SOFT SENSOR BASED NONLINEAR CONTROL OF A CHAOTIC REACTOR

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Abstract: Control of nonlinear systems exhibiting complex dynamic behavior is a challenging task because such systems present a variety of behavioral patterns depending on the values of physical parameters and intrinsic features. Understanding the behavior of the nonlinear dynamic systems and controlling them at the desired conditions is important to enhance their performance. In this work, a soft sensor based nonlinear controller strategy is presented and applied to control a chemical reactor that exhibit multi-stationary unstable behavior, oscillations and chaos. In this strategy, an extended kalman filter is designed to serve as a soft sensor that provides the estimates of unmeasured process states. These states are used as inferential measurements to the nonlinear controller that is designed in the framework of globally linearizing control. The results evaluated for stabilizing the reactor for different conditions including deterministic and stochastic disturbances show the better performance of the soft sensor based nonlinear control strategy over that of a PID controller with modified feedback mechanism.

Keywords: Soft Sensor; extended Kalman filter; nonlinear state estimation; chaotic behavior; geometric controller

1. INTRODUCTION

Control of nonlinear systems exhibiting complex dynamic behavior is a challenging task because such systems present a variety of behavioral patterns depending on the values of their physical parameters and intrinsic features. Depending on the parameter values, these systems can operate at steady state or present oscillatory and chaotic motions. In case of chemical reactors, such unconventional behavior can be attributed to some sort of nonlinear interaction between several quantities that can be stored or sometimes inter-converted within the system. The oscillatory and chaotic phenomenon displayed by the chemically reacting systems has desirable as well as undesirable features. The desirable feature of chaos is that it enhances mixing and chemical reactions and provides a vibrant mechanism for transport of heat and mass. On the other hand, the intrinsic features of the reacting systems with the interactive influence of chemical or thermal energy may cause irregular dynamic behavior leading to degraded performance. In such situations, chaos is considered as undesirable and should be avoided. The presence of chaotic behavior in chemical reactors has been demonstrated theoretically and experimentally by several researchers [Uppal et al. (1976); Schimitz et al. (1979); Wu (2000); Blanco and Bandoni (2007)]. Understanding the dynamic behavior of the chaotic reactor and controlling it under stable operating conditions is important to enhance the performance of the reactor. Various methods including a proportional-Integral (PI) controller [Pellegrini and Biardi (1990)] and a modified PI/PID controller [Bandyopadhyay et al. (1997)] have been used for controlling and operating the chaotic reactors under favorable conditions. However, the complex nature of dynamical systems severely limits the use of conventional linear controllers to provide the desired operating performance. Therefore, advanced control strategies have become an important part of control structure. But most advanced controllers rely on mathematical models of the process incorporating process state variable information in controller formulation. In most systems, the state variables desired by the controller can not be easily available through measurement or available with large measurement delays. Such timely unavailable state variables may restrict the implementation of advanced model based controllers for nonlinear systems. If such inaccessible or non-measurable state variables can be made available either by hard sensing or soft sensing techniques. The nonlinear model based controllers can be implemented effectively. The measurement problems and the delays associated with the hard sensors have led to the development of soft sensors as alternative measurement tools. Model based estimation methods such as extended versions of Kalman filters / nonlinear observers can serve as soft sensors by means of providing reliable estimates for unmeasured variables in nonlinear dynamic systems. The potentiality of model based methods for state estimation have been reported for various systems [Venkateswarlu and Gangiah (1992); Schelur and Schmidt (1993); Sargantanis and Karim (1994); Jana et. al (2006)].

This work presents a soft sensor based nonlinear controller to alter the dynamics of a chaotic chemical reactor and drive the system response to the desired condition. An extended Kalman filter (EKF) is designed and used as a soft sensor to provide the reactor species concentrations that serve as inferential measurements to the nonlinear controller. The controller is designed in the globally linearizing control (GLC) framework of Kravaris and Chung (1987). The sensitivity of the soft sensor is studied with respect to the effect of measurement noise as well as the estimator design parameters. The proposed soft sensor based nonlinear controller is evaluated by applying it for the control of a non-isothermal continuous stirred tank reactor (CSTR) that exhibit multi-stationary unstable behavior, oscillations and chaos. The controller is also studied towards the influence of stochastic and deterministic load disturbances. Further the results of the present control strategy are compared with those of a proportional-integral-derivative (PID) controller that involve a modified feedback mechanism.

2. SOFT SENSOR BASED NONLINEAR CONTROL STRATEGY

The strategy consists of an extended Kalman filter (EKF) for estimating unmeasured process variables of a nonlinear system. These estimated states serve as inferential measurements to a globally linearizing controller (GLC) which drives the system response to the desired condition. The schematic of this strategy is shown in Fig. 1.

2.1 Process Representation

The mathematical model of the nonlinear dynamical system can be expressed by the following state space form

$$\dot{x}(t) = f(x(t), t) + w(t), \quad x(0) = x_0 \tag{1}$$

where *x(t)* is *n*-dimensional state vector, f is a nonlinear function of state x and w is additive Gaussian noise with zero mean. The linear measurement relation is given by

$$y(t_k) = Hx(t_k) + v(t_k) \tag{2}$$

The nonlinear measurement model with observation noise can be expressed as

$$y(t_k) = h(x(t_k)) + v(t_k) \tag{3}$$

where h is a nonlinear function of state x and v is the vector of observation noise. The state vector, *x(t)*, of (1) can be estimated from the known process measurements, $y(t_k)$, of (2) using nonlinear estimation techniques. The statistical expectations of the covariance matrices associated with $x(0)$, $w(t)$ and $v(t_k)$ are referred as the initial state covariance matrix, P_0, process noise covariance matrix, Q, and observation noise covariance matrix, R. The matrices $P_{0,}$ $Q(t)$ and $R(t_k)$ are generally selected as estimator design parameters which are used to reflect errors in the initial state, process model and process measurements.

2.2 Extended Kalman Filter (EKF)

State estimation methods based on filtering or observation can deliver reliable on-line estimates for state variables defining a process on the basis of available process knowledge including a dynamic model and the incoming data from process measurement sensors. In this study, an extended Kalman filter is used as a soft sensor to provide the estimates of unmeasurable state variables. By this algorithm, state estimation is carried out through recursive implementation of the prediction and correction equations. More details concerning the EKF for state estimation in nonlinear systems can be referred to elsewhere [Gilles (1987); Venkateswarlu and Jeevan Kumar (2006)].

2.2.1Prediction equations

By starting with an initial estimate x_0 and its covariance P_0 at time t_{k-1} and no measurements are taken between t_{k-1} and t_k, the propagating expressions for the estimate and it's covariance from t_{k-1} to t_k are,

$$\dot{\hat{x}}(t/t_{k-1}) = f(\hat{x}(t/t_{k-1}), t) \tag{4}$$

$$\dot{P}(t/t_{k-1}) = F(\hat{x}(t/t_{k-1}), t)P(t/t_{k-1}) + F^T(\hat{x}(t/t_{k-1}), t)P(t/t_{k-1}) + Q(t) \tag{5}$$

where $F(x(t/t_{k-1}),t)$ is the state transition matrix whose i,j^{th} element is given by

$$F(x(t/t_{k-1}), t) = \frac{\partial f_i(x(t), t)}{\partial x_j(t)}\Big|_{x(t)=\hat{x}(t/t_{k-1})} \tag{6}$$

The solution of the propagated estimate $x(t/t_{k-1})$ and its covariance $P(t/t_{k-1})$ at time t_k are denoted by $x(t_k/t_{k-1})$ and $P(t_k/t_{k-1})$. By using measurements at time $t_{k,}$, the update estimate $x(t_k/t_k)$ and $P(t_k/t_k)$ are computed.

2.2.2 Correction equations

The equations to obtain corrected estimates are

$$\hat{x}(t_k/t_k) = \hat{x}(t_k/t_{k-1}) + K(t_k)[y(t_k) - h(x(t_k/t_{k-1}))] \tag{7}$$

$$P(t_k/t_k) = (1 - K(t_k)H_x(x(t_k)))P(t_k/t_{k-1}) \tag{8}$$

$$K(t_k) = P(t_k/t_{k-1})H_x^T(x(t_k))(H_x(x(t_k))P(t_k/t_{k-1})H_x^T(x(t_k)) + R)^{-1} \tag{9}$$

where

$$H_x(x(t_k)) = \frac{\partial h_i(x(t_k))}{\partial x(t_k)}\Big|_{x(t_k)=\hat{x}(t_k/t_{k-1})} \tag{10}$$

The recursive initial conditions for state and covariance are defined by

$$\hat{x}(t_k/t_{k-1}) = \hat{x}(t_k/t_k) \tag{11}$$

$$P(t_k/t_{k-1}) = P(t_k/t_k) \tag{12}$$

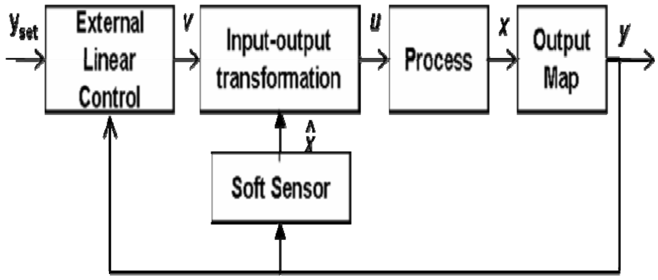

Fig. 1. Schematic of soft sensor based nonlinear control.