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Nonlinear model predictive control of multivariable processes using block-structured models

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Abstract

Block-structured models, such as Wiener or Hammerstein models, have been used in nonlinear model predictive control to reduce the cost of identification and online computation. The solution of a nonlinear dynamic optimization problem has been avoided by inverting the nonlinear element and solving the resulting linear problem in the past. However, by exploiting the block structure for sensitivity calculation, the original nonlinear problem can also be solved at low computational cost. At the same time, greater modeling flexibility is achieved. Recently, a new Hammerstein model structure has been proposed for multivariable processes with input directionality, which exploits such increased modeling flexibility. This paper deals with nonlinear model predictive control constrained by models of Hammerstein or Uryson structure. A method for efficient calculation of sensitivity information is developed. In a simulation example, the method is shown to combine low computational cost with a significant reduction of the loss of optimality compared to the previous methods.

Keywords: Multivariable nonlinear control; Nonlinear model predictive control; Block-structured model; Hammerstein model; Uryson model; Block-oriented model

1. Introduction

Nonlinear model predictive control (NMPC) poses challenging problems both in modeling and computation. The development of the nonlinear, dynamic process models either requires large amounts of identification data or deep physical insight for rigorous modeling. The resulting optimization problem has to be solved within the short cycle times required in closed-loop NMPC. Numerous model reduction techniques have been explored to reduce the original process model (Marquardt, 2001), or to totally avoid online optimization (Srinivasan, Bonvin, Visser, & Palanki, 2003).

Tailored solution algorithms have been developed for NMPC based on Wiener (Norquay, Palazoglu, & Romagnoli, 1998) and Hammerstein (Zhu & Seborg, 1994) models. The solution strategies are based on the inversion of the nonlinear element to avoid nonlinear dynamic optimization and to reduce it to a linear problem. We will refer to this strategy as the "nonlinearity inversion controller" in the sequel. To obtain a unique solution with the nonlinearity inversion method, the nonlinearity of the model needs to be bijective, which is generally not the case. In particular, in multi-input multi-output (MIMO) cases severe restrictions on the model structures are imposed.

In contrast to the nonlinearity inversion controller, we aim at a direct solution of the nonlinear dynamic optimization problem constrained by a block-structured model. Therefore, first order derivatives of the objective and constraints with respect to the decision variables of the dynamic optimization problem are required. For rigorous dynamic models, the calculation of this sensitivity information oftentimes dominates the computational cost of the solution process. We reduce the computational cost by exploiting the block structure for efficient calculation of sensitivity information. Our method covers all MIMO Hammerstein as well as Uryson (Gallman, 1975) models.

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Block-structured models consisting of nonlinear static and linear dynamic elements have been used to reduce both, the modeling and the computational effort. Structuring the model in this way leads to an approximate model, which is inferior in prediction quality to a rigorous nonlinear model, but provides a viable compromise between the low predictive capabilities of a linear model and the costly development of a rigorous nonlinear dynamic model. Applications range from such different fields as neuroprothesis, where a rigorous nonlinear model could not be obtained (Hunt, Munih, Donaldson, & Barr, 1998), to the control of an industrial C_2 splitter, where a Wiener structure was used in combination with a rigorous steady-state process model (Norquay, Palazoglu, & Romagnoli, 1999). The Hammerstein structure is especially well suited for identification of chemical process systems. Here, steady-state information is often available from rigorous process models or from historical plant data. Using these data sources, the nonlinear steady-state gain function can be identified without further plant tests. The linear element of a Hammerstein model can then be identified independently using binary signals such as steps or pseudo-random binary sequences (Bai, 2004) resulting in a standard linear identification problem. In essence, the identification effort for such a Hammerstein model is only marginally larger than that for a linear model, since no additional plant tests are required to identify the nonlinear gain. In contrast, such simplified identification is not possible for Wiener models, since no method for the independent identification of the linear and nonlinear elements exists for this structure. We will not treat the topic of identification in this paper, but focus on the application of block-structured models in NMPC, and refer the reader to Harnischmacher and Marquardt (2006a) for the identification perspective.

Several model structures have been proposed for multivariable Hammerstein models. A model based on separate nonlinearities has been proposed by Kortmann and Unbehauen (1987). It is suitable for the nonlinearity inversion controller. It will be used for comparison in this paper and refer to it as the KU model in the sequel. The KU model severely restricts the nonlinear maps to be used. Recently, a new model structure has been proposed by Harnischmacher and Marquardt (2006a), which allows the incorporation of arbitrary nonlinear maps. This model structure will be used for the first time in nonlinear model predictive control in this paper.

After the presentation of a problem statement in the following section, the sensitivity equations are derived for multivariable Hammerstein and Uryson models in Section 3, since they play a key role in the solution of optimal control problems constrained by such models. Closed-loop optimal control is discussed in Section 4. The new method is put into perspective with competing NMPC technologies, before it is benchmarked on a simulation example in Section 5.

2. Open-loop control formulation

The constrained, discrete-time, open-loop optimal control problem

$$\min_{\boldsymbol{u}_1,\ldots,\boldsymbol{u}_K} \Phi = \sum_{k=1}^{K} \Phi_k(\boldsymbol{x}_k, \boldsymbol{u}_k) \tag{1a}$$

$$\text{s.t. } \boldsymbol{x}_k = \boldsymbol{f}(\boldsymbol{x}_{k-1}, \boldsymbol{u}_{k-1}), \tag{1b}$$

$$\boldsymbol{0} \geqslant \boldsymbol{g}(\boldsymbol{x}_k, \boldsymbol{u}_k, t_k), \tag{1c}$$

$$k = 1 \ldots K \tag{1d}$$

is given with the objective function $\Phi(\cdot)$, the manipulated variables $\boldsymbol{u}_k$, partly measurable state variables $\boldsymbol{x}_k$, inequality constraints $\boldsymbol{g}(\cdot)$, process model $\boldsymbol{f}(\cdot)$, and given initial conditions $\boldsymbol{x}_0$.

The process model $\boldsymbol{f}(\cdot)$ either needs to be identified from plant data or modeled based on physical process understanding. Without simplifications, either route is often prohibitively costly and in the latter case, some kind of model reduction may be required, before problem (1) can be solved in real-time. The lack of economically obtainable, approximate, nonlinear dynamic process models is considered to be a major obstacle to the spread of nonlinear model predictive control in industry (Lee, 2000). In this paper, it is assumed that $\boldsymbol{f}(\cdot)$ can be approximated by a discrete-time Hammerstein or Uryson model (Pearson, 1999). The block diagrams of these models are depicted in Fig. 1 for the SISO case. An approximation of process dynamics by means of these model structures always leads to a structural plant-model mismatch, but greatly simplifies the identification problem. Thus, there is a qualitative difference between a rigorous model and a block-structured model with respect to

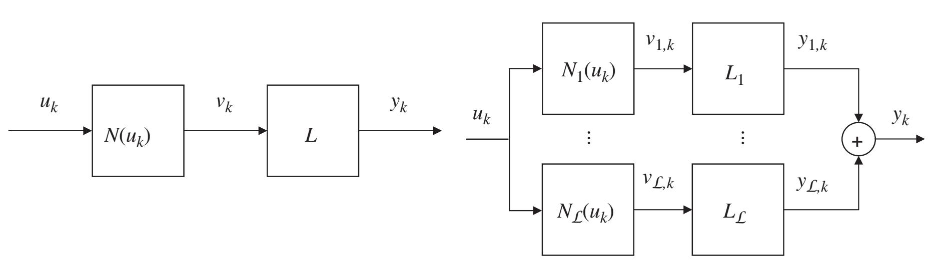

Fig. 1. SISO Hammerstein model (left), SISO Uryson model (right).