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Filtered predictive control design using multi-objective optimization based on genetic algorithm for handling offset in chemical processes

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ABSTRACT

The purpose of this paper is to present the linear filtered positional generalized predictive controller (GPC) synthesis using both a positional process model and cost function to ensure stability and offset-free behavior (reference tracking and disturbance rejection), which involves selecting an integral polynomial weighting filter for the setpoint and output of the process, thereby extending the applicability of the predictive controllers to different reference shapes and step disturbances for handling chemical processes. Additionally, robustness aspects are incorporated into the control design of the weighting polynomials, an implementation which involves the filter tuning parameters using a multi-objective optimization based on genetic algorithm. Numerical simulations are conducted featuring two nonlinear chemical processes models (CSTR and boiler level) to assess the efficiency, stability and robustness of different reference shapes and load disturbance rejection.

1. Introduction

The generalized predictive controller (GPC) is one of the most relevant design methods of model-based predictive controllers (MBPC) and it has had major success in industrial and academic contexts. GPC has been successfully implemented in several applications, showing good robustness and performance in dealing with linear and nonlinear processes (Haber et al., 2011; Neshasteriz et al., 2010; Qin and Badgwell, 2003; Mahfouf et al., 2000). Table 1 presents some publications, in the last decade, using the GPC controller to deal with offset-free behavior (reference tracking and disturbance rejection) in different areas.

The pattern formulation of the standard GPC synthesis of Clarke et al. (1987a) is based on a linear process model, CARIMA – controlled auto-regressive integrated moving-average, a quadratic cost function and a control law, both using an incremental structure (implicit design approach). This assumption adds an incremental implementation to the GPC and, therefore, ensures offset-free (reference tracking and disturbance rejection) behavior in many closed-loop control systems. This formalism of the design has been extensively explored in the predictive control literature, and different ways of handling are given to this controller (Belda, 2013; Wang and Rossiter, 2008; Jipuang et al., 2002).

Clarke et al. (1987b) proposal about the incremental GPC, also known as the T-GPC, is to insert a polynomial (herein referred as $T_f(q^{-1})$) that represents the disturbance dynamic in the process model, where this polynomial can be used to deal with disturbance rejection (Rossiter, 2004; Clarke, 1994). Despite the several proposals presented in the control literature using T-GPC, a way to optimally calibrate this polynomial has not been properly explored.

The paper of Jipuang et al. (2002) presents a way of handling disturbance rejection, a CARIMA model for a GPC with the $T_f(q^{-1})$ was inserted as a filter in the process output,

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Table 1 – Publications using the GPC controller.

Reference	Applications
Gangloff et al. (2006)	Surgical robot to reference trajectory
Ott et al. (2008)	Flexible endoscope for handling physiological motions
Neshasteriz et al. (2010)	Industrial processes control with second order plus dead time
Yanfei et al. (2012)	Cascade control for polymerizer temperature
Ouari et al. (2014)	Wind energy conversion system
Lu et al. (2016)	Control of a solar power plant

which is chosen in order to have unity gain under steady-state conditions. The GPC design was intended to have the pole-placement form and it was demonstrated that the use of $T_f(q^{-1})$ can give enhanced robustness against high frequency noise, unmodeled dynamics and good output response.

Wang and Rossiter (2008) extended the GPC design to deal with disturbance rejection and reference tracking of periodic nature, inserting a sinusoidal transfer function and a prefilter in the GPC design, thus changing the prediction model. The authors explored numerical simulations and they gave greater emphasis to sinusoidal reference tracking, mainly in the pre-filter analysis, but to disturbance rejection, the acceptable percentage of its not being clear.

Another reference tracking control technique is based on the work of Belda (2013), which incorporated integrators into the standard GPC design for reference signals in sine and triangular profiles, without altering the initial system model. The only exception was that the optimization function of the predictive control for each reference shape was changed distinctly.

The purpose of this paper is to review and provide a new formalism for the control designs, extending the set of possibilities for the GPC design, using both the positional structure of the process model and the cost function representations, at the same time obtaining an integral controller by selecting a filter in the integral polynomial pattern for the setpoint and output signals. This control synthesis, called filtered positional GPC (FP-GPC) controller design, produces an incremental controller, able to stabilize linear and nonlinear processes, for handling offset and for ensuring satisfactory closed-loop performance.

Additionally, aspects of robustness and performance are incorporated into the design tuning of the weighting polynomials of the FP-GPC controller, where the calibration of two filter design parameters is performed using a multi-objective optimization (optimal tuning) based on sensitivity function and integral absolute error (IAE). To date, the approach to the implementation of the FP-GPC controller design and the multi-objective optimization based on genetic algorithm for tuning the filter parameters of controller have been explored in few applications in the control literature.

The assessment of the proposed FP-GPC controller design is implemented in two nonlinear chemical processes (CSTR and boiler level) with different reference shapes and load disturbance. Aspects such as performance, stability and robustness for handling offset are shown. The choice of these processes was motivated, as significant benchmark models, by the fact that they are characterized by a nonlinear behavior, which makes the FP-GPC controller challenging even in a linear implementation.

It is important to emphasize the following issues: (i) the main contribution of this paper is the proposal of a new mathematical formalism to the GPC controller using both cost function and process model in the positional form. A filter in the reference and output signals is inserted, achieving a controller design called FP-GPC. The filter parameters of this controller are tuned using a multi-objective optimization genetic algorithm to ensure performance and robustness to the controlled system; (ii) little or no emphasis has been given to the positional GPC controller design due to closed-loop stability problems; (iii) it is not the focus of this paper to establish a comparative study between FP-GPC the T-GPC (Clarke, 1994; Rossiter, 2004) nor standard GPC (Clarke et al., 1987a); (iv) the closed-loop stability and the analysis of the tuning set (output and control horizons and the energetic factor) of the standard GPC lie outside the scope of this paper; (v) the relevance of this paper is related to evaluating the influence of the filter parameters on the closed-loop response quality, establishing a trade-off between performance and robustness, in the control theory, using a multi-objective optimization based on genetic algorithm to ensure reference tracking and disturbance rejection, which also stands as a contribution of this paper.

This paper is organized as follows: Section 2 presents the mathematical formalism of the FP-GPC controller design. Section 3 discusses some important concepts of the performance and robustness indices found in the control literature. Section 4 describes the multi-objective optimization based on genetic algorithm to find the optimal values of the filter parameters of the FP-GPC controller. Numerical results for two benchmark chemical processes are presented in Section 5. Finally, conclusions are given in Section 6.

2. Filtered predictive controller design

Consider the deterministic CAR (controlled auto-regressive) model of the controlled process characterized by the following positional discrete equation:

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t-1) \tag{1}$$

where $y(t)$ is the process output, $u(t)$ is the control signal, d is the dead-time and the roots of the polynomials $A(q^{-1})$ and $B(q^{-1})$ are the open-loop poles and zeros from on-line or off-line estimated models, respectively. The FP-GPC control law is obtained by minimizing the cost function given by

$$J = \sum_{j=1}^{N_y} \{\phi_y(t+j) - \phi_r(t+j)\}^2 + \lambda \sum_{j=1}^{N_u} u^2(t+j-d-1) \tag{2}$$

where $\phi_y(t+j)$ and $\phi_r(t+j)$ are auxiliaries of the output variables and reference signals, respectively, defined as

$$\phi_y(t) = P(q^{-1})y(t) = \frac{K_\alpha \alpha(q^{-1})}{\Delta} y(t), \quad \phi_r(t) = P(q^{-1})r(t) = \frac{K_\alpha \alpha(q^{-1})}{\Delta} r(t) \tag{3}$$

where $r(t)$ is the setpoint, $\Delta = (1-q^{-1})$, λ is the control weighting, N_y is the output prediction horizon and N_u is the control horizon. Polynomials $P(q^{-1})$ and $\alpha(q^{-1})$ are correlated with closed-loop system dynamic and filtering aspects, respectively, and K_α represents the filter gain.