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A swarm intelligence-based tuning method for the sliding mode generalized predictive control

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ABSTRACT

This work presents an automatic tuning method for the discontinuous component of the Sliding Mode Generalized Predictive Controller (SMGPC) subject to constraints. The strategy employs Particle Swarm Optimization (PSO) to minimize a second aggregated cost function. The continuous component is obtained by the standard procedure, by Quadratic Programming (QP), thus yielding an online dual optimization scheme. Simulations and performance indexes for common process models in industry, such as nonminimum phase and time delayed systems, result in a better performance, improving robustness and tracking accuracy.

1. Introduction

Controllers play a central role in industrial plants, since they are designed to regulate process variables in accordance with some performance criteria. A low energy consumption is also of practical interest, thus arising the well known *trade-off*: tracking or regulation accuracy *versus* energy consumption. To cope with these issues, controller parameters must be appropriately adjusted and research in this subject keeps its relevance since the work by [1], regarding Proportional Integral Derivative (PID) controller. This tuning method allows getting an easier initial set for PID parameters. When some *intelligence* is incorporated into the closed loop, one has an online or automatic tuning method [2]. Metaheuristic algorithms, such as Particle Swarm Optimization (PSO) are quite feasible in such cases. PSO is a natural inspired computation technique introduced by [3] and it is characterized for its simplicity and high efficiency in searching global optimal solutions in problem spaces. This feature attracted the attention of control engineers in the sense of a simple way of searching optimal or semi-optimal tuning of controller's parameters [4].

Besides PID, known for its simplicity due to just three parameters to tune, Model Predictive Controllers (MPC) are interesting for linear, nonlinear, time-delayed and nonminimum phase systems [5]. It offers a straightforward design method to anticipate future control actions within some time horizon (control horizon), in order to track a future behavior (in some prediction horizon), predicted by an explicit model. The most common model forms in the various MPC products rely on convolution (Finite Step Response FSR and Finite Impulse Response FIR) models, such as Dynamic Matrix Control (DMC), but recent controllers suggest a trend toward state space formulations which provides flexibility in representing stable, unstable, integrating and unmeasured disturbances, just as the Controller Auto-Regressive Integrated Moving-Average (CARIMA) model in the Generalized Predictive Control (GPC) [6,7]. According to [8,9], the objective function of GPC is very similar to that of DMC, with the fundamental difference of using a Diophantine equation and CARIMA model to formulate the dynamic matrix. Abu-Ayyad and Dubay [7] showed that GPC and Extended Predictive Control (EPC) can handle the system matrix ill-conditionality better than other MPC methods and, therefore, it still motivates the development and applications of GPC, as in [6]. The direct treatment of practical constraints such as actuator and output limits is carried out by the minimization or maximization of some objectives, expressed in its simpler form as an aggregated

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quadratic cost function. For this optimization scenario, Quadratic Programming (QP) based on active-set algorithm is usual and PSO can be also applied to tune its parameters, as proposed by [10–13]. Considering its wide application in environments subject to disturbances, robustness is a necessary feature and must be taken into account. An attempt to aggregate robustness into GPC by combining GPC with Sliding Mode Control (SMC) was firstly reported in [14].

SMC is a nonlinear control scheme known to be robust to model uncertainties, disturbances and unmodeled dynamics, being quite suitable for industrial environments. Since the considerations by [15], the research on SMC theory and its applications have been of increasing interest, providing an engineering look at SMC. Key aspects were clarified, such as the chattering phenomena, both in continuous and discrete time. The key idea consists in choosing a state variables function (sliding surface) in which all trajectories must reach in finite time (reaching phase) and, once reached, cannot escape, *sliding* to the desired final value (sliding phase). A control law is then designed to force the trajectories towards this surface (corrective action) and, moreover, to keep them thereafter (equivalent control [16]). This control law must be discontinuous or, at least, it must contain a discontinuous component. In classical SMC, a possibility is for instance the tuning of sliding surface parameters, as obtained by [17,18]. A GPC based on PSO was compared with the traditional QP-based GPC in a greenhouse experiment, giving better results without great increase of computational burden [19].

The well succeeded *melting* of Sliding Mode Predictive Controllers (SMPC) motivated other works and applications [20–30]. Most of the work referenced is concerned with common process control problems, such as delayed and nonminimum phase systems, often represented by a First Order Plus Dead Time (FOPDT) transfer function. For this type of continuous-time models, Camacho and Smith [20] proposed a set of tuning equations for the initial values of the discontinuous component of the control law, as a function of the characteristic parameters of the FOPDT model. When other model structures are considered, including discrete and higher order systems, these equations are no longer valid and computational intelligent approaches are interesting in order to help online tuning of the controller. In [6] it is stated that, for the MPC controllers used in process industries today, the tuning emphasis is on disturbance rejection and suggest as trends and research directions the development of improved disturbance estimators and robust controllers, by means of randomized algorithms which would rely on extensive offline simulation. Tuning is therefore commonly based on offline simulation and the actual performance of the online controller. It is typically carried out using the nominal model and via trial and error try do determine steady state behavior, providing initial tuning values for the parameters. Such simulations need to consider expected model errors and incorporate the characteristics of unmeasured (stochastic) disturbances obtained, for instance, from the actual controller. In this sense, a tuning strategy incorporated into the control loop can provide adaptability and robustness, without significant increase of the computational load, considering the hardware technology currently available. In [2], it also corroborates that while tuning guidelines for initial tuning values may be found in the literature, these rules are not general and do not learn from the controller operation and system response.

Following some design steps of the SMPC presented in [27], here named Sliding Mode Generalized Predictive Controller (SMGPC), this paper keeps QP active-set for the optimization of the continuous component of the control law responsible for the sliding phase, but proposes PSO as an optimization tool for selecting optimal parameters for the discontinuous component of the control law, thus yielding a dual optimization scheme (henceforth named Dual-SMGPC), applicable to a wider class of systems. Moreover, now its parameters are adaptive, providing robustness during reaching phase. In order to test the way PSO can find the optimum solutions, besides the common approach of getting the results from the initial population, two other variations are compared: restarting the population after some iterations while keeping a member in the next population, and a totally random new population after restarting, to avoid possible local minimum. In traditional SMGPC, these parameters are kept constant and calculated offline, normally through simulations. Simulations on common process models will be presented and the results compared with SMGPC without PSO, with a fixed pair (K_d, δ). The remaining of this paper is organized as follows: Section 2 states the GPC and both optimization problems (QP and PSO), discussing adjustments criteria; Section 3 presents and comment simulations results; Section 4 provides some conclusions and encourage future works.

2. Controller design

The SMGPC presented here is based on a Controller Auto-Regressive Integrated Moving-Average model (CARIMA), considered linear around each operating point and described as

$$\Delta A(q^{-1})y(k) = B(q^{-1})\Delta u(k-d-1)+\xi(k), \tag{1}$$

where d is the delay from input to output (here considered as a multiple of the sampling time), u is the input signal, q^{-1} is the backward-shift operator, $\Delta : 1-q^{-1}$ and ξ is the zero mean white noise. A and B are polynomials in q^{-1} defined as

$$A(q^{-1}) = 1+a_1q^{-1}+a_2q^{-2}+\ldots+a_{na}q^{-na}, \tag{2}$$

$$B(q^{-1}) = b_0+b_1q^{-1}+b_2q^{-2}+\ldots+a_{nb}q^{-nb}. \tag{3}$$

According to the SMC theory [16], the first step to design the controller is to define a sliding surface, $S(t)$, along which the process can slide to find its desired final value. Very often, $S(t)$ is chosen in such a way that represents a desired system dynamics and/or control objective. For instance, $S(t)$ could be the tracking error $e_o = y-w$, with w being some reference signal. The problem of tracking a reference value can be reduced to keeping $S(t)$ at zero. From [25,27], the j-step ahead prediction of $S(k)$ with information until the actual instant $t=k$ is given by

$$\hat{S}(k+j) = P_s(q^{-1})(\hat{y}(k+j)-w(k+j))+Q_s(q^{-1})\Delta u(k+j-1-d). \tag{4}$$

Polynomials $P_s(q^{-1})$, $Q_s(q^{-1})$ have degree np and nq respectively, and allow to design the desired dynamics in the sliding condition.

A common adjustment is choosing $P_s(q^{-1})$ and $Q_s(q^{-1})$ as a first order system:

$$\frac{Q_s(q^{-1})}{P_s(q^{-1})} = \frac{(1-\alpha)q^{-1}}{1-\alpha q^{-1}}, \tag{5}$$

with $0<\alpha\le 1$, since all roots of $P_s(q^{-1})$ must be inside the unit circle [27]. As $\alpha \to 0$ the dynamic is faster.

The cost function aggregates two simultaneous objectives:

$$J_C = \sum_{j=N_1}^{N_y} [\hat{S}(k+j)]^2 + \sum_{j=1}^{N_u} \lambda[\Delta u(k+j-1)]^2 \tag{6}$$

where λ is set constant and $N_1 - N_y$ is the period of time in which one desires the output tracks the reference signal and N_u is the control horizon. For these parameters, [27] suggested some intuitive relations, which can be used as initial values. Other online tuning strategies for these specific parameters are available in the literature [2].