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CONTROL OF NONLINEAR PROCESSES USING QUALITATIVE REASONING

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ABSTRACT

The advantages and disadvantages of heterogeneous controllers, composed of multiple simple controllers, for regulating nonlinear processes are studied. These controllers are developed to provide more robustness in the face of sizable disturbances and faults. Qualitative reasoning techniques are applied to reason with incomplete knowledge of the plant and its disturbances. The qualitative algorithm QSIM (Kuipers, 1986) provides the framework for developing and analyzing models at different levels of abstraction, based on the available information. Together with NSIM, which permits the parameters and functions to be bounded, its effectiveness for the construction of stability proofs is demonstrated.

KEYWORDS

Robust control; qualitative reasoning; heterogeneous controllers

INTRODUCTION

There is always uncertainty when designing or operating a chemical plant. The equations governing the plant may not be known exactly, the disturbances may be known only within rough bounds, or faults may occur. Combinations of simple controllers (e.g., constant-action and proportional controllers) have been demonstrated to guarantee stability (robustness) and good performance, in the face of disturbances, for simple linear processes (Kuipers and Åström, 1992). They can be viewed as an extension of gain scheduling (Shamma et al., 1990) with smooth transitions between the different control laws. In this work, these *heterogeneous* controllers are applied and extended for the control of a more complex nonlinear process in the face of sizable disturbances. In general, they are expected to perform worse than model-based controllers for small disturbances, but will be more robust in the face of larger disturbances and even faults.

Following Kuipers and Åström, qualitative reasoning techniques are used herein to verify controller behavior given incomplete knowledge of a process and its disturbances. These techniques are useful for analysis at different levels of abstraction and lead to strong conclusions based upon the available information. The QSIM algorithm (Kuipers, 1986) is used. It has been used for the modeling and simulation of chemical systems by Dalle Molle et al. (1988, 1990). No numerical information is provided, and hence, their analysis is restricted to simple systems. This approach is extended herein to include numerical information.

THE QSIM ALGORITHM

The QSIM algorithm provides a framework for developing models in the form of qualitative differential equations (QDEs), which are abstractions of ordinary differential equations (ODEs), where the values of the variables are described qualitatively and the functional relationships between the variables may be known incompletely. Each variable, including the parameters, is a real-valued function of time with a finite number of critical points (e.g., for the temperature, the critical values may be the melting and boiling points). Its value at any given point in time is specified in terms of its relations with an ordered set of *landmark* values. The landmarks of a variable may include zero, $\pm\infty$, and all the known critical values. In each state, a variable is characterized by its magnitude (with respect to its landmarks) and the direction of change (increasing, decreasing or steady). The constraints are qualitative expressions involving the common mathematical operations (such as addition, multiplication, differentiation and proportionality).

Given a QDE and a qualitative description of an initial state, QSIM derives a tree of qualitative state descriptions, where the paths from the root to the leaves of the tree represent the possible behaviors of the system. This set of behaviors is *guaranteed* to include the solutions of every ODE consistent with the QDE and its initial state (soundness) but it may include spurious aphysical behaviors (incompleteness). With purely qualitative models, the resulting behavior tree is usually too large to be useful, especially for highly coupled systems. This limitation may be overcome by incorporating quantitative information into the qualitative model.

Usually functional relationships and parameter values are known with some uncertainty. In NSIM (Kuipers, 1989; Kay et al., 1993), an extension of QSIM, parameters may be assigned lower and upper bounds and functions may be bounded by lower and upper envelopes. These permit NSIM to eliminate behaviors that are inconsistent with the numerical information, while describing the remaining behaviors more quantitatively. NSIM produces bounds on the trajectories of the state variables that are guaranteed to include *all* of the behaviors consistent with the approximate model. It transforms the QDEs to a set of ODEs, that are guaranteed to include any behavior consistent with the QDEs, and performs numerical simulations to determine lower and upper bounds on the state variables. These bounds, however, are usually conservative. The addition of numerical information allows the simulation of more complex chemical systems (Vinson et al., 1992).

HETEROGENEOUS CONTROLLERS

A heterogeneous controller (Kuipers and Åström, 1992) combines simple control elements across regions (usually overlapping) of state space, with a smooth transition between the different regions. It offers the advantage that each component (usually a P or PI controller) has well known and theoretically proven properties and is implemented easily. The global control law, $u\{x\}$, is defined as the weighted average of the local control laws $u_i\{x\}$:

$$u\{x\} = \sum_i \alpha_i\{x\} u_i\{x\} \qquad \sum_i \alpha_i\{x\} = 1 \tag{1}$$

where x is the state vector and $a_i\{x\}$ is a monotonic (not necessarily linear) function of x, that may be regarded as a measure of the *appropriateness* of applying the local control law i; in other words, of describing the system with the controller associated with region i. Such heterogeneous controllers can thus be viewed as an extension of gain scheduling, where a specific control law is selected for a given operating region and smooth transitions are made between controllers.

Controllers that operate on different time scales may also be combined. For example, a proportional controller

$$u = k_1(x - x_s) + u_s \tag{2}$$

may be designed to respond quickly to a disturbance, bringing the system close to the setpoint, x_s. Then, a second, much slower, controller may control the bias term

$$u'_s = -k_2(x - x_s) \tag{3}$$

with $k_2 << k_1$, thus providing zero-offset (PI-type control).

EXAMPLE

The performance of a heterogeneous controller was tested on a simple, yet nontrivial, problem (Economou et al., 1986). The process consists of an ideal CSTR where the reversible exothermic reaction

$$A \underset{k_{-1}}{\overset{k_1}{\Leftrightarrow}} R$$

is carried out (Figure 1). The following equations model the process:

$$\frac{dA}{dt} = \frac{1}{\tau}(A_i - A) - k_1 A + k_{-1} R \quad (4)$$

$$\frac{dR}{dt} = \frac{1}{\tau}(R_i - R) + k_1 A - k_{-1} R \quad (5)$$

$$\frac{dT}{dt} = \frac{-\Delta H_r}{\rho c_p}(k_1 A - k_{-1} R) + \frac{1}{\tau}(T_i - T) \quad (6)$$

where $k_1 = C_1 \exp\{-Q_1/RT\}$ and $k_{-1} = C_{-1} \mathrm{epx}\{-Q_{-1}/RT\}$. The variables A, R and T represent the state variables of the system, and are the concentrations of the species and the temperature in the reactor, respectively. The inlet temperature is selected as the manipulated variable. A control objective is to operate the reactor as close to the optimal point as possible, while maintaining the stability of the closed-loop system in the face of sizable disturbances. The equilibrium conversion increases with the reactor temperature at lower temperatures and decreases at higher temperatures (Figure 2a). Thus, the gain of the plant changes sign as a function of the reactor temperature, which makes it impossible to utilize a controller designed with a linearized model and a fixed gain.

To verify this, the process was linearized around T = 430K and a PID controller was tuned with Internal Model Control (IMC - K_c =-1660, $\tau_I = 60$, $\tau_D = 60$, $\tau_F = 60$ - Lewin et al., 1988) . Since the controller gain is negative, the system becomes unstable when a state disturbance (initial condition change) that pushes the reactor beyond T_{opt} is introduced (Figure 3).

A heterogeneous controller, having three regions, was implemented and tested. It consists of a proportional controller having a negative gain in the low-temperatures region, a proportional controller having a positive gain in the high-temperature region, and a zero-action (dead-band) controller in the region around the maximum of the conversion-temperature curve (Figure 2b). Figures 4 and 5 show the behavior of the system for disturbances that bring the reactor temperature above and below T_{opt}, respectively. Stability is achieved in both cases.

NSIM was used to verify this result for a range of disturbances. In this case, the differential equation model of the process was provided, with no parameter uncertainty, but the magnitute of the disturbance was specified within a range. For disturbances that bring the reactor temperature into the range 445-450K, the NSIM bounds show that the stability of the response is guaranteed (Figure 6). Note that the bounds on R appear to deviate after approximately 150 seconds. This may be attributed to two reasons: the conservatism of the NSIM bounds and round-off error (the distance between the upper and the lower envelope is on the order of 10^{-4}).

CONCLUSIONS

1. Combinations of simple controllers are shown to provide satisfactory control of a nonlinear process. Although they are not expected to perform as well as a model-based controller for small disturbances, they provide satisfactory control and are more robust in response to larger disturbances. More extensive testing is underway for processes with parameter and functional bounds (i.e., varying degrees of process/model mismatch), as well as more complex reactor models.
2. The QSIM/NSIM algorithm is used for controller verification. It allows reasoning with imperfectly known functions and parameter values, providing bounds that guarantee to include all possible behaviors of the system. Thus, it can be used for proof construction. However, the resulting bounds are often too conservative, leading to ambiguities that result in conservative process designs and operations.

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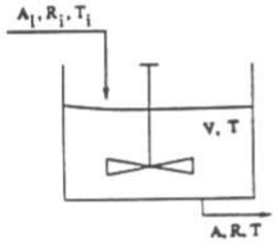

Fig. 1. Continuous stirred tank reactor for the reaction $A \leftrightarrow R$.

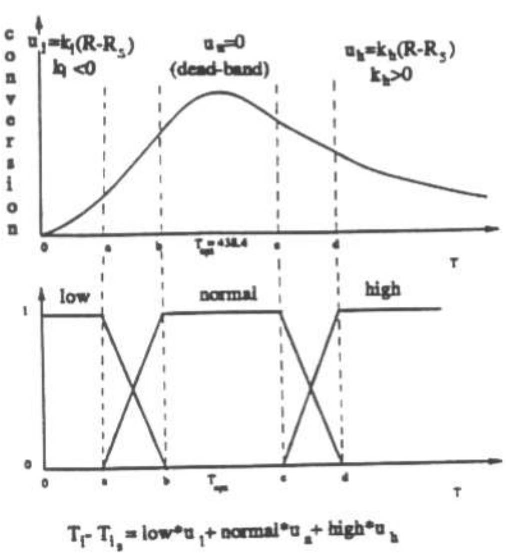

Fig. 2. The equilibrium diagram for the reaction $A \leftrightarrow R$, and the heterogeneous controller.

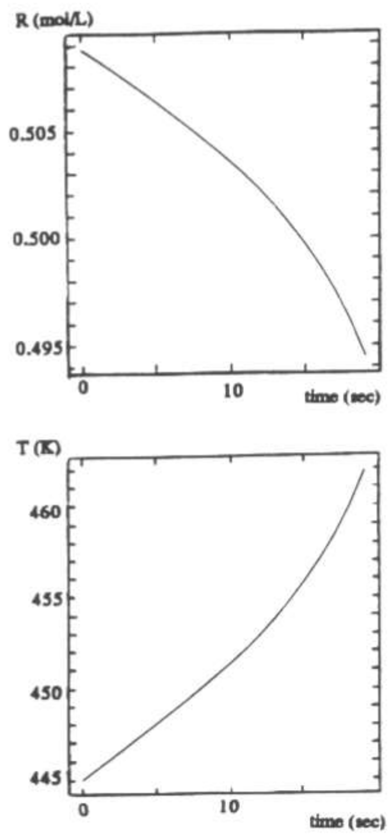

Fig. 3. Reactor response with the PID controller when a disturbance pushes the operating temperature to T=445K.

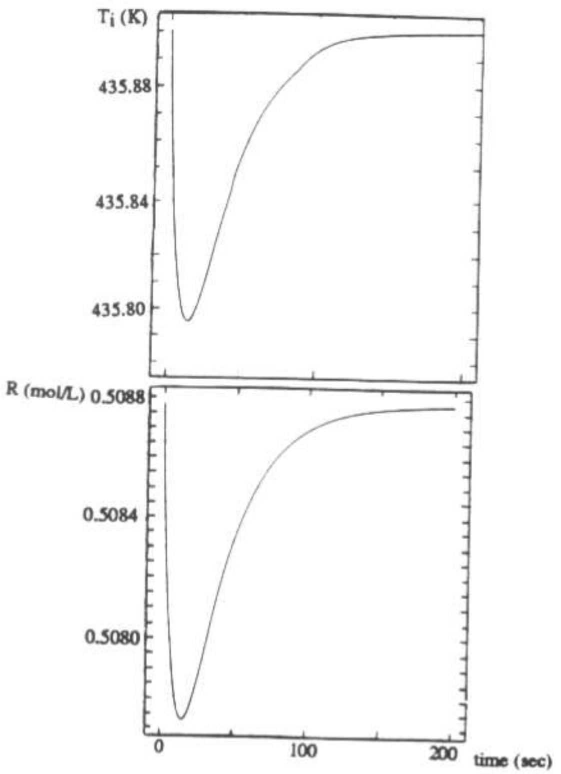

Fig. 4. Reactor input and output response with the heterogeneous controller when a disturbance pushes the operating temperature to T=445K.

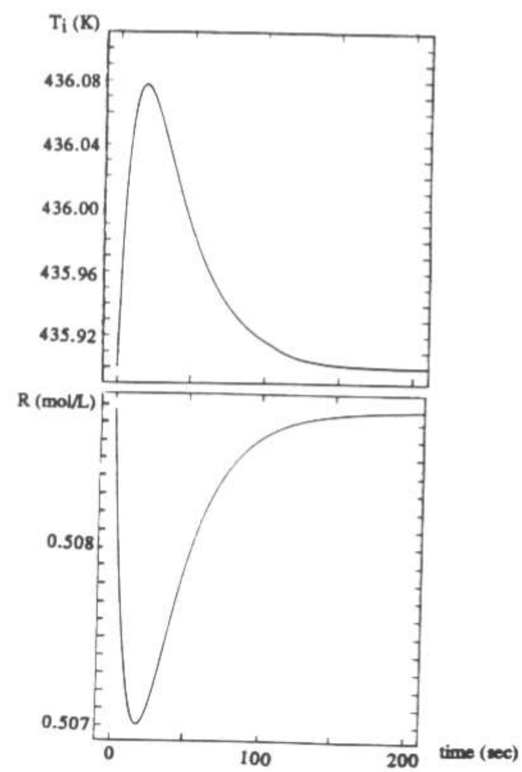

Fig. 5. Reactor input and output response with the heterogeneous controller when a disturbance pushes the operating temperature to T=430K.

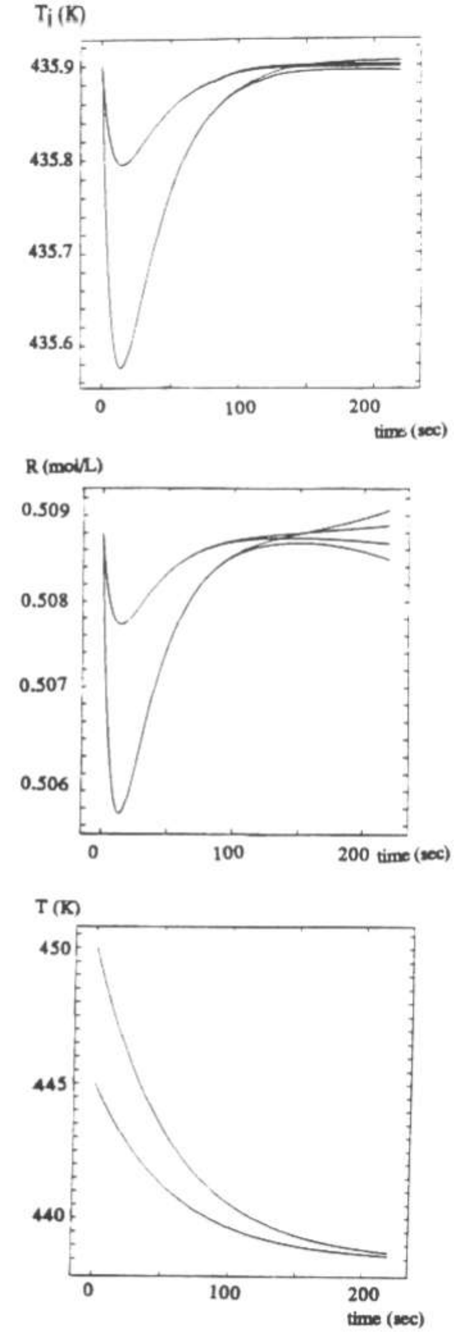

Fig. 6. NSIM bounds of the reactor response when a disturbance pushes the operating temperature into the range 445-450K.