Abstract

This dissertation considers two main research topics. First, this thesis explores the applicability of Proper Orthogonal Decomposition (POD) and Galerkin projection in the design of Model Predictive Control (MPC) schemes for tubular chemical reactors. These processes pose very interesting control problems, since their behavior is modeled by highly nonlinear Partial Differential Equations (PDEs), and they require the satisfaction of both their input (physical limitation of the actuators) and state constraints (e.g., the temperature inside the reactor must be below a given value in order to avoid the formation of byproducts). In this study, POD is used together with Garlerkin projection for reducing the high-dimensionality of the discretized systems used to approximate the PDEs that model the reactors. Then, based on the resulting reduced-order models, Kalman filters and predictive controllers are designed. Although a significant model order reduction can be obtained with POD and Galerkin projection, these techniques do not reduce the number of state constraints (linear inequality constraints) which is typically very large. In this thesis we propose two methods to tackle this problem. In the first method we use univariate polynomials to approximate part of the basis vectors derived with the POD technique, and then we apply the theory of positive polynomials to find good approximations of the state constraints by Linear Matrix Inequalities (LMIs). In the second method, we exploit the similarities between the coefficients of consecutive state constraints for developing a greedy algorithm that selects a small number of constraints from the complete set. This algorithm reduces dramatically the number of state constraints, and consequently the memory needed for storing them and the time required for solving the optimization problem.

The second main research subject of this thesis is related to speeding up the evaluation of reduced-order models derived by POD from nonlinear high-dimensional systems. Unlike the Linear Time Invariant (LTI) case, the model-order reduction by POD and Galerkin projection does not conduce to an important computational saving when the high-dimensional models under consideration are nonlinear or Linear Time Variant (LTV). Therefore, this thesis introduces two methods for coping with this situation. The first method takes advantage of the input-output nonlinear mapping capabilities, and the fast on-line evaluation of Multi-Layer Perceptrons (MLPs) for accelerating the evaluation of the POD models. The second method exploits the polynomial nature of POD models derived from input-affine high-dimensional systems with polynomial nonlinearities, in order to generate compact and efficient formulations that can be evaluated much faster. Moreover, in this study it is shown how the use of sequential feature selection algorithms can provide a significant boost in the computational saving. Although this method is not as general as the first one, it might be applied to models with non-polynomial nonlinearities, provided that the nonlinearities can be approximated by low degree polynomials. In addition, conditions for guaranteeing the local stability of these POD models with polynomial nonlinearities are discussed.