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Robust nonlinear predictor for dead-time systems with input nonlinearities

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ABSTRACT

Since the seminal work of Smith, predictor structures have been used to control processes with dead-time. Predictors allow the control of this type of process with a delay-free nominal model, which simplifies the control design. In this paper, a nonlinear filtered Smith predictor (NLFSP) structure is proposed for systems with input nonlinearities. It is shown that the NLFSP maintains the characteristics of the linear filtered Smith predictor and that with appropriate tuning, it can increase the robustness of the closed-loop system or improve the disturbance rejection response. The NLFSP is applied to a simulated CSTR process to demonstrate these characteristics.

1. Introduction

As pointed out by Palmor in [1], three are the main difficulties introduced by the delay: (i) effects of the disturbances are not noticed until the dead-time has elapsed, (ii) the effect of the control action takes some time to be noticed in the controlled variable, and (iii) the control action that is applied based on the actual error tries to correct a situation that originated some time before.

Since the seminal work of Smith [2], one solution to avoid (or attenuate) these effects is the use of the Smith predictor (SP). Predictors are structures which allow the control of dead-time process with a delay-free nominal model, which simplifies the control design of the so called primary controller [1,3]. An important property of the Smith predictor comes from the fact that robustness margins are not related with nominal dead-time value. This characteristic is very interesting since it is not necessary to consider nominal dead-time length from a robust stability point of view. This property, however, does not hold for any predictor. For instance, model predictive controllers (MPC) algorithms implicitly define a predictor structure, but, as was shown in [4] for the specific case of the generalized predictive control (GPC), the implicit optimal predictor makes the stability margins of the controller dependent on the nominal dead-time. This kind of problem is related to the implicit disturbance model and observer. Also in [4], it was shown that substituting the implicit predictor by an explicit SP based predictor resulted in a more robust controller that inherited the advantageous characteristics of the SP.

Predictors for nonlinear systems are discussed in various works. In [5–7], the authors propose a predictor-based controller to stabilize the process with input time-delay, where the delay can be time-varying and state-dependent. However, the proposed predictor structure does not guarantee an offset-free prediction for constant disturbances, which compromises the reference tracking capabilities of the closed-loop system. In [8], the SP is applied to a class of nonlinear systems, but the analysis of the predictor is made in conjunction with the proposed globally linearizing control (GLC) strategy, which linearizes the process, thus allowing the use of mathematical tools for linear systems. In [9], the authors follow the idea presented in [8], and extend the SP to a more general nonlinear system model, but, because of how the SP handles disturbances, this structure was dropped in favor of a Kalman filter based predictor, but the effects of the tuning parameters on robustness is not thoroughly analyzed. In [10], the SP is used to control a nonlinear system through a network, which causes a time-delay, but the system is locally controlled by a linearizing compensator, hence a linear SP is used.

Following the ideas presented in [4] for the linear case, in this work a nonlinear filtered Smith predictor (NLFSP) will be proposed to improve robustness of dead-time systems with input nonlinearities. The proposed NLFSP presents the same properties as the linear FSP, i.e., nominal set-point performance is not affected by the filter,

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robustness can be improved by a suitable tuning of the predictor filter and it can also be applied to unstable processes [11]. The use of the FSP with nonlinear processes was presented in [4], and applications can be found in [12,13], but no theoretical analysis is made in these works. Thus, in this paper, the properties of the NLFSP will be proved for a class of nonlinear systems using recent nonlinear systems' theory in a way that the predictor structure can be studied independently of the primary control law that will be applied.

The rest of the paper is organized as follows. In Section 2 the general dead-time system equation with input nonlinearities will be described, including some specific models commonly used to represent this type of systems. In Section 3 the optimal predictor will be analyzed and in Section 4 the NLFSP will be introduced. Simulation results will be presented in Sections 5 and 6 to illustrate the advantages of the NLFSP and, finally, the conclusions are given in Section 7.

2. System description

This work considers the control of processes that can be modeled by an uncertain time-invariant discrete dead-time system with input nonlinearities given by

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + g(\mathbf{u}(k-d)) + \mathbf{w}(k), \tag{1}$$

where $\mathbf{A}$ is a square matrix with dimension n, $\mathbf{x}(k) \in \mathbb{R}^n$ is the state vector for the system, $g(.)$ is a nonlinear function $g: \mathbb{R}^m \to \mathbb{R}^n$, $\mathbf{u}(k) \in \mathbb{R}^m$ is the control vector at time k in a way that $\mathbf{u}(k-d) = [u(k-d), u(k-d-1), \ldots, u(k-d-m)]^T$, $\mathbf{w}(k)$ is the unmeasurable additive disturbance, and d is the dead-time. It is assumed that $|g(\mathbf{u})| = \infty \Leftrightarrow |\mathbf{u}| = \infty$.

Notice that $\mathbf{w}(k)$ is an unmeasurable signal at instant k that can describe any kind of mismatch between the measured state at $k+1$ and its expected value at k, including model mismatch and unmeasurable process disturbances [14]. Its value can only be known at time $k+1$, where $\mathbf{w}(k)$ is computed as

$$\mathbf{w}(k) = \mathbf{x}(k+1) - (\mathbf{A}\mathbf{x}(k) + g(\mathbf{u}(k-d))). \tag{2}$$

For this kind of description, closed-loop stability implies that $\mathbf{w}(k)$ can be bounded by a compact set.[1]

The aim of this paper is to propose a robust dead-time compensation for systems with input nonlinearities which is able to: (i) keep the Smith predictor main advantages (the controller can be designed using a delay-free nominal model and good robustness characteristics), (ii) avoid Smith predictor original drawbacks (slow disturbance rejection and requirement of open-loop stable processes), (iii) reduce, or even eliminate, the nominal dead-time effect over closed loop robustness. But first, it is necessary to describe the systems on which the proposed theory can be applied.

2.1. Models with input nonlinearities

Nonlinear models are usually used when it is required a better representation of the system dynamics for optimal performance, e.g., it is not possible to represent variable gain or asymmetrical dynamics with linear models [15,16]. In this work, the focus will be nonlinear models whose nonlinearities lie only on the system inputs. Despite this limitation, a variety of nonlinear dynamics and static nonlinearities can be represented by this kind of model. Particularly, the commonly known Volterra and Hammerstein models used to represent many real nonlinear processes can be included in this set of models.

The representation of nonlinear processes by Volterra series has various successful applications in process control [17–20], specially because they allow the description of asymmetrical dynamics and gain variations of the process [16]. This model can be viewed as a generalization of the impulsive response for linear systems and its equation is given below

$$y(k) = \sum_{i_1=1}^{\infty} h_{1i_1} u(k-i_1) + \sum_{i_1=1}^{\infty}\sum_{i_2=1}^{\infty} h_{2i_1i_2} u(k-i_1)u(k-i_2) + \cdots + \sum_{i_1=1}^{\infty}\cdots\sum_{i_m}^{\infty} h_{mi_1\ldots i_m} u(k-i_1)\cdots u(k-i_m),$$

where the parameters h are the coefficients of the model and m is the model order. Since this model only uses the inputs to explain the output of the process, the number of coefficients is usually very high. An alternative to this representation is to also use the information of past outputs, resulting in the auto-regressive Volterra (AR-Volterra) model [17], which is described by

$$A(q^{-1})y(k) = B(q^{-1})u(k-1) + \sum_{i_1=1}^{\infty}\sum_{i_2=1}^{\infty} h_{2i_1i_2} u(k-i_1)u(k-i_2) + \cdots + \sum_{i_1=1}^{\infty}\cdots\sum_{i_m=1}^{\infty} h_{mi_1\ldots i_m} u(k-i)\cdots u(k-i_m), \tag{3}$$

where q^{-1} is the delay operator, i.e., $y(k)q^{-j} = y(k-j)$, $A(q^{-1}) = 1 + a_1q^{-1} + \cdots + a_{n_a}q^{-n_a}$ and $B(q^{-1}) = b_0 + b_1q^{-1} + \cdots + b_{n_b}q^{-n_b}$ are polynomials on q^{-1} of order n_a and n_b, respectively. In practice, the infinite summations are also truncated after N terms, although the choice of N is not a trivial matter. More information about identification and control of Volterra models can be found in [17].

The Hammerstein model is another interesting nonlinear model with input nonlinearities. Such model structure may account for nonlinear effects encountered in most chemical processes, where the nonlinear behaviour of many distillation columns, pH neutralization processes, heat exchangers, as well as furnaces and reactors can be effectively modelled by a nonlinear static element followed by a linear dynamic element [21,22]. In essence, the Hammerstein models generalize the well-known gain-scheduling concept for nonlinear control. The model is given by the following equation

$$A(q^{-1})y(k) = B(q^{-1})g(u(k-1)) \tag{4}$$

where polynomials $A(q^{-1})$ and $B(q^{-1})$ are the same defined for the Volterra model and $g(.) : \mathbb{R} \to \mathbb{R}$ is a function that models the static characteristics of the process gain. If $g(.)$ is chosen as a polynomial function, the Hammerstein model is actually a simplified version of the AR-Volterra model.

3. Optimal predictors

In this section, the optimal predictor, which is commonly found in MPC algorithms, e.g., GPC, extended prediction self-adaptive control (EPSAC), extended horizon adaptive control (EHAC), [23] for the linear case, and practical nonlinear model predictive control (PNMPC) [24] and other MPC variations for the nonlinear case [25], will be thoroughly analyzed considering the system with input nonlinearities described in this paper.

From Eq. (1), note that there is no effect of $\mathbf{u}(k)$ over $\mathbf{x}(k+1)$, $\mathbf{x}(k+2)$, ..., $\mathbf{x}(k+d)$ due to the dead-time. As consequence, in absence of uncertainties, namely $\mathbf{w} = 0$, $\mathbf{x}(k+d)$ depends only on past inputs, so this can be obtained knowing the current state of the plant $\mathbf{x}(k)$ and the input sequence $\mathbf{u}(k-d), \mathbf{u}(k-d-1), \ldots, \mathbf{u}(k-1)$. However, this assumption does not hold in practice because it is

[1] Closed-loop stability guarantees that both $|\mathbf{x}(k)| < \infty$, and $|g(\mathbf{u}(k-d))| < \infty$ for all k, so that $|\mathbf{w}(k)| < \infty$ for all k. In other words, uncertainty effect is limited for non-diverging responses in such a way that $\mathbf{w}(k)$ is bounded.