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Modelling and predictive control of a neutralisation reactor using sparse support vector machine Wiener models

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ABSTRACT

This paper has two objectives: (a) it describes the problem of finding a precise and uncomplicated model of a neutralisation process, (b) it details development of a nonlinear Model Predictive Control (MPC) algorithm for the plant. The model has a cascade Wiener structure, i.e. a linear dynamic part is followed by a nonlinear steady-state one. A Least-Squares Support Vector Machine (LS-SVM) approximator is used as the steady-state part. Although the LS-SVM has excellent approximation abilities and it may be found easily, it suffers from a huge number of parameters. Two pruning methods of the LS-SVM Wiener model are described and compared with a classical pruning algorithm. The described pruning methods make it possible to remove as much as 70% of support vectors without any significant deterioration of model accuracy. Next, the pruned model is used in a computationally efficient MPC algorithm in which a linear approximation of the predicted output trajectory is successively found on-line and used for prediction. The control profile is calculated on-line from a quadratic optimisation problem. It is demonstrated that the described MPC algorithm with on-line linearisation based on the pruned LS-SVM Wiener model gives practically the same trajectories as those obtained in the computationally complex MPC approach based on the full model with on-line nonlinear optimisation repeated at each sampling instant.

1. Introduction

Good control of neutralisation processes is necessary in chemical engineering, biotechnology and waste-water treatment industries [16]. Both steady-state and dynamic properties of the neutralisation process are nonlinear, which means that it is difficult to control by the classical linear control methods (e.g. PID), in particular when the set-point or other operating conditions change significantly and fast. In addition to its industrial significance, the neutralisation process is a classical benchmark used for evaluation of different nonlinear model structures and control methods. Due to nonlinearity of the process adaptive control techniques may be used, in particular a model reference adaptive neural network control strategy [23], an adaptive nonlinear output feedback control scheme containing an input–output linearising controller and a nonlinear observer [15], an adaptive nonlinear Internal Model Controller (IMC) [22] and an adaptive backstepping state feedback controller [47]. An alternative is to use multi-model controllers, e.g. a multi-model PID controller based on a set of simple linear dynamic models [5], a multi-model robust H_∞ controller [11], or fuzzy structures, e.g. a fuzzy PI controller [10], a fuzzy PID controller [19] and a fuzzy IMC structure [21]. An adaptive fuzzy sliding mode controller is presented in [7], a nonlinear IMC structure is discussed in [30]. Another options are a neural network linearising scheme cooperating with a PID controller [23], a model-free learning controller using reinforcement learning [41] and an approximate multi-parametric nonlinear MPC controller [14].

Unlike the classical control approaches, such as PID, in which the model of the process is used only during development of the controller, in Model Predictive Control (MPC) algorithms [42] a dynamic model of the controlled process is used directly on-line. The model calculates predictions of the output (or state) variables, which are next used during optimisation of the control sequence. Prediction and optimisation are repeatedly performed on-line. Optimisation makes it possible not only to find the best possible control profile which results in excellent set-point tracking and disturbance compensation, but also to take into account constraints imposed on process inputs (manipulated variables) and outputs (controlled variables) or state variables in a natural and efficient manner. Furthermore, the MPC approach is very universal as it allows to control multiple-input multiple-output processes. That is why the MPC algorithms have been successfully used for years in numerous advanced applications. Example applications of MPC include a mobile robot [1], an automotive engine [2], an active queue management system in TCP/IP networks [4], a flexible

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manipulator [9], an electric vehicle [27], a cutting process [33], a multi-tank water system [36], an unmanned aerial vehicle [38], a distillation column [43], an air conditioning system [46].

The neutralisation process may be controlled by MPC algorithms. A multiple-model control strategy based on a set of classical linear MPC controllers is described in [8,11]. A neural network trained off-line to mimic the nonlinear MPC algorithm may be also used [3]. A continuous-time MPC algorithm using a piecewise-linear approximation, which simplifies implementation, is discussed in [31]. When a nonlinear model is used directly in MPC for prediction, the MPC optimisation problem solved at each sampling instant on-line is a nonlinear task. Applications of such nonlinear MPC algorithms to the neutralisation process are reported in [26,45]. On-line nonlinear optimisation is not only computationally demanding, but also convergence problems are possible, the obtained solution may be a local minimum, not the global ones. A practical solution leading to reduction of computational burden is to use for prediction not the full nonlinear model, but its local linear approximation or an approximation of the predicted trajectory [24]. Successive on-line linearisation makes it possible to eliminate the necessity of solving on-line a nonlinear MPC optimisation problem as at each sampling instant an easy to solve quadratic optimisation task is solved. Nonlinear MPC algorithms with successive on-line model or trajectory linearisation applied to the neutralisation process are described in [25]. An excellent review of possible MPC approaches to the neutralisation process is given in [16].

The basic issue to address during development of MPC algorithms is the choice of the model. Although a number of black-box model structures exist [28], e.g. polynomials, fuzzy systems, neural networks, wavelets, etc., in case of the neutralisation reactor a cascade block-oriented Wiener model may be efficiently used, e.g. [23,26,30,45]. The Wiener structure consists of a linear dynamic part and a nonlinear steady-state one connected in series [12,18]. As the steady-state part of the Wiener model a neural network may be used [25]. Neural networks are excellent approximators, but training (although performed off-line) is a quite demanding nonlinear optimisation problem. In order to find a good neural model a number of networks (with different initial weights and different number of hidden nodes) are trained and the best one is finally chosen for application. An interesting alternative is to use a Support Vector Machine (SVM) approximator [37]. Although the SVM model is nonlinear, its identification requires solving convex optimisation problems, typically quadratic programming ones. An extension of the SVM approximator is a Least Squares Support Vector Machine (LS-SVM), whose identification is even simpler as only least-squares problems are solved [39]. An important disadvantage of LS-SVM is lack of spareness, i.e. the number of support vectors is the same as the number of training samples. To reduce the number of parameters some pruning algorithms may be used, e.g. the approach discussed by the authors of the LS-SVM approximator [40] which consists in eliminating the support vectors with the smallest absolute value of spectrum. A more complicated pruning algorithm is detailed in [20], the sequential minimal optimisation (SMO) pruning method is introduced in [48].

This paper reports model identification and pruning of the neutralisation reactor. Two pruning methods of the Wiener LS-SVM model are compared with a classical pruning algorithm. Next, the MPC algorithm with successive on-line trajectory linearisation and quadratic optimisation is developed for the pruned model of the process. The discussed MPC algorithm is compared with a computationally complex MPC approach with on-line nonlinear optimisation repeated at each sampling instant. The effect of model pruning on its quality, control performance of MPC and its computational complexity is discussed. Although both SVM and LS-SVM approximators have been used in MPC, e.g. a multiple-tank system process is considered in [17], a flight control problem in [38] and an air-conditioning system in [46], in the cited works computationally demanding on-line nonlinear optimisation is used at each sampling instant.

This paper is organised as follows. Section 2 reminds the general idea of MPC and Section 3 describes the structure of the LS-SVM Wiener model. The main parts of the paper, given in Sections 4 and 5, discuss the MPC algorithm with on-line trajectory linearisation for the LS-SVM Wiener model, its identification and pruning. Section 6 thoroughly discusses development of the model and predictive control of the considered neutralisation reactor. Finally, Section 7 concludes the paper.

2. Predictive control problem formulation

Let the input (the manipulated variable) of the considered dynamic system be denoted by u and the output (the controlled output) of the system be denoted by y. In MPC algorithms [42] at each consecutive sampling instant k not only the current value $u(k)$ of the manipulated variable is calculated, but a set of future increments

$$\Delta \boldsymbol{u}(k) = \left[\Delta u(k|k)\ \Delta u(k+1|k) \ldots \Delta u(k+N_{\mathrm{u}}-1|k)\right]^{\mathrm{T}} \tag{1}$$

is found, where N_{u} is the control horizon and the increments are defined as

$$\Delta u(k+p|k) = \begin{cases} u(k|k) - u(k-1) & \text{if } p=0 \\ u(k+p|k) - u(k+p-1|k) & \text{if } p \geq 1 \end{cases}$$

The symbol $u(k+p|k)$ denotes the value of the input signal for the future sampling instant $k+p$ calculated at the current instant k. It is assumed that $\Delta u(k+p|k)=0$ for $p \geq N_{\mathrm{u}}$. The objective of the MPC algorithm is to minimise differences between the set-point trajectory and the corresponding predicted values of the output signal over the prediction horizon, $N \geq N_{\mathrm{u}}$, and to penalise excessive control increments. Hence, the future decision variables of MPC (Eq. (1)) are determined from an optimisation procedure. The cost-function is typically

$$J(k) = \sum_{p=1}^{N} (y^{\mathrm{sp}}(k+p|k) - \hat{y}(k+p|k))^2 + \sum_{p=0}^{N_{\mathrm{u}}-1} \lambda (\Delta u(k+p|k))^2 \tag{2}$$

where the set-point for the sampling instant $k+p$ known at the current instant k is $y^{\mathrm{sp}}(k+p|k)$ (very frequently it is assumed that $y^{\mathrm{sp}}(k+p|k) = y^{\mathrm{sp}}(k)$ for all $p=1,\ldots,N$), the future value of the process output signal predicted for the instant $k+p$ at the instant k is denoted by $\hat{y}(k+p|k)$, $\lambda > 0$ is a weighting coefficient (the bigger the λ, the slower the algorithm). The problem of tuning MPC algorithms, i.e. adjusting parameters λ, N, N_{u}, is discussed elsewhere [42]. If it is necessary to take into account some constraints imposed on the manipulated and controlled variables, the future control increments (1) are found on-line at each sampling instant from the following optimisation problem

$$\begin{aligned} &\min_{\Delta u(k|k),\ldots,\Delta u(k+N_{\mathrm{u}}-1|k)} \quad \{J(k)\} \\ &\text{subject to} \quad u^{\min} \leq u(k+p|k) \leq u^{\max}, \quad p=0,\ldots,N_{\mathrm{u}}-1 \\ &-\Delta u^{\max} \leq \Delta u(k+p|k) \leq \Delta u^{\max}, \quad p=0,\ldots,N_{\mathrm{u}}-1 \\ &y^{\min} \leq \hat{y}(k+p|k) \leq y^{\max}, \quad p=1,\ldots,N \end{aligned} \tag{3}$$

where $u^{\min}$, $u^{\max}$, $\Delta u^{\max}$, $y^{\min}$, $y^{\max}$ define constraints imposed on the magnitude of the input variable, on the increment of the input variable and on the magnitude of the predicted output variable, respectively. The MPC optimisation task (3) is solved on-line at each sampling instant which gives the future control increments (1), but only the first element of the determined sequence is applied to the process, i.e. $u(k) = \Delta u(k|k) + u(k-1)$. At the next