y_{11}\sin\theta_{11} - \widetilde{V} Y_{12}\sin(\theta_{12}-\delta) \\
&\widetilde{D} = \widetilde{V}^2 \Big\{ \frac{T''_{d0}(X'_d - X''_d)}{(X'_d + X_e)^2}\sin^2\delta \\
&\qquad\qquad + \frac{T''_{q0}(X_q - X''_q)}{(X_q + X_e)^2}\cos^2\delta \Big\},
\end{aligned}$$

where δ: phase angle, $\dot{\delta}$: rotor speed, $\widetilde{M}$: inertia coefficient, $\widetilde{D}(\delta)$: damping coefficient, P_{in}: mechanical input power, $P_e(\delta)$: generator output power, $\widetilde{V}$: reference bus voltage, E_I: open circuit voltage, E_{fd}: field excitation voltage, X_d: direct axis synchronous reactance, X'_d: direct axis transient reactance, X_e: external impedance, $Y_{11}\angle\theta_{11}$: self-admittance of the network, $Y_{12}\angle\theta_{12}$: mutual admittance of the network, and $I_d(\delta)$: direct axis current of the machine. Put x=$[x[1], x[2], x[3]]^T$=$[E_I - \hat{E}_I, \delta - \hat{\delta}_0, \dot{\delta}]^T$ and $u = E_{fd} - \hat{E}_{fd}$, so that

$$\begin{bmatrix} \dot{x}[1] \\ \dot{x}[2] \\ \dot{x}[3] \end{bmatrix} = \begin{bmatrix} f_1(x) \\ f_2(x) \\ f_3(x) \end{bmatrix} + \begin{bmatrix} g_1(x) \\ 0 \\ 0 \end{bmatrix} u \tag{16}$$

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where

$$\begin{aligned} f_1(x) &= -\frac{1}{kT_{d0}}(x[1]+\hat{E}_I-\hat{E}_{fd}) \\ &\quad +\frac{(X_d-X_d')\widetilde{V}Y_{12}}{k}X_3\cos(\theta_{12}-x[2]-\hat{\delta}_0) \\ f_2(x) &= x[3] \\ f_3(x) &= -\frac{\widetilde{V}Y_{12}}{\widetilde{M}}(x[1]+\hat{E}_I)\cos(\theta_{12}-x[2]-\hat{\delta}_0) \\ &\quad -\frac{Y_{11}\cos\theta_{11}}{\widetilde{M}}(x[1]+\hat{E}_I)^2-\frac{\widetilde{D}}{\widetilde{M}}x[3]+\frac{P_0}{\widetilde{M}} \\ g_1(x) &= \frac{1}{kT_{d0}}, \quad k=1+(X_d-X_d')Y_{11}\sin\theta_{11}. \end{aligned}$$

Parameters are

$$\begin{array}{llll} \widetilde{M}= & 0.016095[pu] & T_{d0}= & 5.09907[sec] \\ \widetilde{V}= & 1.0[pu] & P_0= & 1.2[pu] \\ X_d= & 0.875[pu] & X_d'= & 0.422[pu] \\ Y_{11}= & 1.04276[pu] & Y_{12}= & 1.03084[pu] \\ \theta_{11}= & -1.56495[pu] & \theta_{12}= & 1.56189[pu] \\ X_e= & 1.15[pu] & X_d''= & 0.238[pu] \\ X_q= & 0.6[pu] & X_q''= & 0.3[pu] \\ T_{d0}''= & 0.0299[pu] & T_{q0}''= & 0.02616[pu] \\ \hat{E}_I= & 1.52243[pu] & \hat{\delta}_0= & 48.57^\circ \\ \dot{\hat{\delta}}_0= & 0.0[deg/sec] & \hat{E}_{fd}= & 1.52243[pu]. \end{array}$$

Set $\mathbf{X} = [x^T, x[4]]^T = [x[1], x[2], x[3], x[4]]^T$, $n = 3$, $\hat{X}_0 = \hat{\delta}_0 = 48.57^\circ$, $d_0 = 1$, $C(x)$=$x[2]$, $L = 1$, $\mathbf{Q}$=diag$(1,1,1,1)$,R=1,$\sigma_i = 0.33294(0\le i\le M)$ and $x[4](0)$= 1. Experiments are carried out for the new control(AACC), and the ordinary linear optimal control(LOC)[2].

1) AACC(New,umax=5):
M=1, $\hat{X}_1 = 80^\circ$, $D_0 = (-\infty, a-\hat{\delta}_0]$, D_1=$[a-\hat{\delta}_0, \infty)$. The parameters are suboptimally selected along the algorithm of section III. Ω=$\{\eta_i, N_{1i}, N_2, d_1, a\}$,$G$=100, $\widetilde{q}$=100, $\widetilde{L}$=8, P_c=0.8, P_m=0.03. The constrained input value is $u_{max} = -u_{min} = 5$. It results that η_i=3.258824, N_{10}=7.592941, N_{11}=3.710588, N_2=3.258824, d_1=0.332941 and a=59.705882°.

2) AACC(New,umax=10):
The parameters are suboptimally selected by using the same way of the AACC(New,umax=5). The constrained input value is $u_{max} = -u_{min} = 10$. It results that η_i=2.692941, N_{10}=8.408235, N_{11}=5.923529, N_2=5.270588, d_1=0.333529 and a=66.470588°.

3) AACC(Old,umax=5):
The parameters are suboptimally selected by using the same way of the AACC(New,umax=5) which uses the fixed weight of the gradient optimization automatic choosing function[8]. Ω=$\{\eta_i, N_{1i}, N_2, a\}$. It results that η_i=0.372941, N_{10}=7.360000, N_{11}=3.865882, N_2=5.588235 and a=60.784314°.

4) AACC(Old,umax=10):
The parameters are suboptimally selected by using the same way of the AACC(Old,umax=5). The constrained input value is $u_{max} = -u_{min} = 10$. It results that η_i=2.931765, N_10=2.118824, N_{11}=0.488235, N_2=6.541176 and a=63.039216°.

Table I shows performances by the AACC(New), the AACC(Old) and the LOC. The cost function of Table I is

$$\widetilde{J} = \frac{1}{2}\int_0^{20}\left(\mathbf{X}^T\mathbf{Q}\mathbf{X} + u^T\mathbf{R}u\right)dt.$$

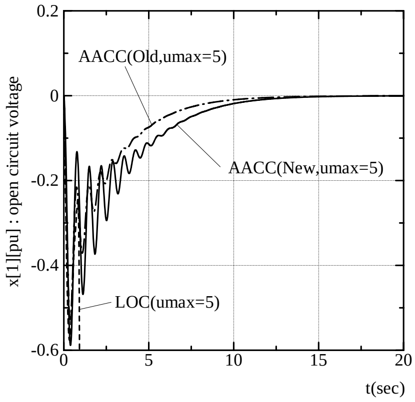

Fig. 4 Responses of LOC, AACC(Old), AACC(New) $(x^T(0) = [0, 1.0, 0])$

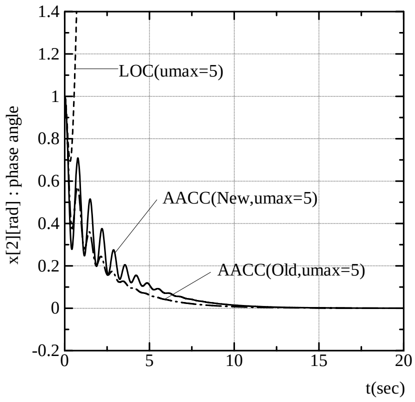

Fig. 5 Responses of LOC, AACC(Old), AACC(New) $(x^T(0) = [0, 1.0, 0])$

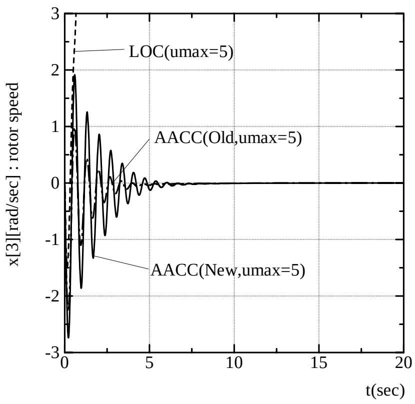

Fig. 6 Responses of LOC, AACC(Old), AACC(New) $(x^T(0) = [0, 1.0, 0])$

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TABLE I
PERFORMANCES

Method		$x^T(0)$: initial point				
		$[0, 0.4, 0]$	$[0, 1.0, 0]$	$[0, 1.2, 0]$	$[0, 1.3, 0]$	$[0, 1.377, 0]$
umax=5	LOC	0.95375	×	×	×	×
	AACC(Old)	0.92449	1.94488	1.91524	×	×
	AACC(New)	0.99706	2.68654	2.25723	1.91616	2.62815
umax=10	LOC	0.95375	×	×	×	×
	AACC(Old)	0.92527	1.96434	1.88441	2.24908	×
	AACC(New)	0.95353	2.60857	2.35065	2.00983	2.73808

× : very large value

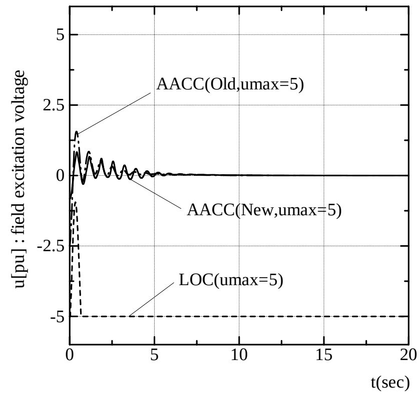

Fig. 7 Responses of LOC, AACC(Old), AACC(New) $(x^T(0) = [0, 1.0, 0])$

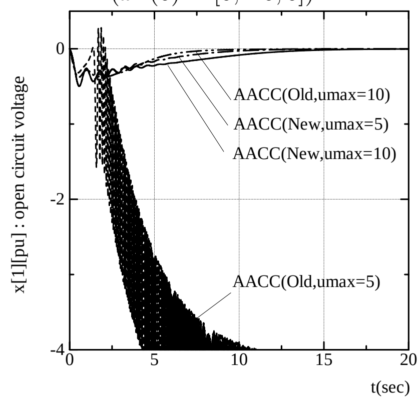

Fig. 8 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.3, 0])$

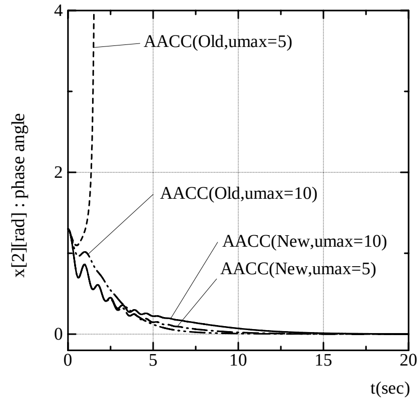

Fig. 9 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.3, 0])$

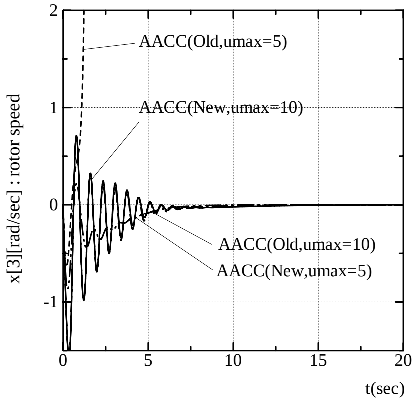

Fig. 10 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.3, 0])$

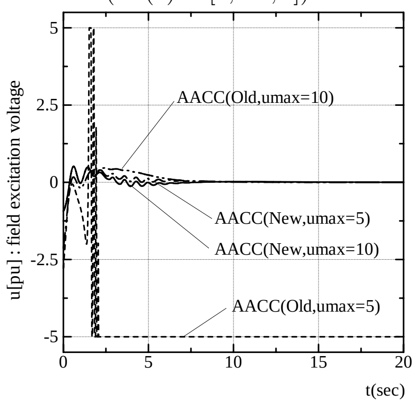

Fig. 11 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.3, 0])$

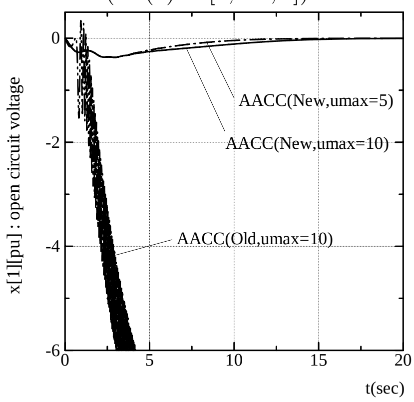

Fig. 12 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.377, 0])$

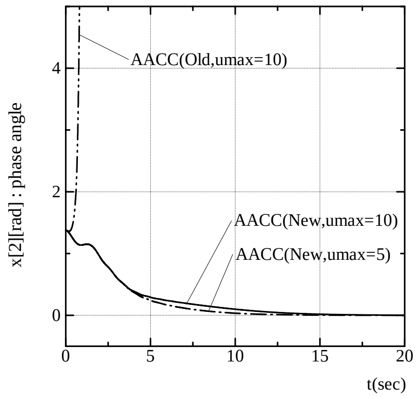

Fig. 13 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.377, 0])$

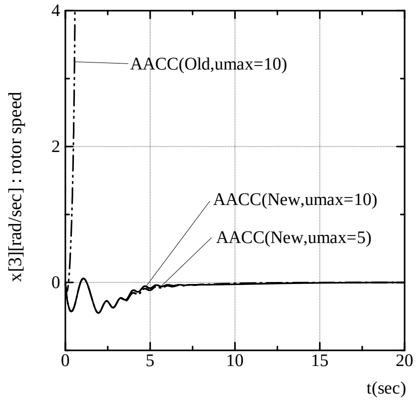

Fig. 14 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.377, 0])$

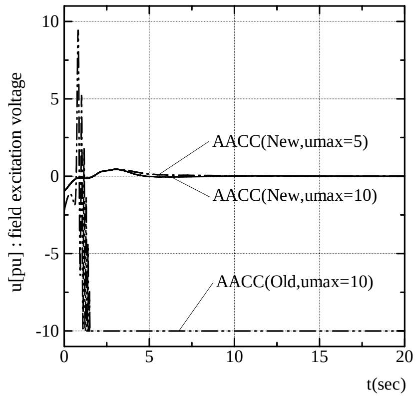

Fig. 15 Responses of AACC(Old), AACC(New) $(x^T(0) = [0, 1.377, 0])$

Figs. 4, 5, 6 and 7 show the responses in case of $x^T(0) = [0, 1.0, 0]$. Figs. 8, 9, 10 and 11 show the responses in case of $x^T(0) = [0, 1.3, 0]$. Figs. 12, 13, 14 and 15 show the responses in case of $x^T(0) = [0, 1.377, 0]$. These results indicate that the stable region of AACC(New) is better than the AACC(Old) and LOC.

V. Conclusions

We have studied an augmented automatic choosing control with constrained input designed by Lyapunov functions using the weighted gradient optimization automatic choosing functions for nonlinear systems. This approach was applied to a field excitation control problem of power system to demonstrate the splendidness of the AACC. Simulation results have shown that this controller could improve performance remarkably well.

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