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ORIGINAL ARTICLE

Stability analysis of embedded nonlinear predictor neural generalized predictive controller

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Abstract Nonlinear Predictor-Neural Generalized Predictive Controller (NGPC) is one of the most advanced control techniques that are used with severe nonlinear processes. In this paper, a hybrid solution from NGPC and Internal Model Principle (IMP) is implemented to stabilize nonlinear, non-minimum phase, variable dead time processes under high disturbance values over wide range of operation. Also, the superiority of NGPC over linear predictive controllers, like GPC, is proved for severe nonlinear processes over wide range of operation. The necessary conditions required to stabilize NGPC is derived using Lyapunov stability analysis for nonlinear processes. The NGPC stability conditions and improvement in disturbance suppression are verified by both simulation using Duffing's nonlinear equation and real-time using continuous stirred tank reactor. Up to our knowledge, the paper offers the first hardware embedded Neural GPC which has been utilized to verify NGPC–IMP improvement in realtime.

1. Introduction

Nowadays one of the most efficient networked controllers dealing with nonlinear process is the model predictive controllers' family. Model Predictive Control (MPC) is proving its continuous success in industrial applications particularly in the presence of constraints and varying operating conditions, thereby allowing processes to operate at the limits of their achievable performance. The basic control strategy in MPC is the selection of a set of future control moves (control horizon) and minimizes a cost function based on the desired output trajectory over a prediction horizon with a chosen length. This requires a reasonably accurate internal model identification that captures the essential nonlinearities of the process under

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control in order to predict multi-step ahead dynamic behavior [1]. In many practical applications, the mathematical model of physical process is either unknown or too complicated to be used for control. In this case, nonlinear system identification is an inevitable step in a nonlinear MPC project [2].

In many reported applications of MPC, a linear model is assumed. However, MPC based on linear models, often results in poor control performance for highly nonlinear processes because of the inadequateness of a linear model to predict dynamic behavior of a nonlinear process [3]. Unlike linear system identification, there is no uniform way to parameterize nonlinear variable dead time dynamic systems. Therefore there is a strong requirement of a good fitting model for nonlinear MPC applications.

Among existing techniques, the universal approximation features of neural networks make them a powerful tool for modeling nonlinear systems [4,5]. The structure of neural networks may be classified as Feed Forward or Recurrent neural networks [6]. Most of recent publications in nonlinear system identification use Feed Forward Neural Networks (FFNNs) for system identification due to its simplicity, without losing accuracy, than other types [7,8].

In this paper, the Generalized Predictive Controller (GPC) introduced by Clarke and his coworkers in 1987 has been adopted [9]. This is because the GPC provides advantages over other controller types in controlling non-minimum phase plants, open-loop unstable plants and plants with variable or unknown dead time. It is also robust with respect to modeling errors, over and under parameterization and sensor noise. However, the previous researches of GPC were focusing on linear process or approximated linearized process around certain operating point(s). This approximation of classical GPC was far from controlling severe nonlinear process over wide range of operation.

This problem has been resolved in the last twenty years by using artificial neural network predictive controllers with complex nonlinear processes [10–15]. Therefore for nonlinear plants, the ability of the GPC to make accurate predictions can be enhanced if a neural network is used to learn the dynamics of the plant instead of standard linearization techniques that were used in classical GPC as in the work of [15–17].

The using of Approximate Nonlinear Generalized Predictive Controller (A-NGPC) technique as in work of [18] shows limitations in achieving nonlinear stability robustness. Therefore many researches like for example the work of [18,19] recommend another technique called Nonlinear Predictor Neural Generalized Predictive Controller (NP-NGPC), or simply called Neural GPC (NGPC) in this paper. Regardless from complexity added in this technique, it offers efficient nonlinear system modeling and so better stability achievement.

The fact that Cost Function Minimization (CFM) algorithm used inside generalized predictive controller is massive time consuming let it sometimes not convenient for fast processes. The selection of a minimization method can be based on several criteria such as; number of iterations to a solution, computational costs and accuracy of the solution. Nowadays, there are several minimization algorithms that have been implemented in GPC such as Non-gradient, Simplex and Successive Quadratic Programming. However all of those approaches are iteration intensive in such a way making the realtime control difficult.

Very few literatures address real-time implementation of NGPC for fast processes due to massive calculation problem. Therefore to improve the usability of NGPC in industrial applications, a faster optimization algorithm is needed. The Newton–Raphson algorithm is one of the most widely used methods for minimization. It is a quadratic algorithm converging better than others [20,21]. It requires less iteration numbers for convergence and reduces the calculation. Usually by using Newton–Raphson, very little iterations are sufficient to converge to an acceptable minimization of cost function in many of nonlinear processes. Therefore in this paper we are going to adopt in addition to NGPC, the Newton–Raphson cost function minimization algorithm.

Although some papers have studied realtime implementation of linear predictive controllers in industrial application likes work of [22–24]; up to our knowledge there is a lack of researches cover implementation of realtime embedded nonlinear predictive controllers.

Finally, this work can be considered an extension to already published paper of [25]. Although the work of [25] proves that NGPC coupled with IMP can suppress high class of disturbance values in small range of operation, this paper extends the proof to realtime embedded NGPC in wide range of operation.

1.1. Paper outline

In Section 2, the paper explains the methodology used within the paper. The mathematical conditions to stabilize NGPC under class of disturbances are derived. The paper verifies the conditions required for successful integration between NGPC and IMP technique. Also the paper presents the proposed prototype for realtime embedded NGPC. In Section 3, the stability performance results are presented for both NGPC and traditional GPC. Also the enhancement of hybrid NGPC–IMP technique is verified under severe class of disturbance. Finally, the new realtime embedded NGPC is used to control industrial continuous stirred tank reactor. In Section 4, the paper concludes the realtime and simulation results.

2. Paper methodology

The paper studies the conditions required to stabilize NGPC controlling nonlinear process under class of output disturbances using Lyapunov stability theorems. The paper proves that NGPC stability approaches Stable-In-Sense Lyapunov (SISL) equilibrium state when controlling severe nonlinear process without disturbances. While NGPC stability approaches Uniform Ultimately Bounded (UUB) Lyapunov equilibrium state when there are high class of disturbances perturb closed loop output.

In this paper, the superseding of NGPC over ordinary GPC is proved while controlling nonlinear non-minimum phase process with variable dead time. Also the improvement of disturbance mitigation using hybrid NGPC–IMP technique is verified for nonlinear non-minimum phase process under high disturbances and wide range of operation.

The paper extends the research to cover two severe nonlinear processes as a case study. The first one is the theoretical Duffing's nonlinear equation with variable dead time in wide range of operation and the second is industrial severe nonlinear process like Continuous Stirred Tank Reactor (CSTR).