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An explicit optimal input design for first order systems identification

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Abstract: This paper focuses on the problem of closed loop online identification of the time constant in the single input single output (SISO) first order linear model. A new explicit approach for the simultaneous online optimal experiment design (OED) and model parameter identification is presented. Based on the observation theory and a model based predictive control (MPC) algorithm, this approach aims to solve an optimal control problem where input and output constraints may be specified. This constrained control objective aims to maximize the sensitivity of the model output with respect to the unknown model parameter (the time constant). The control law is derived explicitly offline and simple to be implemented: the input may be computed fast online while the unknown model time constant is estimated at the same time.

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1. INTRODUCTION

When using dynamic models for simulation, control or optimization, all model parameters need to be numerically known. Among the dynamic models, the first order linear model is the simplest model: it is based on a static gain and a time constant. Methods to estimate the value of the parameters of a considered model concern the identification task (see Ljung (1999)), which relies on experimental data. OED may be useful if no data exist for identification, since it aims to design new experimental data (see Franceschini and Macchietto (2008)) which are often used offline for the identification procedure, hence decoupling these two procedures.

This paper focuses on the coupled online OED and parameter estimation for such a first order linear model, where the time constant (that may vary during the time) has to be estimated. For such estimation problem, one may first think to apply a step input. But, this input in not sufficiently persistent (i.e., when the steady is reached in that case after some time, the output does not contain enough information on the dynamic, and the time constant can not be estimated). Pseudo-random binary sequence (PRBS) is a better open loop approach, since it features a rich input signal. However, open loop control does not allow to maintain the process output is a prescribed region, for example if the process has still to be used in the meantime for production. Therefore, an input design for identification based on closed loop control is required. In Shouche et al. (2002), the authors developed a constrained MPC based on an auto regressive model with external inputs (ARX) with a persistent input constraint, where the parameters are estimated online by regression. This led to a non-convex simultaneous online identification and control problem.

The new method developed here for the SISO first order linear model is a particular development of a general approach (Qian et al. (2013, 2014)) developed for multivariable nonlinear models. In these papers, an approach combining the closed loop online parameter identification with OED has been proposed for the input design. Based on a MPC, it aims to compute online the optimal input that maximize a norm of the sensitivities of the process outputs with respect to the unknown model parameters, which are estimated at the same time by an observer. The predictive controller handles input and output constraints while its cost function is based on the sensitivity criterion. Here, based on this approach, for the SISO first order linear model, the problem is to design a controller and an estimator that both allow to estimate the unknown time constant (that may varies) and to maintain the process in a prescribed region. Based on the linearity of the model and assuming that the argument of the MPC is a single value (hence, the control horizon is tuned to one), an explicit controller can be derived offline, which avoid to solve any online optimization task.

This paper is structured as follows: Section 2 deals with some recalls on the previous general approach of Qian et al. (2013, 2014) developed for multivariable nonlinear models. Section 3 contains the proposed algorithm for the

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constrained optimal closed loop online identification of the time constant in a SISO first order linear model. In section 4, the simulation results demonstrate the efficiency of this approach.

2. PRELIMINARIES

In Qian et al. (2013, 2014), the algorithm features the following steps:

Offline synthesis

- define a dynamic (nonlinear or linear) non autonomous system modelled by ordinary differential equations. This model contains known and unknown model parameters.
- define the sensitivity dynamic model of the model state with respect to the unknown model parameters.
- define an augmented dynamic model, where the state contains the model state and the unknown model parameters. It is used to define an observer that aims to estimate the unknown model parameters and (if possible) the model state.
- define a nonlinear MPC constrained optimization problem based on the maximization of the norm of the sensitivity dynamic model state to design a persistent input.

Online computations

- at each current time t_k , get the measure of the process output $y_p(t_k)$
- then, based on the process input applied $u(t_k)$ and $y_p(t_k)$, integrate the observer to get the current estimate of the unknown parameters
- then, based on the measure $y_p(t_k)$, the parameter estimations, the nonlinear MPC constrained optimization problem is solved since, in a general case, and due to the nonlinearity of the problem, the search for the optimal control $u^{max}(t_k)$ to be applied at each sample time requires the online integration of the 2 prediction models used with the nonlinear MPC resolution.
- then, $u^{max}(t_k)$ is applied from $t_k + \epsilon$ to t_{k+1} , where ϵ is the time necessary for the whole loop (i.e, take the measure, integrate the observer, solve the constrained optimization problem). Hence, the main cost in time is related to the resolution of the constrained optimization problem involving model integrations, which might be important compared to the sampling time.

3. NEW ALGORITHM

3.1 Main ideas

For the previous approach, let us now consider the simplest SISO case: the well known first order model where $x \in \mathbb{R}$ is the measured state, u is the measured input, with one unknown parameter (the time constant T > 0), the known static gain $G \in \mathbb{R}^*$, $y_p(t_k)$ is the measured process output at the current time t_k considered as the initial time:

$$\begin{cases} \dot{x}(t) = \frac{-1}{T}x(t) + \frac{G}{T}u(t), \ t > t_k \\ x(t = t_k) = x(t_k) = y_p(t_k) \end{cases}$$
(1)

In that case, the whole online numerical resolution may be simplified to get an explicit controller derived offline, hence reducing the online computational burden.

Offline synthesis The control law may be designed offline as follows:

- define the sensitivity dynamic model, in the time domain.
- define an augmented dynamic model, where the state contains the model state and the unknown time constant. It is used to define an observer that aims to estimate the unknown time constant.
- get the predicted step response of the sensitivity model into the prediction horizon N_p . It is based on the Laplace transform applied to the process model and to the sensitivity model: hence, the formula is parametrized for any initial conditions of the model state $x(t_k)$ and the sensitivity model state $x_s(t_k)$
- due to the convexity of the constrained quadratic problem, get the worst control law $u_{min}(t_k)$ (that minimize the MPC cost function) and therefore the persistent control law $u^{max}(t_k)$ (that maximize the MPC cost function as requested by the method) to be applied at each time t_k .

Online computations

- at each current time t_k , get the process measure $y_p(t_k)$
- then, based on the process input applied $u(t_k)$ and $y_p(t_k)$, integrate the observer to get the current estimate of the time constant $\hat{T}(t_k)$
- then, based on the measure $y_p(t_k)$ and the estimation $\hat{T}(t_k)$, the optimal control to apply $u(t_k) = u^{max}(t_k)$ (constrained in magnitude) is computed, simply obtained from the evaluation of the explicit control law defined offline based on $u_{min}(t_k)$ and the input bounds.
- then, $u^{max}(t_k)$ is applied from $t_k + \epsilon$ to t_{k+1} , where ϵ is the time necessary for the whole loop (i.e, take the measure, integrate the observer, compute $u^{max}(t_k)$). Hence, the main cost in time is the observer integration: it is low in that case compared to the sampling time (if it is larger than the order of the ms). Therefore, the proposed algorithm for the SISO first order model is a very fast control algorithm.

Following the existing general method given in Qian et al. (2013, 2014), the steps of the main ideas for this new input design are detailed in the following parts.

3.2 Sensitivity model

Using the considered SISO model (1), the sensitivity model state $x_s = \frac{\partial x}{\partial T}$ is given by:

$$\begin{cases} \dot{x}_s(t) = \frac{1}{T^2} x(t) - \frac{1}{T} x_s(t) - \frac{G}{T^2} u(t), \ t > t_k \\ x_s(t = t_k) = x_s(t_k) \\ x_s(t = 0) = 0 \end{cases}$$
(2)

3.3 Observer design

From the first order model (1), the augmented state is $x_a(t) = [x(t) \frac{1}{T}]^T$ in the augmented model:

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