Modeling and Control of NOx Decomposition Process with Operating-Point Dependent Dynamics

Hui Peng * Member
Tohru Ozaki ** Non-member
Yukihiro Toyoda *** Member
Valerie Haggan-Ozaki **** Non-member

A modeling and control method for a class of nonlinear systems whose dynamics depend on a process variable is presented. Two ExpARMAX (exponential ARMAX) models, a type of global NARMAX (nonlinear ARMAX) model are used to develop a multi-step predictive control algorithm which does not use on-line parameter estimation for the nonlinear system. One ExpARMAX model is used as the internal model of the predictive controller, and the other is used to predict future values of the measurable disturbances used in the predictive controller. The global ExpARMAX models only require off-line identification, and their local linearization forms are similar to linear ARMAX models. Case studies taken from a selective catalytic reduction (SCR) process for the reduction of Nitrogen Oxide (NOx) emissions of thermal power plants verify the effectiveness of the method.

Keywords : nonlinear system, local linearization, NARMAX models, identification, predictive control, SCR process

1. Introduction

In practical control problems, there is a class of nonlinear processes where the dynamic characteristics described by static gain, zero, and/or pole *etc.* depend on some process variable. If the variable is used efficiently, a more suitable model and control may be built for the process under study. In some industrial processes, it is not hard to find which variable caused the nonlinearity. For example, in thermal power plants, a signal called load demand causes the steam temperature response process and the SCR process to be nonlinear. In these processes, the relations between the input, output and exogenous variables may be treated as linear at certain fixed load levels or operating points, but at different load levels the linear relations are not the same, *i.e.* the gain, poles and zeros of the processes vary with the load level. This paper considers the modeling and control problem for such a class of nonlinear systems.

In the general nonlinear modeling framework, the time-varying linear model resorting to on-line parameter estimation usually uses a local linearization model for describing smooth nonlinear dynamics, especially in process control. If the operating-point of the process changes quickly, as happens in the SCR process, the model/plant mismatch may become very large because of the limit of convergence velocity in on-line parameter estimation. In the on-line estimation case, also, sometimes a suitable additional noise has to be added into the plant in the case when the plant dynamics are sufficiently exciting. This may not be acceptable for reasons of safety and reliability.

If a nonlinear system is BIBO stable, and thus may be approximated by a linear model around the operating point, then it can be described by a global NARMAX (nonlinear ARMAX) model[1]. The NARMAX model may represent a large class of nonlinear systems when necessary smoothness conditions are satisfied. However, the problem is how to construct a NARMAX model that may be conveniently estimated and be used to design a control algorithm. Johansen and Foss[2] discussed a method of constructing a global NARMAX model using a set of linear ARMAX models. In this way, the local ARMAX models valid within certain operating regions are interpolated to construct a global NARMAX model. Prasad *et al.*[3] applied the method to control thermal power plants. The load demand which results in system nonlinearity is used as a parameter, not contained in the models, which is used to switch among different plant models identified at different load levels. Although standard system identification algorithms can be used to identify the NARMAX model in that scheme, the identification of those local linear ARMAX models may be quite expensive of experiment time and cost in an actual application.

Before the idea of NARMAX model was presented, a nonlinear system local linearization method based on the exponential auto-regressive models[4] had been proposed. Although the exponential auto-regressive models are a special type of NARMAX model, many studies have shown that the exponential auto-regressive models are important tools for analyzing nonlinear phenomena. The several versions of the model built on the idea of exponential auto-regression models have been applied in different types of nonlinear time series analysis, such as the machine tool chatter analysis[5], among others. In process control, such as the temperature control of thermal power plants, there have also been applications[6~7].

In this paper, modeling and predictive control based on two global exponential auto-regressive-type models (ExpAR-type models) which do not use on-line parameter estimation are investigated for a class of systems with nonlinearly measurable signal dependent dynamics. One ExpAR-type model is used as an internal model for the proposed predictive control algorithm, and the other is built to predict the future values of some process variables treated as disturbances in order to improve control performance. The measurable signal resulting in system nonlinearity is introduced into the ExpAR-type models, so that the models may change their inherent characteristics to describe the

* Central South University, Changsha 410083, China. Currently a Visiting Researcher at the Institute of Statistical Mathematics. 4-6-7, Minami Azabu, Minato-ku, Tokyo 106-8569
** The Institute of Statistical Mathematics. 4-6-7, Minami Azabu, Minato-ku, Tokyo 106-8569
*** Niihama National College of Technology. 7-1, Yagumo-cho Niihama, Ehime 792-0805
**** Sophia University. 4, Yonbancho, Chiyoda-ku, Tokyo 102-0081

system dynamics at a new operating-point.

The generalized predictive control (GPC) algorithm[8] which uses on-line parameter estimation is effective in coping with some of the smooth nonlinear systems which may be modeled by using slowly time-varying linear model. In some of the nonlinear model-based GPC algorithms, it is very hard to represent the multi-step-ahead predictions of output as a linear formula of the future inputs. The result is that the optimal control may not be obtained easily[9]. Using the proposed nonlinear ExpAR-type model as an internal model to design a multi-step predictive controller may avoid the above problem. In this paper, some of the beneficial properties of GPC *i.e.* rolling optimization (on-line optimization), multi-step prediction based on an internal model and feedback correction will be applied to design a multi-step predictive controller. The goal is to avoid the problems which result from the on-line estimation of time-varying parameters, and to obtain satisfactory control performance.

2. Nonlinearity Caused by Process Signal

An example of a nonlinear system is provided by the SCR process in thermal power plants. This is a typical nonlinear system with nonlinearly measurable signal-dependent dynamics. The purpose of SCR process control is to reduce the NOx concentration in exhaust gas from the boiler of a thermal power plant by injecting a chemical reducing agent, NH3 gas, into the SCR device for protecting the environment. The diagram of the SCR device and control system configuration is shown in Fig.1.

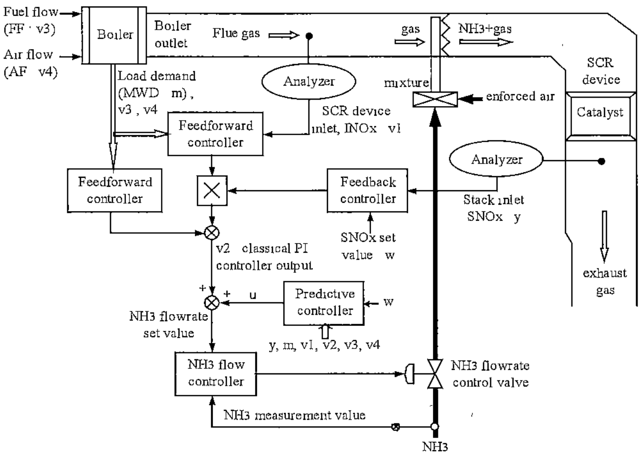

Fig. 1. A diagram of a SCR device and control system.

The main variables in a general SCR process[10] and the proposed predictive controller as is shown in Fig.1 are as follows

- $y(t)$: outlet NOx concentration which is the variable to be controlled;
- $u(t)$: the output of proposed predictive controller;
- $m(t)$: load demand causing nonlinearity;
- $v_1(t)$: disturbance, inlet NOx concentration;
- $v_2(t)$: disturbance, existing PI controller output;
- $v_3(t)$: disturbance, fuel flow;
- $v_4(t)$: disturbance, air flow.

The control performance of the existing feedback PID controller plus feedforward compensator is not satisfactory because of the effect of the larger time-delay (about 120 seconds) of the NOx analyzer and the load-dependent non-linearity, especially during larger load variation. Only under PID control, larger oscillations may occur in $y(t)$ around the set-point, so that too much of the expensive NH3 gases (input) have to be injected, resulting in an increased running cost. In general, improving control performance can reduce the consumption of NH3 gas.

At certain fixed load levels or operating points, the dynamics of the SCR process may be described using a linear model. Considering the system structure in Fig.1, a linear CARIMA model may be used to describe the process dynamics at some fixed load level as follows

$$\begin{aligned} A(q^{-1})y(t) &= B(q^{-1})u(t-k_d)+D_1(q^{-1})v_1(t-1) \\ &\quad + B(q^{-1})v_2(t-k_d)+D_3(q^{-1})v_3(t-k_d) \\ &\quad + D_4(q^{-1})v_4(t-k_d)+C(q^{-1})\xi(t)/\Delta \end{aligned} \quad \cdots\cdots (1)$$

here A, B, D_1, D_3, D_4, and C are the order $k_a, k_b, k_{d1}, k_{d3}, k_{d4}$, and k_c polynomials in the operator q^{-1} respectively; the first element of A and C are 1; ξ is a white noise, Δ is the difference operator $(1-q^{-1})$, and k_d is pure time-delay. A set of identification experiment data (sampling period 10s) is used to identify model (1) off-line by means of the iterative Gauss-Newton algorithm[11] (***IGNA***) which is realized by the function '***armax***' in the MATLAB System Identification Toolbox. The unit-step response, the static gains, and the pole/zero distribution maps of the SCR process obtained at three load levels are showed in Fig.2-4.

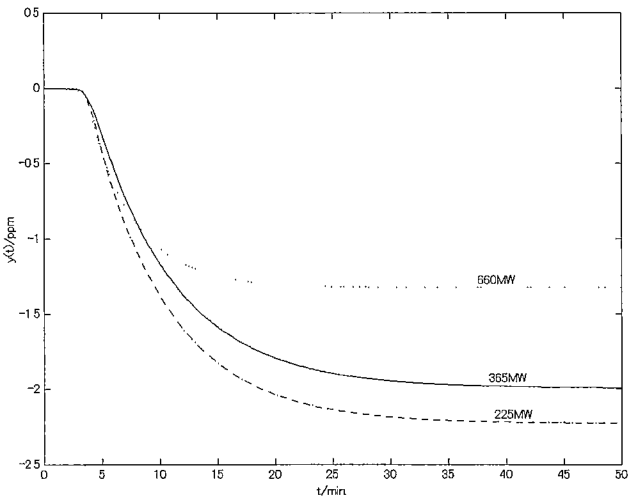

Fig. 2. Unit-step-responses of SCR process; the static gains are -1.32(660MW), -1.90(365MW), and -2.14(225MW) ; $k_d=10$, $k_b=12$, and $k_a=k_{d1}=k_{d3}=k_{d4}=k_c=10$.

Fig.2 clearly shows quite considerable changes in static gain on the unit-step response at different load levels due to non-linearities. The steady-state gain and step-response sequences monotonously vary with load. The poles and zeros of the process also vary remarkably with load level as is showed in Fig.3 and 4. Therefore, the nonlinear properties of the SCR process are due to variation in static gain and dynamic characteristics at different loads. The temperature control process of thermal power plants has also shown similar nonlinearity[3].

3. Local Linearization Approach

〈3·1〉 **ExpARMAX Model** Based on the nonlinear modeling framework using exponential auto-regressive model[4], we propose a global ExpARMAX model which only requires off-line identification to characterize a class of SISO smooth nonlinear systems with nonlinearly measurable signal dependent dynamics as illustrated in Section 2 as follows

$$A_t(q^{-1})y(t) = B_t(q^{-1})u(t-k_d) + \mathbf{D}(q^{-1})\mathbf{v}(t-k_d) + C(q^{-1})\xi(t)/\Delta \qquad (2)$$

where

$$\begin{cases} A_t(q^{-1}) = 1 + a_{t,1}q^{-1} + \cdots + a_{t,k_a}q^{-k_a} \\ B_t(q^{-1}) = b_{t,0} + b_{t,1}q^{-1} + \cdots + b_{t,k_b}q^{-k_b} \\ \mathbf{D}(q^{-1}) = \mathbf{d}_{1,0} + \mathbf{d}_{1,1}q^{-1} + \cdots + \mathbf{d}_{1,k_v}q^{-k_v} \\ C(q^{-1}) = 1 + c_1 q^{-1} + \cdots + c_{k_c}q^{-k_c} \end{cases}$$

$$\begin{cases} a_{t,i} = \varphi_{ai}(0) + \varphi_{ai}(1)e^{-\lambda_a(m(t-i)-m_0)^2}, \ i = 1,2,\cdots,k_a \\ b_{t,j} = \varphi_{bj}(0) + \varphi_{bj}(1)e^{-\lambda_b(m(t-j-1)-m_0)^2}, \ j = 0,1,\cdots,k_b \end{cases}$$

here, $\mathbf{v} \subset \Re^l$ is the disturbance vector and $\mathbf{D}$ is the related vector polynomial, $m(t)$ is the signal causing system nonlinearity, φ_{ai} and φ_{bj} are the constants, λ_a and λ_b are the scaling factors, and m_0 is the center point.

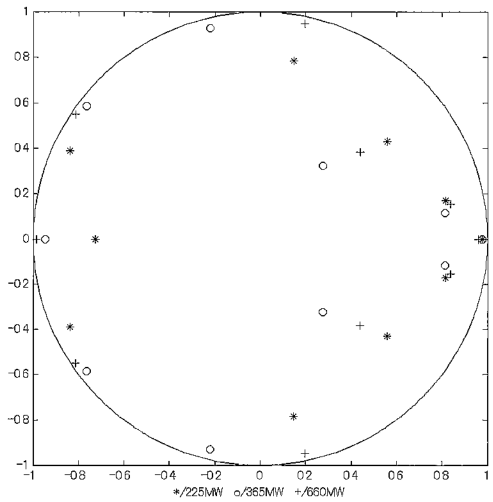

Fig. 3. Poles of the SCR process described by model (1) at some load levels.

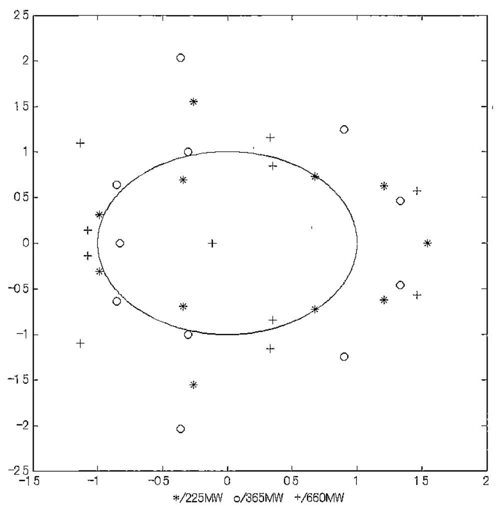

Fig. 4. Roots of the control polynomial $B(q^{-1})$ in model (1) at some load levels.

Remark 1: The variable $m(t)$ causing nonlinearity is introduced into the coefficients of A_t determining inherent dynamics and B_t affecting dynamic response, so that the model may characterize the nonlinear dynamics caused by the change of the signal. The varying zones of the coefficients are $a \in [\varphi_{ai}(0), \varphi_{ai}(0) + \varphi_{ai}(1)]$, $b \in [\varphi_{bj}(0), \varphi_{bj}(0) + \varphi_{bj}(1)]$. If $m(t)$ is fixed at some specific time, model (2) gives a locally linearized description of the system at the operating-point.

Remark 2: Model (2) may be regarded as a kind of linear parameter-varying (LPV) model in some cases, but it may describe more complicated dynamics than a general LPV model if we let $m(t)$ be $y(t)$, or $u(t)$, or their compositions. Besides, some LPV-style models[12] require on-line parameter estimation, with all its attendant problems. To avoid such problems, all the parameters of model (2) are estimated off-line.

〈3·2〉 ExpARX Predictor · In a general multi-step predictive control algorithm with measurable disturbances, the influence of the future value of disturbances to control performance is usually not considered. Actually, it is important that more accurate future values of disturbance variables are obtained to improve control performance. Therefore, the following ExpARX model which only requires off-line identification is constructed as a predictor of disturbance variables

$$\Phi_a(q^{-1})\mathbf{z}(t) = \Phi_b(q^{-1})\mathbf{z}(t-k_d) + \zeta(t) \qquad (3)$$

where

$$\mathbf{z}(t) = \Delta\mathbf{v}(t)/C(q^{-1})$$

$$\Phi_a(q^{-1}) = diag\{\Phi_{1a}(q^{-1}), \cdots, \Phi_{la}(q^{-1})\}$$

$$\Phi_b(q^{-1}) = \begin{bmatrix} 0 & \Phi_{12b}(q^{-1}) & \cdots & \Phi_{1lb}(q^{-1}) \\ \Phi_{21b}(q^{-1}) & 0 & \cdots & \Phi_{2lb}(q^{-1}) \\ \vdots & \vdots & \ddots & \vdots \\ \Phi_{l1b}(q^{-1}) & \Phi_{l2b}(q^{-1}) & \cdots & 0 \end{bmatrix}$$

$$\begin{cases} \Phi_{ia}(q^{-1}) = 1 + \phi_{ia,1}q^{-1} + \cdots + \phi_{ia,k_p}q^{-k_p} \\ \Phi_{ijb}(q^{-1}) = \phi_{ijb,1} + \phi_{ijb,2}q^{-1} + \cdots + \phi_{ijb,k_p}q^{-k_p+1} \\ \Phi_{iib}(q^{-1}) = 0 \qquad i,j = 1,2,\cdots,l \end{cases}$$

$$\begin{cases} \phi_{ia,j} = \phi'_{ia,j}(0) + \phi'_{ia,j}(1)e^{-\lambda_{ia,1}(m(t)-\omega_{ia,1})^2} \\ \qquad + \phi'_{ia,j}(2)e^{-\lambda_{ia,2}(\Delta m(t)-\omega_{ia,2})^2} \\ \Delta m(t) = m(t) - m(t-1) \\ i = 1,2,\cdots,l; \ j = 1,2,\cdots,k_p \end{cases}$$

$$\begin{cases} \phi_{i\beta b,j} = \phi'_{i\beta b,j}(0) + \phi'_{i\beta b,j}(1)e^{-\lambda_{ia,1}(m(t)-\omega_{ia,1})^2} \\ \qquad + \phi'_{i\beta b,j}(2)e^{-\lambda_{ia,2}(\Delta m(t)-\omega_{ia,2})^2} \\ i = 1,2,\cdots,l; \ \beta = 1,2,\cdots,l; \ j = 1,2,\cdots,k_p \end{cases}$$

Assume $\zeta(t) \subset \Re^l$ in (3) is an independent white noise vector. After identifying model (3) off-line, the multi-step-ahead prediction of the measurable disturbances can be computed on the basis of the estimated model as follows

$$\begin{cases} \hat{\mathbf{z}}(t+j\,|\,t) = (\mathbf{I} - \hat{\Phi}_a(q^{-1}))\hat{\mathbf{z}}(t+j\,|\,t) \\ \qquad + \hat{\Phi}_b(q^{-1})\hat{\mathbf{z}}(t-k_d+j\,|\,t) \\ \hat{\mathbf{z}}(t+k\,|\,t) = \hat{\mathbf{z}}(t+k) \ \text{if} \ k \le 0, \ j = 1,2,\cdots,N_p \end{cases}$$

Remark 3: The variable $m(t)$ causing nonlinearity is also introduced into the predictor so that it describes the nonlinear dynamics. The exponential factors $e^{-\lambda_{ia,1}(m(t)-\omega_{ia,1})^2}$ in (3) introduce a message about the system operating-point into the predictor, and the factor $e^{-\lambda_{ia,2}(\Delta m(t)-\omega_{ia,2})^2}$ makes the predictor express the effect caused by the varying rate of operating-point.

〈3·3〉 **The Hybrid Identification Algorithms (HIA)**

Identification of model (3) is a nonlinear optimization problem, since the parameters to be estimated include the nonlinear factors of the exponential functions. Although model (3) only requires off-line identification, it must be identified using the input-output-data covering the whole operating range of the system. The classical nonlinear parameter optimization methods, such as the Gauss-Newton method, estimates all parameters simultaneously regardless of the properties of the parameters, expending too much computation time. A hybrid identification algorithm may be used to estimate model (3) as follows.

Variable rotation methods (VRM):

For model (3) without parameter constraints, define $\theta_l = (\phi'_{ia,j}(0), \phi'_{ia,j}(1), \phi'_{ia,j}(2), \cdots)$ the linear parameter-set of the model, and $\theta_n = (\lambda_{ia,1}, \lambda_{ia,2}, \omega_{ia,1}, \omega_{ia,2}, \cdots)$ the nonlinear parameter-set of the model. The following procedure is used to identify all the parameters:

(i) Determine the model order

Fix θ_n from prior knowledge. Use ***IGNA*** in Section 2 to estimate θ_l and to compute FPE (final predictive error) at various orders. The suitable order is that with smallest FPE value.

(ii) Estimate θ_l and θ_n in turn

Take a suitable termination tolerance $J_{e,\min}$ of the quadratic estimation error function $J_e(\theta_l, \theta_n)$, so that the estimation terminates within reasonable time:

(A1) Fix θ_n. Use ***IGNA*** to estimate θ_l, yielding

$\theta_l = \arg\min_{\theta_l} J_e(\theta_l, \theta_n)$. If $J_e(\theta_l, \theta_n) < J_{e,\min}$, then terminate the estimation procedure, else:

(A2) Fix θ_l. Apply the trust region method[13, Appendix A] to estimate θ_n, yielding

$\theta_n = \arg\min_{\theta_n} J_e(\theta_l, \theta_n)$. If $J_e(\theta_l, \theta_n) < J_{e,\min}$, then terminate the estimation procedure, else go back to A1).

In (A1), estimating θ_l is equivalent to a linear system estimation problem. In (ii), θ_l and θ_n will converge to a set of locally optimum parameters, and the problem of convergence is similar to that of classical nonlinear parameters optimization methods. If the SCR process presented in Section 2 is taken as an example, comparisons of identification accuracy between the ExpARMAX or ExpARX model and a global linear ARMAX or ARX model with the same orders are shown in Fig.5 and Fig.6. The two plots show that the fitting or multi-step-ahead prediction accuracy of the ExpAR-type models is far better than that of the global linear models.

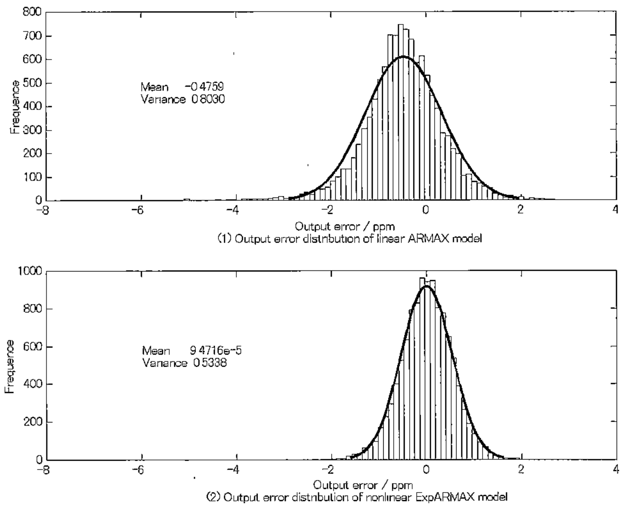

Fig. 5. Distributions of model output errors, $k_a = 4$, $k_b = 6$, $k_c = 4$, $k_{d1} = k_{d3} = k_{d4} = 4$, $k_d = 10$.

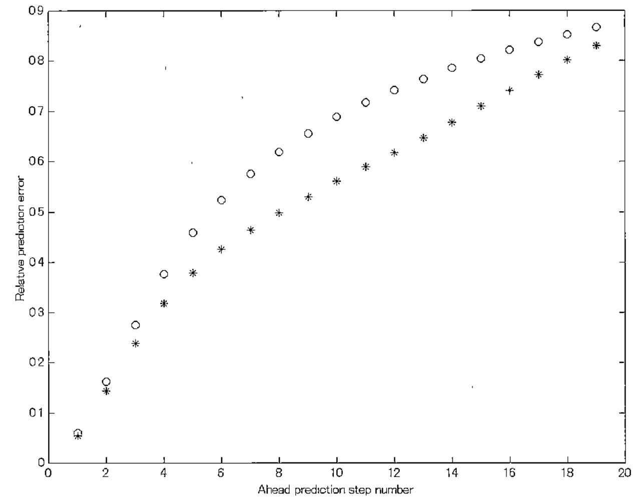

Fig. 6. Relative error of multi-step-ahead prediction, '*' marks the error of ExpARX predictors, 'o' marks the error of global linear ARX predictors, $k_p = 30$.

4. Nonlinear Predictive Control Based on Exp-type Models

〈4·1〉 **The Jth-step-ahead Prediction** Consider the system described by (2). If we constrain $\{\Delta u(t), \Delta u(t+1), \cdots, \Delta u(t+N_u-1)\}$ to be F_t- measurable, where F_t denotes the σ-algebra generated by the data up to and including time t, then the jth-step-ahead optimal output prediction is

$$\hat{y}(t+j\,|\,t) = E\{y(t+j\,|\,t)\,|\,F_t\} = G'_j(q^{-1})\Delta u(t+j-1) + y_0(t+j\,|\,t) \qquad (4)$$

where

$$y_0(t+j\,|\,t) = \frac{F_j(q^{-1})}{C(q^{-1})}y(t) + \frac{H_j(q^{-1})}{C(q^{-1})}\Delta u(t-1) + \frac{E'_j(q^{-1})}{C(q^{-1})}\mathbf{D}(q^{-1})\Delta\mathbf{v}(t+j-k_d) \qquad (5)$$

E'_j, F_j, G'_j, and H_j are recursive solutions of two Diophantine equations below

$$C(q^{-1}) = E'_j(q^{-1})A_t(q^{-1})\Delta + q^{-j}F_j(q^{-1}) \qquad (6)$$

$$E'_j(q^{-1})B_{t+j}q^{-k_d+1} = C(q^{-1})G'_j(q^{-1}) + q^{-j}H_j(q^{-1}) \qquad (7)$$

The derivation of (4) is similar to that given by Kinnaert[14], and it is omitted here.

⟨4·2⟩ **Multi-step Predictive Control** Take the prediction horizon N_p and the control horizon N_u. Define

$$\left.\begin{aligned} \hat{\mathbf{Y}}(t) &= [\hat{y}(t+k_d \mid t), \cdots, \hat{y}(t+N_p \mid t)]^{\mathrm{T}} \\ \mathbf{Y}_0(t) &= [y_0(t+k_d \mid t), \cdots, y_0(t+N_p)]^{\mathrm{T}} \\ \Delta\mathbf{U}(t) &= [\Delta u(t), \Delta u(t+1), \cdots, \Delta u(t+N_u-1)]^{\mathrm{T}} \\ \mathbf{Y}_r(t) &= [y_r(t+k_d \mid t), \cdots, y_r(t+N_p \mid t)]^{\mathrm{T}} \end{aligned}\right\} \quad \cdots\cdots (8)$$

here, $\mathbf{Y}_r(t)$ is the desired output sequence. From (4) and (8), and assuming $\Delta u(t+j)=0,\ j \geq N_u$, we obtain

$$\hat{\mathbf{Y}}(t) = \mathbf{G}_t \Delta\mathbf{U}(t) + \mathbf{Y}_0(t) \quad \cdots\cdots (9)$$

where $\mathbf{G}_t$ is composed of the coefficients of polynomial $G_j^{'}\ (j=N_p)$ in the Diophantine equation (7), and

$$\mathbf{G}_t = \begin{bmatrix} g_{k_d-1} & g_{k_d-2} & \cdots & & \mathbf{0} \\ g_{k_d} & g_{k_d-1} & g_{k_d-2} & \cdots & \\ \vdots & \vdots & \vdots & & \\ g_{N_p-1} & g_{N_p-2} & g_{N_p-3} & \cdots & g_{N_p-N_u} \end{bmatrix}_{(N_p-k_d+1)\times N_u}$$

where $\mathbf{G}_t$ is a $(N_p-k_d+1)\times N_u$ matrix with zero entries g_i for $i<0$. Minimizing the cost function below, the optimal control increments can be obtained:

$$\min_{\Delta\mathbf{U}(t)} \tilde{J} = \left\|\hat{\mathbf{Y}}(t) - \mathbf{Y}_r(t)\right\|^2_{\mathbf{I}_{N_p-k_p+1}} + \left\|\Delta\mathbf{U}(t)\right\|^2_{\mathbf{R}} \quad \cdots\cdots (10)$$

subject to

$\Delta u_{\min} \leq \Delta u(t+j-1) \leq \Delta u_{\max}$, for $j=1$ to N_u

$y_{\min} \leq \hat{y}(t+j \mid t) \leq y_{\max}$, for $j=k_d$ to N_p

where $\|\mathbf{X}\|^2_{\mathbf{Q}} = \mathbf{X}^{\mathrm{T}}\mathbf{Q}\mathbf{X}$, $\mathbf{I}_{N_p-k_p+1}$ is the $(N_p-k_p+1)\times(N_p-k_p+1)$ identity matrix, with weighting $\mathbf{R} = diag(\gamma_1, \gamma_2, \cdots, \gamma_{N_u})$. The constrained optimization problem (10) can be reformulated as a constrained quadratic optimization problem below:

$$\min_{\Delta\mathbf{U}(t)} \tilde{J} = \frac{1}{2}\Delta\mathbf{U}(t)^{\mathrm{T}}(\mathbf{G}_t^{\mathrm{T}}\mathbf{G}_t + \mathbf{R})\Delta\mathbf{U}(t) + [\mathbf{Y}_0(t) - \mathbf{Y}_r(t)]^{\mathrm{T}}\mathbf{G}_t\Delta\mathbf{U}(t) \quad \cdots\cdots (11)$$

subject to

$$\begin{bmatrix} \mathbf{G}_t \\ -\mathbf{G}_t \end{bmatrix} \Delta\mathbf{U}(t) \leq \begin{bmatrix} \mathbf{Y}_{\max} - \mathbf{Y}_0(\mathrm{t}) \\ -\mathbf{Y}_{\min} + \mathbf{Y}_0(\mathrm{t}) \end{bmatrix}$$

$$\Delta\mathbf{U}_{\min} \leq \Delta\mathbf{U}(t) \leq \Delta\mathbf{U}_{\max}$$

The Quadratic Programming (QP) algorithm available in MATLAB SIMULINK Toolbox is applied to the above optimization. Of the N_u future control actions that minimize $\tilde{J}$, only the first one is used

$$u(t) = u(t-1) + \Delta u(t) \quad \cdots\cdots (12)$$

At the next sampling time, a new optimization problem is formulated whose solution provides the next control action. This is referred to as the receding horizon principle. In (5) and (8), the future value of disturbances will be applied. Use the predictions computed from the estimated model (3) to replace the future values.

5. Case Studies

Simulation results for the proposed predictive control algorithm (EEPC) based on ExpARMAX model (2) and ExpARX model (3) for the SCR process showed in Section 2 are shown in Fig.7-9 with $N_p=20$, $N_u=4$, $\gamma_i=1$, the desired output is 39.5 ppm. A comparison of the control performance of the basic EEPC using the true future values of the disturbances and the PID is showed in Fig. 7. From Fig.7 we can see that the basic EEPC greatly reduced the vibration amplitude of the outlet NOx concentration $y(t)$ and the consumption of expensive NH_3 gas $u(t)$ compared with PID control.

Looking at the result for EEPC without ExpARX predictor (dot-dashed plot in Fig.8), the disturbances are assumed to remain constant at the current value during the prediction horizon. Fig.8 shows that during large load variance, the control performance of EEPC is far better than PID control, and after using an ExpARX predictor of the future measurable disturbances the EEPC control result is obviously improved. It is also verified in Fig.9 that the multi-step-prediction accuracy of the ExpARX model is much better than the global linear ARX model whose order is same as the ExpARX model and which is identified off-line by using the same identification data as the ExpARX model.

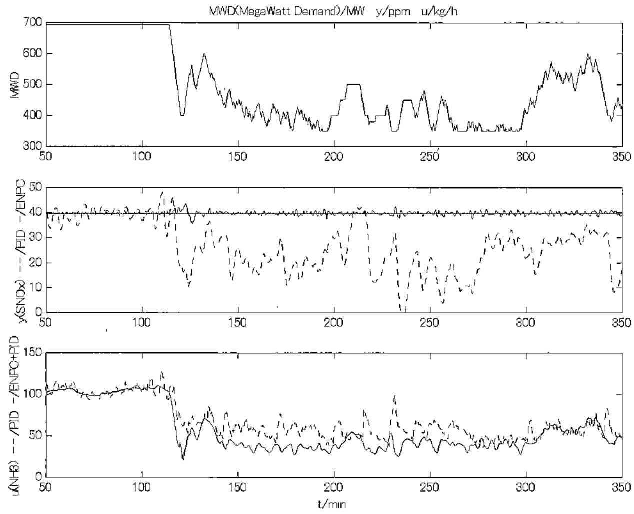

Fig. 7. Comparison of the control performance of basic ENPC (solid) and PID (dot-dashed).

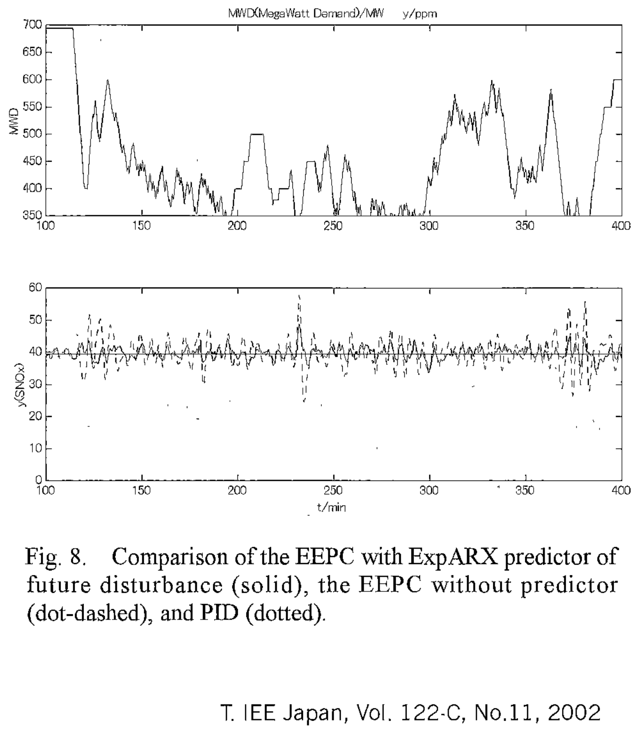

Fig. 8. Comparison of the EEPC with ExpARX predictor of future disturbance (solid), the EEPC without predictor (dot-dashed), and PID (dotted).

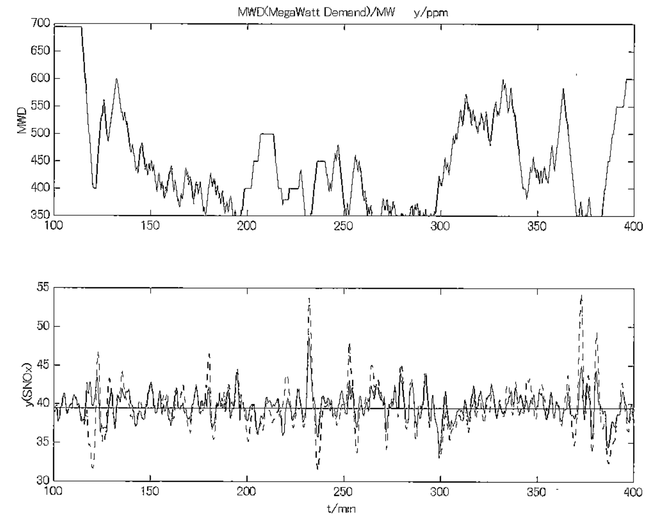

Fig. 9. Comparison between the EEPC using ExpARX predictor (solid) and the EEPC using the global linear ARX predictor (dot-dashed) of future disturbance.

6. Conclusion

For a class of nonlinear systems whose static and dynamic characteristics are dependent on a measurable signal, a multi-step predictive control algorithm based on two global nonlinear exponential auto-regressive-type models (ExpAR-type models) was presented. The proposed ExpAR-type models, which do not need on-line estimation, have a basic structure similar to linear AR models, and have the capability of describing the nonlinear dynamics of the system because they have time-varying coefficients dependent on operating- point state. The significant advantages of the proposed predictive control algorithm for nonlinear systems are that (1) its internal model does not need on-line estimation as is usually done in GPC, (2) the multi-step-ahead prediction of output can be formularized as a linear version of future control since its internal model structure similar to linear AR, and (3) more precise multi-step-ahead prediction of measurable disturbances could be used to improve control performance.

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Appendix A. The trust region method

The solution of the unconstrained nonlinear parameters optimization problem below

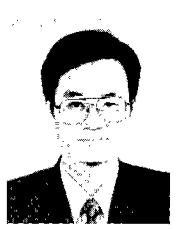
$$\min_{\theta_n} J_e(\theta_l, \theta_n) \quad \cdots\cdots (13)$$

may be obtained by solving a series of easier quadratic programming subproblem as follows[13]

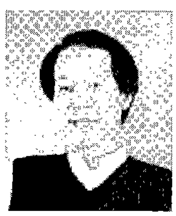
$$\min_{\mathbf{s}} \left\{ \psi_k(\mathbf{s}) \triangleq \mathbf{g}_k^T \mathbf{s} + \frac{1}{2}\mathbf{s}^T \mathbf{B}_k \mathbf{s} : \left\|\bar{\mathbf{D}}_k \mathbf{s}\right\| \le \Delta_k \right\} \quad \cdots\cdots (14)$$

where the increment $\mathbf{s}_k = \theta_{n,k+1} - \theta_{n,k}$, $\mathbf{g}_k \triangleq \nabla J_e(\theta_l, \theta_{n,k})$, $\mathbf{B}_k$ is a symmetric approximation to the Hessian matrix $\nabla^2 J_e(\theta_l, \theta_{n,k})$, $\bar{\mathbf{D}}_k$ is a scaling matrix, Δ_k is a positive scalar representing the trust region size, and $\|\bullet\|$ denotes the 2-norm. Let $0<\mu<\eta<1$, and $0<\gamma_1<1<\gamma_2$. For $k=0,1,\cdots$, the detailed procedures are as follows

1) Compute $J_e(\theta_l, \theta_{n,k})$ and the model $\psi_k(\mathbf{s})$;
2) Solve the solution $\mathbf{s}_k$ to the subproblem (14);
3) Compute
   $\rho_k^J = (J_e(\theta_l, \theta_{n,k} + \mathbf{s}_k) - J_e(\theta_l, \theta_{n,k}))/\psi_k(\mathbf{s}_k)$;
4) If $\rho_k^J > \mu$ then set $\theta_{n,k+1} = \theta_{n,k} + \mathbf{s}_k$. Otherwise set $\theta_{n,k+1} = \theta_{n,k}$;
5) If $\rho_k^J \le \mu$ then set $\Delta_{k+1} \in (0, \gamma_1 \Delta_k]$;
6) If $\rho_k^J \le (\mu, \eta)$ then set $\Delta_{k+1} \in [\gamma_1 \Delta_k, \Delta_k]$;
7) If $\rho_k^J \ge \eta$ then set $\Delta_{k+1} \in [\Delta_k, \gamma_2 \Delta_k]$.

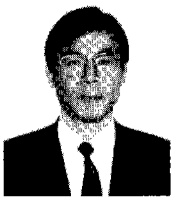


Hui Peng (Member) was born in Changsha, China, on July 23, 1963. He received the M.S. degree in automatic control from Central South University in 1986, and is presently as professor at Central South University, China. He has worked on nonlinear systems modeling and predictive control, development of computer process control systems, and financial process modeling and assets dynamic allocation control. IEE of Japan, IEEE member.



Tohru Ozaki (Non-member) received the B.S. (Mathematics) from the University of Tokyo in 1969. He obtained the degree of Doctor of Science from the Tokyo Institute of Technology in 1981. He is Professor of the Department of Prediction and Control, Institute of Statistical Mathematics, Tokyo. He is also Professor of the Department of Statistical Science, Graduate University of Advanced Studies, Japan.

Yukihiro Toyoda (Member) received the M.S. degree in Mechanical Engineering in 1977 from Hiroshima University, and the Ph.D. degree in Electrical and Electronic Systems Engineering from Kyushu University in 2000. He worked for Honda R&D Co.,Ltd. and Bailey Japan Co.,Ltd. and he has been working for the Mechanical Engineering Dept. of Niihama National College of Technology since 2002. His main interests are in nonlinear modeling for control and its application to industrial processes. IEE of Japan, SICE, ISCIE, IEEE member.



Valerie Haggan-Ozaki (Non-member) received the B.S. (Mathematics) from the University of Leeds, U.K., in 1970. She obtained the degree of the M.S. (Mathematical Statistics) and the Ph.D. (Mathematical Statistics) from the University of Manchester, U.K., in 1971 and 1973, respectively. She is Professor of the Department of Comparative Culture, Sophia University, Japan.