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Support vector regression model predictive control on a HVAC plant

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Abstract

Some industrial and scientific processes require simultaneous and accurate control of temperature and relative humidity. In this paper, support vector regression (SVR) is used to build the 2-by-2 nonlinear dynamic model of a HVAC system. A nonlinear model predictive controller is then designed based on this model and an optimization algorithm is used to generate online the control signals within the control constraints. Experimental results show good control performance in terms of reference command tracking ability and steady-state errors. This performance is superior to that obtained using a neural fuzzy controller.

Keywords: Support vector regression; HVAC (heating, ventilation and air-conditioning); Nonlinear model predictive control; Modeling; Temperature; Relative humidity

1. Introduction

Heating, ventilation and air-conditioning (HVAC) are widely used. Most currently used HVAC systems control room temperature solely, leaving relative humidity to find its own level. Accurate temperature and relative humidity control, however, is required in some industrial and scientific processes (ASHRAE, 1999). Consisting of many mechanical, hydraulic and electrical components, the overall dynamics of HVAC plants are highly nonlinear. The interaction between the temperature and humidity control loops is rather complex, and considerable constraints are imposed by the nonideal behavior of actuators such as dampers and valves. Obtaining accurate models for these systems is a difficult and challenging task. Most existing methods for control of HVAC system make use of conventional control theory, either linear or nonlinear (Arguello-Serrano & Velez-Reyes, 1999). Recently, neural networks (NNs) (Khalid, Omatu, & Yusof, 1995) and fuzzy logic (Thompson & Dexter, 2005) have been successfully used. In this paper, a new method of support vector regression (SVR) will be used to model the forward dynamics of a HVAC system. A model predictive controller is then designed based on the SVR model.

The past two decades have witnessed great success in the use of model predictive control (MPC) in a variety of industrial processes (Camacho & Bordons, 1999; Clarke, 1994; Mayne, Rawlings, Rao, & Scokaert, 2000; Morari & Lee, 1999). In MPC, by setting the current state of the plant as the initial state, the dynamic model of the system is used to predict the controlled variables within a prediction horizon. An optimal control sequence is then obtained by solving a finite horizon open-loop optimal control problem. Only the first control action is finally applied to the process. The procedure is repeated at every sampling instant using the updated information (measurements) of the process. A key advantage of MPC over other control schemes is its ability to incorporate various constraints into the formulation of the control problem.

Although industrial processes usually contain complex nonlinearities, most of the MPC algorithms are based on a linear model of the process. However, a linear model may not be sufficient for highly nonlinear systems. The great success of linear MPC has motivated its extension to nonlinear MPC (Kawathekar & Riggs, 2007; Nagy, Mahn, Franke, & Allgöwer, 2006). Because of its universal approximation ability, feed-forward (FF) NNs have been

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used in MPC (Duarte, Suárez, & Bassi, 2001; Gu & Hu, 2002; Potočnik & Grabec, 2002).

The support vector machine (SVM) (Schölkopf & Smola, 2002) has been developing very fast in recent years. Like conventional FF NNs, the SVM has been used by researchers to solve classification and regression problems. Possessing similar universal approximation ability, SVR can also be used to model nonlinear processes, just as conventional NNs are. In this paper, the SVR is used as a new tool to build a NARX model for a nonlinear dynamic process. SVR has been reported to be used in control. Miao and Wang (2002) used a SVR model in nonlinear MPC for a SISO system. Suykens, Vandewalle, and De Moor (2001) used the least squares support vector machines (LS-SVMs) for the optimal control of nonlinear systems. The formulation of LS-SVM involves equality rather than inequality constraints and utilizes a least squares cost function. In the optimal control method by LS-SVMs, the N-stage optimal control problem and the optimization problem related to the LS-SVM controller are incorporated within one problem formulation. de Kruif and de Vries (2001) have proposed the SVM as a learning mechanism in FF control. While all the above researches were carried out in simulations, this paper will emphasize the 2-by-2 SVR nonlinear MPC conducted in an actual HVAC plant.

Compared with the FF NN models, the SVR model has certain advantages. Firstly, training for the SVR results in a global optimum. This is due to the fact that SVR is formulated as a convex quadratic optimization problem for which there is a global optimum (Fletcher, 1987; Schölkopf & Smola, 2002). Section 2 gives more details on this. On the other hand, the training of FF NNs may become trapped at a local minimum. For NNs, apart from the global minima in the weight space, there are also possibly many local minima where the objective function is larger than that at the global minimum (Haykin, 1999). Thus, mathematically, the SVR model has more attractive properties than the NN model. The second advantage is that the design and training for the SVR model are relatively more straightforward and systematic as compared with those for the NN model. The tuning parameters of SVR are fewer than those of NNs. With the Gaussian kernel function chosen a priori and the value of ε for ε-insensitive loss function determined by the resolution of the sensors and the required control accuracy, there are two design parameters that need to be tuned, i.e. the generalization parameter C and the width parameter σ in the kernel function. With k-fold cross-validation (Duan, Sathiya Keerthi, & Poo, 2003), the optimal values for C and σ with respect to the chosen grid point resolution can readily be found. When using FF NNs, on the other hand, one needs first to decide upon the structure of the network, including the number of hidden layers, the number of neurons per layer and the type of activation function. Furthermore, there are also a greater number of parameters that needs to be carefully chosen, mostly based on experience, for training of the NN to proceed on properly. The third advantage is that it is relatively easier to achieve good generalization when using SVR as compared with NNs. Generalization refers to how well the properly trained model performs on unseen examples. An oversized and over-trained network can give very small residual error during training, but performs poorly on unseen examples. With NNs, proper design of both the network structure and training process to achieve good generalization properties is more of an art. The SVR, on the other hand, is a type of model that is optimized so that prediction error and model complexity are simultaneously minimized. In short, the formulation of SVR captures the main insight of statistical learning theory, i.e. in order to obtain a good generalization, both training error and model complexity are controlled, by explaining the data with a simple model (Schölkopf & Smola, 2002).

This paper is organized as follows: Section 2 gives a brief introduction of SVR. The experimental thermal chamber is then introduced in Section 3 followed by a discussion of the modeling of the forward dynamics of the HVAC system in Section 4. Section 5 describes the design of the SVR MPC controller and Section 6 gives the experimental control results for both temperature and relative humidity using SVR MPC controllers. This is followed by the conclusion in Section 7.

2. Support vector regression

The SVM is a learning method with a theoretical root in statistical learning theory (Vapnik, 1995). The SVM was originally developed for classification, and was later generalized to solve regression problems—SVR (Schölkopf & Smola, 2002; Smola & Schölkopf, 1998). The basic idea of SVR is briefly described here.

First, an input vector $\mathbf{x}$ is mapped onto some usually higher dimensional space (feature space) through a nonlinear mapping:

$$\begin{aligned} \Phi : \mathscr{X} &\rightarrow \mathscr{H} \\ \mathbf{x} &\longmapsto \mathbf{z} = \Phi(\mathbf{x}), \end{aligned} \tag{1}$$

where $\mathscr{X}$ is the input space containing the input vector $\mathbf{x}$ and $\mathscr{H}$ is the feature space containing the mapped vector $\mathbf{z}$. A linear function is then fitted for the data in the feature space. Due to the nonlinear mapping, this linear function in the feature space corresponds to a nonlinear function in the input space. This nonlinear mapping in SVR is implicitly defined by a kernel function k, which computes the dot product in the feature space,

$$k(\mathbf{x}_i, \mathbf{x}_j) = \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j) = \mathbf{z}_i \cdot \mathbf{z}_j, \tag{2}$$

where $\mathbf{z}_i = \Phi(\mathbf{x}_i)$ are the mapped vectors of $\mathbf{x}_i$ in the feature space.

SVR fits the linear function

$$f(\mathbf{z}) = \mathbf{w} \cdot \mathbf{z} + b \tag{3}$$