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Adaptive Inverse Control of Excitation System with Actuator Uncertainty

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Abstract: - This paper addresses an inverse controller design for excitation system with changing parameters and nonsmooth nonlinearities in the actuator. The existence of such nonlinearities and uncertainty imposes a great challenge for the controller development. To address such a challenge, support vector machines (SVM) will be adopted to model the process and the controller is constructed using SVM. The SVM, used to approximate nonlinearities in the plant as well as the actuator, are adjusted by an adaptive law via back propagation (BP) algorithms. To guarantee convergence and for faster learning, adaptive learning rates and convergence theorems are developed. Simulations show that the proposed inverse controller has better performance in system damping and transient improvement.

Key-Words: - nonlnear control, inverse system, support vector machines, adaptive control, model identification, actuator uncertainty

1 Introduction

The excitation control of power generator is one of the most effective and economical techniques for improve dynamic voltage performance and voltage stability of power systems. It has been approached by classic control and linear modern control techniques with good results, but only locally valid. Due to the nonlinearilities of various components of power systems and the inherent characteristics of changing load, the operating points of power system may change during a daily cycle. As a result, a fixed controller that is optimal under one operating condition may become unsuitable for another operating condition. In view of this, engineers have applied the diverse control laws to make controller adapt to plant parameter changes. In the recent decades, various control techniques have been proposed for dealing with large parameter variations. For example, variable structure controls [1], feedback linearization techniques[2], Nonlinear adaptive controls[3-4], Robust Nonlinear Coordinated Control[5], and neural networks controller[6-8].

In real control systems, actuators, sensors and, more in general, a wide range of physical devices contain "nonsmooth" nonlinearities, such as backlash, dead zone or hysteresis [9]. Due to physical imperfections, indeed, such nonlinearities are always present in real plants, particularly in mechanical systems. Nevertheless, control design techniques usually applied in practice do often ignore the presence of such nonlinearities in system components. Although often neglected, these nonlinearities are particularly harmful, because they usually lead to deterioration of system performance. As discussed in [10], "Actuator and sensor nonlinearities are among the key factors limiting both static and dynamic performance of feedback control systems." They are the causes of oscillations, delays and inaccuracy.

In these papers, we will focus on a nonlinear controller design for excitation system with changing parameters and nonsmooth nonlinearities in the actuator. Here an adaptive inverse technique is constructed to cancel the effects of nonlinearities in the plant as well as in the actuator. Support vector machines (SVM)[11-12], a recently introduced machine learning method for pattern recognition and function estimation problems, is discussed in the implement of the proposed adaptive inverse technique. Here two SVM networks are utilized in this adaptive inverse technique, one act as the model identifier to estimate changing parameters as well as to provide plant information as learning signal for the inverse controller, the other is an inverse identifier which act as a adaptive inverse controller. General learning algorithms is employed in the offline learning of SVM networks, and they are adjusted by an adaptive law via back propagation algorithms. To guarantee convergence and for faster learning, an adaptive learning rates and convergence theorems are developed in this paper.

2 Problem Formulation

We consider the third order model of a generator connected to an infinity-bus, called a single machine infinite bus (SMIB) system, which is as follows [13]:

$$\dot{\delta} = \omega - \omega_0 \,,$$

$$\dot{E}_q' = -\frac{x_{d\Sigma}}{x_{d\Sigma}' T_{d0}'} E_q' + \frac{V_s \cos\delta}{x_{d\Sigma}' T_{d0}'}(x_d - x_d') + \frac{V_f}{T_{d0}'}$$

$$\dot{\omega} = \frac{\omega_0}{H} P_m - \frac{D}{H}(\omega - \omega_0) - \frac{\omega_0 E_q' V_s}{H x_{d\Sigma}'} \sin\delta - \frac{\omega_0 V_s^2}{2H}\left(\frac{x_d' - x_q}{x_{d\Sigma}' x_{q\Sigma}}\right)\sin 2\delta \quad (1)$$

where variables are presented in detail in [13], and parameter x_d' is supposed to be randomly distributed in a certain area as changing parameter. If the power angle δ is as the output y and the excitation voltage V_f as the input u, the following third order differential equation can be deduced from (1):

$$\dddot{y} = \frac{D}{H}\ddot{y} - \frac{\omega_0}{H}\frac{E_q' V_s \dot{y}\cos y}{x_{d\Sigma}'} - \frac{\omega_0}{H}\frac{V_s^2 \dot{y}(x_d' - x_q)\cos 2y}{x_{d\Sigma}' x_{q\Sigma}}$$

$$-\frac{\omega_0 V_s \sin y}{H x_{d\Sigma}'} \times \left[-\frac{x_{d\Sigma} E_q'}{x_{d\Sigma}' T_{d0}'} + \frac{(x_d - x_d')V_s \cos y}{x_{d\Sigma}' T_{d0}'}\right] - \frac{\omega_0 V_s \sin y}{H x_{d\Sigma}' T_{d0}'} u \quad (2)$$

Since

$$E_q' = \frac{2[\omega_0 P_m x_{d\Sigma}' - D(\dot{y} - \omega_0) - H\ddot{y} x_{d\Sigma}'] - \omega_0 V_s^2 (x_d' - x_q)\sin 2y}{\omega_0 V_s \sin y} \quad (3)$$

Therefore (2) can be denoted in the form of nonlinear mapping

$$y = f(\dddot{y}, \ddot{y}, \dot{y}, u) \quad (4)$$

During the operation range of the power angle ($0 < \delta < \pi$) there exists a $\partial\dddot{y}/\partial u \neq 0$. In other words, the excitation control system is invertible and so the following inverse system exists:

$$u = g(\dddot{y}, \ddot{y}, \dot{y}, y) \quad (5)$$

From (5), in the viewing of inverse system method, the control signal u can be determined by $(\dddot{y}, \ddot{y}, \dot{y}, y)$. By using the n-order approximation[14], one has $T\dot{y} = y(k+1) - y(k)$, $T\dot{u} = u(k+1) - u(k)$, $T^2\ddot{y} = y(k+1) - 2y(k) + y(k-1)$, and $T^3\dddot{y} = y(k+1) - 3y(k) + 3y(k-1) - y(k-2)$ with T is the sampling period. In this way, (4) and (5) can then be described in the discrete system as:

$$y(k+1) = F(y(k), y(k-1), y(k-2), u(k))$$
$$u(k) = G(y_d(k+1), y(k), y(k-1), y(k-2)) \quad (6)$$

where $u(k) \in R$ and $y(k+1) \in R$ are the control input and system output at time step k and $k+1$, respectively, $F : R^n \times R^n \to R$, and $F \in C^\infty$. Here $F(\cdot)$ and $G(\cdot)$ in (6) are regarded as two unknown nonlinear mapping, while both the relative degree d and plant order n are known. Equation (6) is the so called nonlinear autoregressive moving average (NARMA) model. For a general discrete-time nonlinear system, the NARMA model is an exact representation of its input–output behavior over the range in which the system operates. In the viewing of inverse system method, $u(k)$ can be determined by the sequence vector of $y(k)$, and $y(k+1)$ is replaced by $y_d(k+1)$ in (6) in the essential early or late relation.

In this paper the following nonsmooth nonlinearities have been considered in the actuator:

Dead-Zone: The analytical expression of the dead-zone characteristic is.

$$\omega(t) = N(u(t)) = \begin{cases} m_r(u(t) - b_r), & u(t) \geq b_r \\ 0, & b_l < u(t) < b_r \\ m_l(u(t) - b_l), & u(t) \leq b_r \end{cases} \quad (7)$$

where $b_r \geq 0$, $b_l \leq 0$ and $m_r > 0$, $m_l < 0$ are constants. In general, the break points $|b_r| \neq |b_l|$ and the slopes $m_r \neq m_l$.

Backlash: The backlash nonlinearity is described by

$$\omega(t) = N(u(t)) = \begin{cases} m(u(t) - B_r), \mathit{if}\ \dot{\omega}(t) > 0\ \mathit{and}\ \omega(t) = m(u(t) - B_r) \\ m(u(t) - B_l), \mathit{if}\ \dot{\omega}(t) < 0\ \mathit{and}\ \omega(t) = m(u(t) - B_l) \\ \omega(t_-), \quad \mathit{otherwise} \end{cases} \quad (8)$$

where $m \geq m_0$ is the slope of the lines, with m_0 being a small positive constant, and $B_r > 0$, $B_l < 0$ are constant parameters, $u(t_-)$ means no change occurs in the output control signal $u(t)$.

The idea pursued in this paper is to design adaptive inverse control laws that are able to achieve robust performances in the presence of above changing parameters and nonsmooth nonlinearities.

Assumption 1[9]**.** The desired trajectory $y_d(k)$ and its $(n-1)$ th order derivatives are known and bounded in a compact set Ω_d.

The control objectives are to design an adaptive control law such that: (1) The closed-loop system is stable in the sense that all the signals in the loop are bouned; (2) The tracking error $e(k) = y_d(k) - y(k)$ is adjustable during the transient period by an explicit choice of design parameters and $\lim_{k\to\infty}|y_d(k) - y(k)| \leq \delta_1$ for an arbitrary specified bound δ_1.

3 Function Approximation using SVM

In the SVM approach, one maps the data into a higher dimensional input space and one constructs an optimal separating hyperplane in this space. Hereby one exploits Mercer's theorem, which avoids an explicit formulation of this nonlinear mapping. Compared with ANN and standard SVM, least squares SVM(LS-SVM)[12] has the following advantages: no number of hidden units has to be determined, no centers has to be specified for the Gaussian kernel, and fewer parameters have to be prescribed, so LS-SVM is employed here for the identification and control of considered system.

Let $\{x_t, y_t\}_{t=1}^N$ be the set of input/output training data with input x_t and output y_t . Consider the regression model $y_t = f(x_t) + e_t$ where x_t are deterministic points, f is a smooth function and e_t are uncorrelated errors. For the purpose of estimating the nonlinear f , the following model is assumed:

$$f(x) = \omega^T \varphi(x) + b \tag{9}$$

where $\varphi(x)$ denotes a infinite dimensional feature map. The regularized cost function of the LS-SVM is given as:

$$\min J(\omega, e) = \frac{1}{2}\omega^T\omega + \gamma\frac{1}{2}\sum_{t=1}^N e_t^2$$

$$\text{s.j. } y_t = \omega^T\varphi(x_t) + b + e_t \,, t = 1, \cdots, N \tag{10}$$

In order to solve this constrained optimization, a Lagrangian is constructed:

$$L(w,b,e;\alpha) = J(w,e) - \sum_{t=1}^N \alpha_t \{w^T\varphi(x_t) + b + e_t - y_t\} \tag{11}$$

with α_t the Lagrange multipliers. The conditions for optimality are given by:

$$\partial L/\partial w = 0 \to w = \sum_{t=1}^N \alpha_t \varphi(x_t)$$

$$\partial L/\partial b = 0 \to \sum_{t=1}^N \alpha_t = 0, \cdots, N$$

$$\partial L/\partial e_t = 0 \to \alpha_t = \gamma e_t$$

$$\partial L/\partial \alpha_t = 0 \to y_t = \omega^T\varphi(x_t) + b + e_t \tag{12}$$

Substituting (9-11) into (12) yields the following set of linear equations:

$$\begin{bmatrix} 0 & 1_N^T \\ 1_N & \Omega + \gamma^{-1} I_N \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{13}$$

with $y = [y_1, \cdots, y_N]^T$, $1_N = [1, \cdots, 1]^T$, $\alpha = [\alpha_1, \cdots, \alpha_N]^T$, $\Omega_{ij} = K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$.

The resulting LS-SVM model can be evaluated at a new point x_* as:

$$\hat{f}(x_*) = \sum_{t=1}^M \alpha_t K(x_*, x_t) + b \tag{14}$$

where M is the number of support vectors (SVs), $K(\cdot,\cdot)$ is kernel function, α_k , b are the solutions to (13). Here Gaussian kernel function $K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / (2\sigma^2))$ is selected. As the training of SVM is equivalent to a linear programming problem, it can realize global optimization effectively. Moreover, the learning results decide the number of SVs and this selects the nodes of hidden layer of SVM networks.

It is well known that SVM generalization performance depends on a good setting of hyper-parameters and the kernel parameters. Bayesian evidence framework is an effective ways for parameters optimization of LS-SVM regression, and this approach is described in detail in [15]. According to the Bayesian evidence theory, the inference is divided into three distinct levels. Training of the LS-SVM regression can be statistically interpreted in Level 1 inference. The optimal regularization parameter can be inferred in Level 2. The optimal kernel parameter selection can be performed in Level 3.

4 Model Identifier and Inverse Model Identifier

The excitation system with changing parameters and nonlinear actuator are modeled by a SVM identifier (SVMI) as Fig.1(a), which estimates parameters changing as well as provides plant information as learning signal for the inverse controller. SVM is also used in identifying the inverse model of the plant and actuator called SVM inverse identifier (SVMII) in Fig.1(b), which serves as an inverse controller. The inputs of SVMI are $[u(k), y(k-1), y(k-2), y(k-3)]^T$, the output of SVMI is $\hat{y}(k)$ corresponding to the desired output $y(k)$ .Let $Y_I(k)$ be $[u(k), y(k-1), y(k-2), y(k-3)]^T$, then

$$\hat{y}(k) = \hat{F}(Y_I(k)) = \sum_{t=1}^M \alpha_t K(Y_I(k), Y_I(t)) + b$$

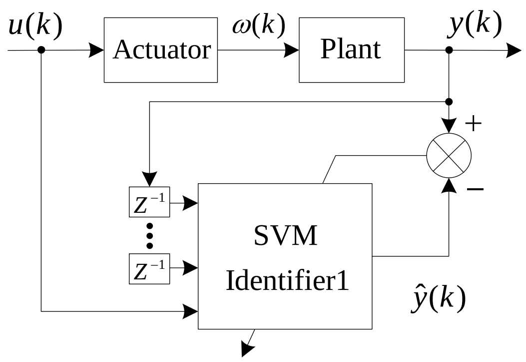
$$= W_I^T \cdot \Phi_I(k) + b \tag{15}$$

where $W_I = [\alpha_1, \alpha_2, \cdots, \alpha_M]^T$ are the weight vectors of LS-SVM networks as in (14), $\Phi_I(k) = [K(Y_I(k), Y_I(1)), \cdots, K(Y_I(k), Y_I(M))]^T$ are the outputs of the kernel function. The inputs of SVMII are $[y(k), \cdots, y(k-3)]^T$, the output of SVMII is $\hat{u}(k)$. Let $Y_C(k)$ be $[y(k), \cdots, y(k-3)]^T$,then

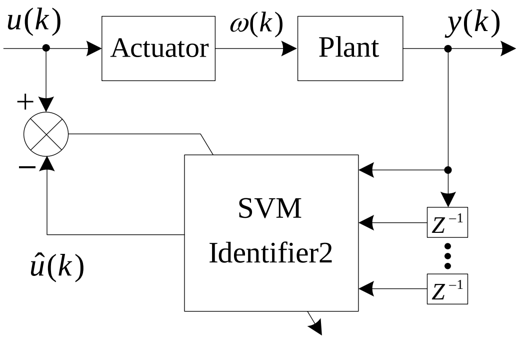
$$\hat{u}(k) = \hat{G}(Y_C(k)) = \sum_{t=1}^M \alpha_t K(Y_C(k), Y_C(t)) + b$$

$$= W_C^T \cdot \Phi_C(k) + b \tag{16}$$

where $W_C = [\alpha_1, \alpha_2, \cdots, \alpha_M]^T$ are the weight vectors of LS-SVM networks, $\Phi_C(k) =$ $[K(Y_C(k), Y_C(1)), \cdots, K(Y_C(k), Y_C(M))]^T$ are the outputs of the kernel function.



(a) SVM identifier (SVMI)



(b) SVM inverse identifier(SVMII)

Fig1 Structure of the SVM identifiers

5 Adaptive Inverse Controller Design

5.1 The structure of adaptive inverse controller

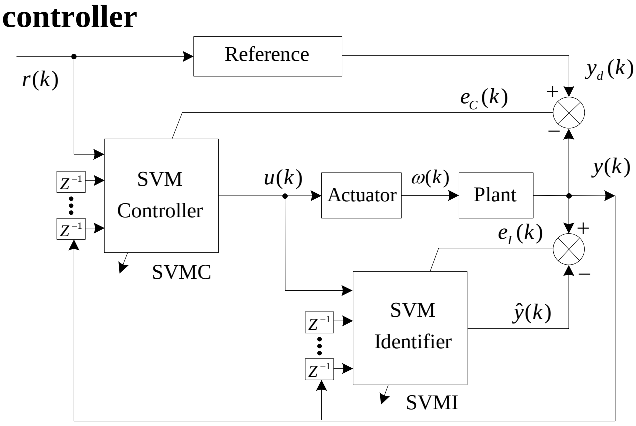


Fig.2 Structure of the proposed adaptive inverse controller

Fig. 2 shows the block diagram of the adaptive inverse control system which includes two SVM networks, that is, SVMC and SVMI. Here, SVMC is just SVMII in Fig.1(b), and SVMI is just the same as in Fig.1(a). The inputs to SVMC are the reference input $r(k)$, the previous plant output $[y(k-1),\cdots,y(k-3)]$, the output of SVMC is the control signal $u(k)$. Using the back-propagation (BP) algorithm, the weights of SVMC are online adjusted such that the error $e_C(k)$, $e_C(k)=y_d(k)-y(k)$, approaches a small value. When SVMC is in training, the information on the process is needed and SVMI is used to estimate the plant sensitivity y_u. The current control signal $u(k)$ and previous plant output $[y(k-1), y(k-2), y(k-3)]$ are the inputs to SVMI, and the output of SVMI is $\hat{y}(k)$. Let $y_d(k)$ and $y(k)$ be the desired and actual responses of the plant, then an error function for SVMC can be defined as:

$$E_C=\frac{1}{2}(y_d(k)-y(k))^2 \tag{17}$$

The error function in (17) is also modified for the SVMI as:

$$E_I=\frac{1}{2}(y(k)-\hat{y}(k))^2 \tag{18}$$

The gradient of error in (17) with respect to the weight vector W_C is represented by

$$\begin{aligned}\frac{\partial E_C}{\partial W_C}&=-e_C(k)\frac{\partial y(k)}{\partial W_C}\\ &=-e_C(k)y_u(k)\frac{\partial u(k)}{\partial W_C}=-e_C(k)y_u(k)\Phi_C(k)\end{aligned} \tag{19}$$

with $y_u(k)=\dfrac{\partial y(k)}{\partial u(k)}$ represents the *sensitivity* of the plant with respect to its input.

In the case of the SVMI, the gradient of error in (18) simply becomes

$$\frac{\partial E_I}{\partial W_I}=-e_I(k)\frac{\partial \hat{y}(k)}{\partial W_I}=-e_I(k)\frac{\partial O_I(k)}{\partial W_I}=-e_I(k)\Phi_I(k) \tag{20}$$

5.2 Learning algorithm of adaptive inverse controller

(1) Back-propagation for SVMI.

From (20), the negative gradient of the error with respect to a weight vector is:

$$-\frac{\partial E_I}{\partial W_I}=e_I(k)\frac{\partial O_I(k)}{\partial W_I}=e_I(k)\Phi_I(k) \tag{21}$$

The weights can now be adjusted following a gradient method as

$$W_I(n+1)=W_I(n)+\eta(-\frac{\partial E_I}{\partial W_I}) \tag{22}$$

where η is a learning rate.

(2) Back-propagation for SVMC.

In the case of SVMC, from (19), the negative gradient of the error with respect to a weight vector is:

$$-\frac{\partial E_C}{\partial W_C} = e_C(k) y_u(k) \frac{\partial O_C(k)}{\partial W_C} = e_C(k) y_u(k) \Phi_C(k) \tag{23}$$

This unknown value $y_u(k)$ can be estimated by using the SVMI. When the SVMI is trained, the behavior of the SVMI is close to the plant, i.e., $y(k) \approx \hat{y}(k)$.

Once the training process is done, the sensitivity can be approximated as:

$$y_u(k) = \frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial \hat{y}(k)}{\partial u(k)} \tag{24}$$

Applying the chain rule to (21), and noting that $\hat{y}(k) = O_I(k)$ of (15).

$$\frac{\partial \hat{y}(k)}{\partial u(k)} = \frac{\partial O_I(k)}{\partial u(k)} = -u(k) W_I^T \cdot \frac{\Phi_I(k)}{\sigma^2} \tag{25}$$

Therefore

$$y_u(k) \approx \frac{\partial \hat{y}(k)}{\partial u(k)} = -u(k) \cdot W_I^T \cdot \frac{\Phi_I(k)}{\sigma^2} \tag{26}$$

5.3 Convergence and stability based on Lyapunov function

The update rule of (22) calls for a proper choice of η. For a small value of η, the convergence is guaranteed but the speed is very slow; on the other hand if η is too big, the algorithm becomes unstable. This section develops a adaptive learning rate in selecting η properly. A discrete-type Lyapunov function can be given by:

$$V(k) = \frac{1}{2} e^2(k) \tag{27}$$

Thus, the change of the Lyapunov function is obtained by:

$$\Delta V(k) = V(k+1) - V(k)$$
$$= \frac{1}{2}[e^2(k+1) - e^2(k)] = \Delta e(k)[e(k) + \frac{\Delta e(k)}{2}] \tag{28}$$

The error difference due to the learning can be represented by

$$e(k+1) = e(k) + \Delta e(k) = e(k) + [\frac{\partial e(k)}{\partial W}]^T \Delta W \tag{29}$$

5.3.1 Convergence of SVMI

From the update rule of (21) and (22)

$$\Delta W_I = -\frac{\eta_I e_I(k) \partial e_I(k)}{\partial W_I} = \frac{\eta_I e_I(k) \partial O_I(k)}{\partial W_I} \tag{30}$$

Theorem 1: Let η_I be the learning rate for the weights of SVMI and $g_{I,\max}$ be defined as $g_{I,\max} := \max_k \|g_I(k)\|$ where $g_I(k) = \frac{\partial O_I(k)}{\partial W_I}$, and $\|\cdot\|$ is the usual Euclidean norm. Then the convergence is guaranteed if η_I is chosen as

$$0 < \eta_I < \frac{2}{g_{I,\max}^2} \tag{31}$$

Proof: From (28)-(30), $\Delta V(k)$ can be represented as

$$\Delta V(k) = \Delta e_I(k)[e_I(k) + \frac{\Delta e_I(k)}{2}]$$
$$= [\frac{\partial e_I(k)}{\partial W_I}]^T \eta_I e_I(k) \frac{\partial O_I(k)}{\partial W_I} \cdot \{e_I(k) + \frac{1}{2}[\frac{\partial e_I(k)}{\partial W_I}]^T \eta_I e_I(k) \frac{\partial O_I(k)}{\partial W_I}\} \tag{32}$$

For SVMI, $\frac{\partial e_I(k)}{\partial W_I} = -\frac{\partial O_I(k)}{\partial W_I}$, we obtain

$$\Delta V(k) = -\eta_I e_I^2(k) \left\| \frac{\partial O_I(k)}{\partial W_I} \right\|^2 + \frac{1}{2} \eta_I^2 e_I^2(k) \left\| \frac{\partial O_I(k)}{\partial W_I} \right\|^4 \equiv -\lambda_I e_I^2(k) \tag{33}$$

Let $g_I(k) = \frac{\partial O_I(k)}{\partial W_I}$, $g_{I,\max} := \max_k \|g_I(k)\|$, and let $\eta_1 = \eta_I g_{I,\max}^2$. Then

$$\lambda_I = \frac{1}{2} \|g_I(k)\|^2 \eta_I (2 - \eta_I \|g_I(k)\|^2)$$

$$= \frac{1}{2} \|g_I(k)\|^2 \eta_I (2 - \eta_1 \frac{\|g_I(k)\|^2}{g_{I,\max}^2}) \geq \frac{1}{2} \|g_I(k)\|^2 \eta_I (2 - \eta_1) > 0 \tag{34}$$

From (34), we obtain $\Delta V(k) = -\lambda_I e_I^2(k) < 0$ and $0 < \eta_1 < 2$, and (31) follows.

Remark 1: The convergence is guaranteed as long as (34) is satisfied, i.e., $\eta_I(2-\eta_1) > 0$ or $\frac{\eta_1(2-\eta_1)}{g_{I,\max}^2} > 0$. This implies that any η_1, $0 < \eta_1 < 2$, guarantees the convergence. However, the maximum learning rate which guarantees the most rapid or optimal convergence is corresponding to $\eta_1 = 1$, i.e., $\eta_I^* = \frac{1}{g_{I,\max}^2}$, which is the half of the upper limit in (31). This shows an interesting result that any other learning rate larger than η_I^* does not guarantee the faster convergence.

5.3.2 Convergence of SVMC

From the update rule of (23)

$$\Delta W_C = -\eta_C e_C(k) \frac{\partial e_C(k)}{\partial W_C}$$
$$= \eta_C e_C(k) y_u(k) \frac{\partial u(k)}{\partial W_C} = \eta_C e_C(k) y_u(k) \frac{\partial O_C(k)}{\partial W_C}$$

(35)

Theorem 2: Let η_C be the learning rate for the weights of SVMC and $g_{C,\max}$ be defined as $g_{C,\max} := \max_k \|g_C(k)\|$,where $g_C(k) = \frac{\partial O_C(k)}{\partial W_C}$,and $S_{\max} = \max_k \|y_u(k)\|$. Then the convergence is guaranteed if η_C is chosen as

$$0 < \eta_C < \frac{2}{S_{\max}^2 g_{C,\max}^2} \tag{36}$$

Proof: From (26), (29), (30) and (35), $\Delta V(k)$ can be represented as

$$\begin{aligned}\Delta V(k) &= \Delta e_C(k)[e_C(k) + \frac{1}{2}\Delta e_C(k)] \\ &= [\frac{\partial e_C(k)}{\partial W_C}]^T \eta_C e_C(k) y_u(k) \frac{\partial O_C(k)}{\partial W_C} \\ &\cdot \{e_C(k) + \frac{1}{2}[\frac{\partial e_C(k)}{\partial W_C}]^T \eta_C e_C(k) y_u(k) \frac{\partial O_C(k)}{\partial W_C}\}\end{aligned} \tag{37}$$

For SVMC, $\partial e_C(k)/\partial W_C = -y_u(k)\partial O_C(k)/\partial W_C$, we obtain

$$\begin{aligned}\Delta V(k) &= -\eta_C e_C^2(k) y_u^2(k) \left\|\frac{\partial O_C(k)}{\partial W_C}\right\|^2 \\ &+ \frac{1}{2}\eta_C^2 e_C^2(k) y_u^4(k) \left\|\frac{\partial O_C(k)}{\partial W_C}\right\|^4 \equiv -\lambda_C e_C^2(k)\end{aligned} \tag{38}$$

Conditions of (35) and (30) are similar except $y_u(k)$ needs to be incorporated in the SVMC. Therefore, it remains to find the limit on $y_u(k)$ .From (24) and (26):

$$\begin{aligned}S_{\max} &= |y_u(k)|_{\max} \\ &= \left| -\frac{u(k) \cdot W_I^T \cdot \Phi_I(k)}{\sigma^2} \right|_{\max} \le \frac{|W_I^T \Phi_I(k)|_{\max} |u(k)|_{\max}}{\sigma^2}\end{aligned} \tag{39}$$

where $S_{\max}$ is the limit on sensitivity and it is estimated from $|W_I^T \cdot \Phi_I(k)|$ and $|u(k)|$. As σ is a certain parameter and $\hat{y}(k) = W_I^T \cdot \Phi_I(k) + b$, we can determine $S_{\max}$ from the learning datasets in Section 4. Thus following the proof of Theorem 1, we obtain

$$0 < \eta_C < \frac{2}{S_{\max}^2 g_{C,\max}^2} \tag{40}$$

where $g_{C,\max} := \max_k \|g_C(k)\|$, $g_C(k) = \frac{\partial O_C(k)}{\partial W_C}$ and $S_{\max} = \max_k \|y_u(k)\|$.

Remark 2: In the case of SVMI, the optimal convergence rate is $\eta_C^* = \frac{1}{S_{\max}^2 g_{C,\max}^2}$, which is the half of the upper limit in (40).

The main implementation procedure of the proposed adaptive inverse controller for excitation system is summarized as follows:

Step1. Determine the input-output variables of SVMI and SVMII Fig.1 referring to the mathematical model of SMIB system as in (1)-(5);

Step2. Generate 'rich' enough exciting or testing signals as off-line training datasets;

Step3. Off-line modelling as well as off-line inverse modelling using general LS-SVM algorithms within Bayesian framework as in (15)-(16);

Step4. Establish the adaptive inverse control system in Fig.3, SVM networks serve as feed-forward controller as well as plant identifier;

Step5. On-line adaptation of SVM networks weights using back-propagation algorithm as in (21)-(26).

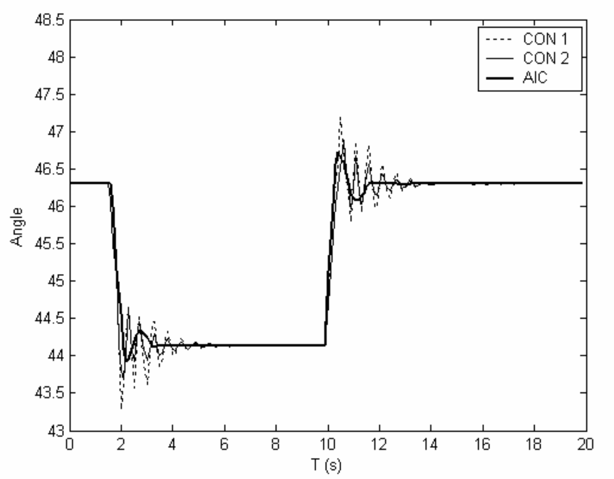
6 Simulation

The performances of the proposed adaptive inverse controller (AIC) are compared with other two controllers, one is the conventional AVR[6], and the other is the neuro-controller[7]. The actual parameters of the plant are given as: x_d =2.156, x_q =2.101, $x_d^{'}$ =0.265, x_T =0.1, x_L =1.46, D =5, H =8, $T_{d0}^{'}$ =10, P_m =0.6. For the simulation of changing parameters, parameter $x_d^{'}$ is randomly distributed between 0.22 and 0.28. The parameters of the dead zone are:, $b_r = 0.12$, $b_l = -0.15$, $m_r = 1.05$, $m_l = 1.1$. The parameters of the backlash are: $m = 1.05$, $B_r = 0.1$, $B_l = -0.1$.

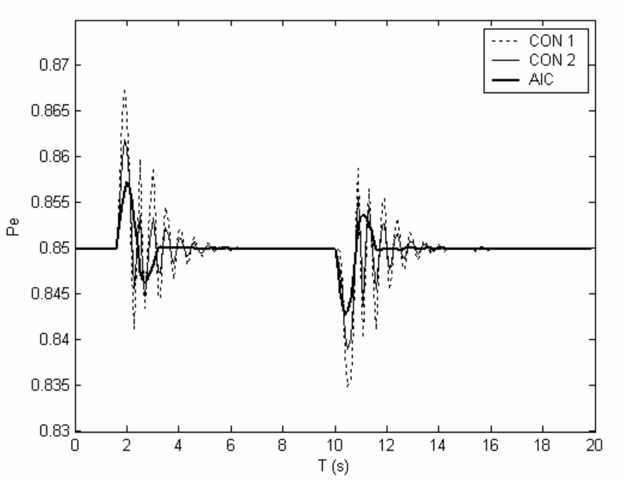
For the off-line learning, we first generate random signals as inputs $u(k)$ to the original system. Here we selected multi-amplitude varying-step square wave as testing signals. By sampling the inputs and outputs at high speed and after computing the derivatives off-line, we obtain training data $\{u(k), y(k), \cdots, y(k-3)\}$ .The training dataset consisted of 500 samples, and LS-SVM parameters are: $\sigma = 0.42$ and $\gamma = 200$. The off-line and online learning procedure of adaptive inverse controller are presented detailly in section 4 and section 5.

The simulation results of these three controller are displayed in Fig.3 and Fig.4, the conventional AVR controllers (CON1) are indicated by dashed lines, neuro-controller (CON2) response by solid lines, and the proposed adaptive inverse controller (AIC) response by thick solid lines.

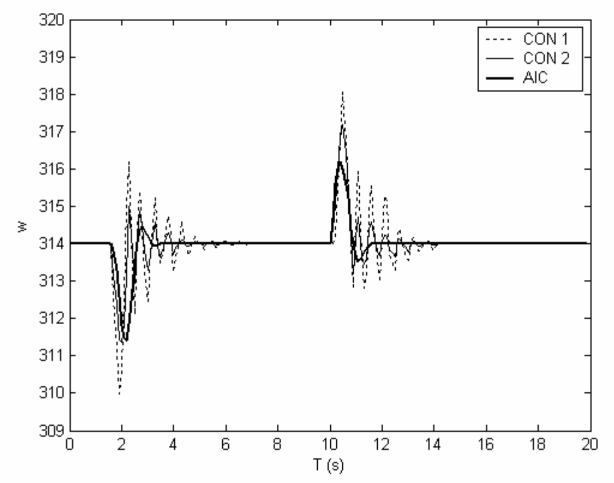
Example 1. Step changes in the reference voltage of the exciter. The plant is operating at a steady-state condition ($P_t = 1.0$ pu, $Q_t = 0.18$ pu.). At t=2 s, a 5% step increase in the reference voltage of the exciter is applied. At t=10 s, the 5% step increase is removed, and the system returns to its initial operating point. Fig. 3 show the performance of these controllers ,and adaptive inverse controller has better improvement in the transient system damping compared to other two controllers.



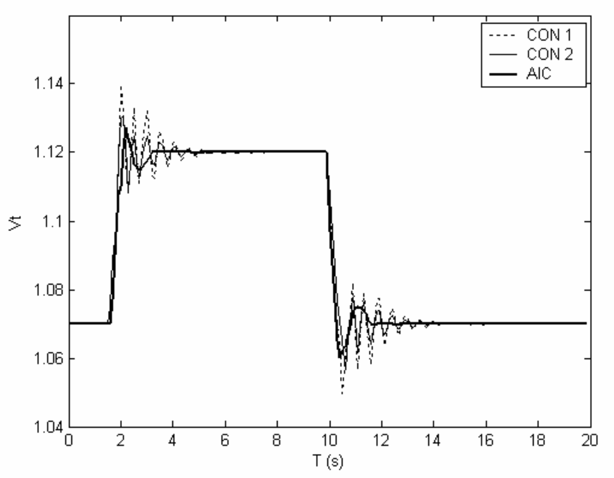
(a) rotor angle



(b) electrical power



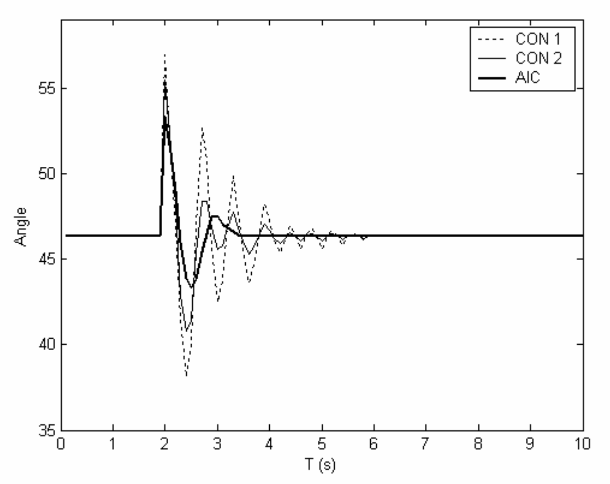
(c) speed



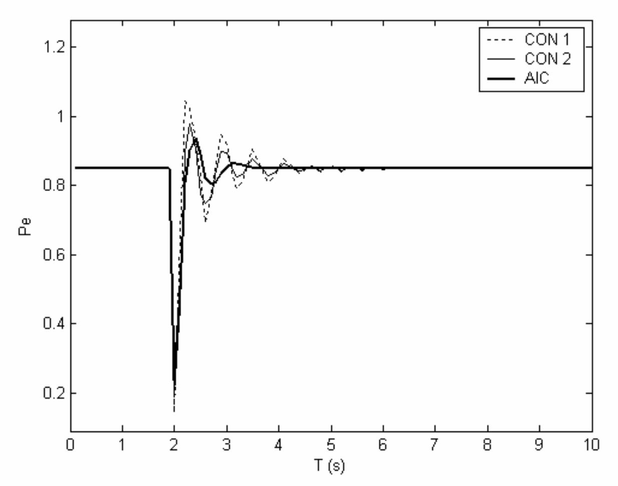
(d) terminal voltage

Fig.3 Response to step changes in the reference voltage of the exciter

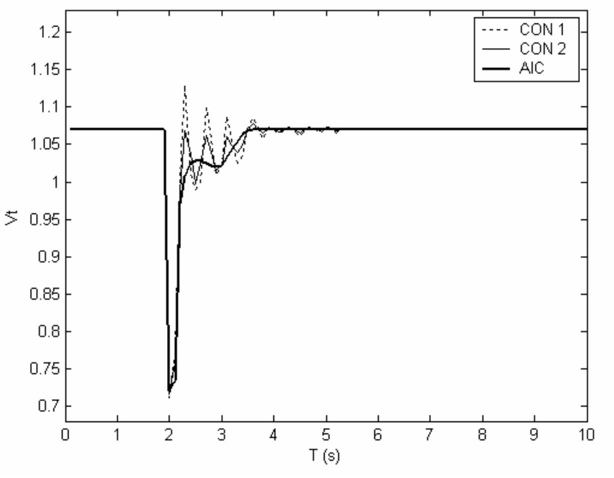
Example 2. Three phases short circuit test. A severe test is now carried out to evaluate the performances of these controllers under a large disturbance. At t=2 s, a temporary three-phase short circuit is applied at the infinite bus for 100 ms from 2 s to 2.1 s for the plant operating at the same steady state condition as previous test. Fig. 4 show that the adaptive inverse controller damp out the low frequency oscillations for the rotor angle and terminal voltage more effectively than other two controllers.



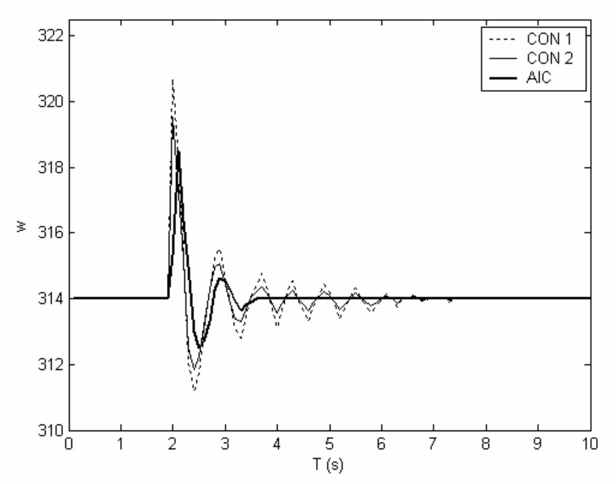
(a) rotor angle



(b) electrical power



(c) speed



(d) terminal voltage

Fig.4 Response to three phases short circuit test

In these two tests, SVM based adaptive inverse controller returns the system to stable conditions with a much better damping compared to other controllers, it can give a good result because it has the capility to learn from all kinds of operating states. Clearly, all the results verify our theoretical findings and demonstrate the effectiveness of the proposed control scheme.

7 Conclusion

In this paper, a novel adaptive inverse control system is proposed for excitation system with changing parameters and nonsmooth nonlinearities in the actuator. The SVM, used to approximate nonlinearities in the plant as well as the actuator, are adjusted by an adaptive law via back propagation algorithms. To guarantee convergence and for faster learning, adaptive learning rates and convergence theorems are developed. Results show that SVM adaptive inverse controller is very promising for future real-time applications. Not only does it improve the system damping and dynamic transient stability more effectively than other two controllers for the large disturbance, but also it has a faster transient response for a small disturbance.

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