AGENT-BASED CONTROL OF DISCRETE SPATIALLY DISTRIBUTED SYSTEMS

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Abstract: From a control system perspective, spatially distributed systems offer challenges because of their distributed nature, nonlinearity, and high order. In addition, the control structure for these spatially distributed networks combine discrete and distributed components, in the form of complex arrays of sensors and actuators. Manipulation of the network states may require simultaneous control actions in different parts of the system and may need transients through several operating regimes to achieve the desired operation. A hierarchical, agent-based control structure is presented whereby local control objectives may be changed in order to achieve the global control objective. The performance of the hierarchical agent-based control approach is illustrated in a case study where the interaction front between two competing autocatalytic species is moved from one spatial configuration to another. The multi-agent control system is able to effectively explore the parameter space of the network and intelligently manipulate the network flow rates such that the desired spatial distribution of species is achieved.

Keywords: Intelligent Agents, Agent-Based Control, Hybrid Control

1. INTRODUCTION

Spatially distributed systems provide a unique and difficult control challenge because of their nonlinearity, spatial distribution and generally high order. In addition, the control structure for these systems tend to be both discrete and distributed as well, in the form of complex arrays of sensors and actuators. Networks of interconnected continuous stirred tank reactors (CSTRs), for example, exhibit highly complex behavior, with multiple steady state operating regimes, and have a large pool of candidates for manipulated variables (Tatara *et al.*, 2004*c*). Most techniques for the control of nonlinear distributed processes focus on distributed parameter systems and involve mathematically complex model reduction and controller synthesis methodologies (Christofides, 2001). So-called hybrid control systems combine process dynamics and discrete control elements through the use of multiple linear models at different operating points (Morari *et al.*, 2003; Baotic *et al.*, 2003). An alternative approach is based on a hierarchical agent-based system with local and global control structures (Tatara *et al.*, 2004*a*).

Recent work on multiple reactor configurations with cubic autocatalytic reactions has demonstrated a rich spectrum of static and dynamic behavior (Birol *et al.*, 2002). The topography of interconnected CSTR networks has been shown to drastically affect the steady state bifurcation structure of the system (Tatara *et al.*, 2004*c*; Tatara *et al.*, 2004*b*). Spatial inhomogeneity of the network can be increased by increasing the number of reactors in the network as well as manipulating the interconnection flow rates of the network. It has also been shown that the number of stable and unstable steady states increase with the inhomogeneity of the network. Larger networks permit more steady states and spatial combinations than smaller networks. Although much of the bifurcation diagram is dominated by unstable steady states, there exists a number of stable steady states for a large range of reactor feed and interconnection flow rates.

Controlling the spatial distribution of autocatalytic species in a network of reactors requires simultaneous manipulation of interconnection flow rates within the system. In a single reactor configuration, only one autocatalytic species is able to survive at a time in a stable manner (Birol and Teymour, 2000). Furthermore, numerical experiments suggest that individual CSTRs in networks are capable of hosting only a single dominant species, while other competing species may be present only in trace quantities (Birol *et al.*, 2002; Tatara *et al.*, 2003*b*). Consequently, if the control objective calls for one species to be replaced with another, a nonlinear control scheme must be used.

For a single CSTR with competing autocatalytic species, the reactor residence time must first be modified such that the undesirable species is washed out of the system, and then set to an appropriate value that is favorable to the existence of the desired species (Chaivorapoj *et al.*, 2002; Chaivorapoj *et al.*, 2003). This concept can be extended to systems with many reactors to effectively control the spatial distribution of autocatalytic species in the network. However, the control problem becomes complex because each CSTR has a feed and exit stream, as well as multiple interconnections to its neighbor(s). Obviously, each manipulated variable (interconnection flow rates, for example) requires an actuator and control structure, along with the appropriate number of sensors for each reactor.

One approach is to implement a nonlinear control scheme based on model reduction techniques. (El-Farra and Christofides, 2004) present a switching technique for feedback controllers whereby a predetermined set of actuator configurations may be used to move the system from one state to another. This methodology benefits from the inherent qualities of guaranteed closed-loop stability and operation within actuator constraints. Transitions between various actuator configurations is achieved through a set of switching rules. The method is only limited to the number of a priori determined set of actuator configurations and switching rules. A control objective may not be satisfied if a suitable configuration is not available. Alternatively, intelligent supervisory knowledge-based control systems have been implemented to control a distributed process with changing operating conditions in an adaptive manner (Kendra *et al.*, 1994). A limitation of supervisory knowledge-based control and agent-based control techniques discussed below is a priori determination of conditions that guarantee closed-loop stability by using well-established techniques. Instead, large number of simulations with preselected and random setpoint changes and disturbances are conducted to collect information about process behavior and identify control strategies and parameter values that have low likelihood of causing undesirable process behavior.

The operation of highly nonlinear systems like autocatalytic replicator networks may benefit from *evolutionary control* because the optimal operating regime may not be known a priori. Agent-based control systems provide the capability for localized and global control strategies that are both reactive in controlling disturbances and proactive in searching for better operational solutions (Jennings and Bussmann, 2003). This paper proposes a hierarchical agent-based control system for a CSTR network. The performance of the hierarchical agent-based control approach is illustrated in a case study where the interaction front between two competing autocatalytic species is moved from one spatial configuration to another.

2. AGENT CONTROL SYSTEM ARCHITECTURE

Software agents are an extension of object-oriented programming in that both agents and objects encapsulate information (Jennings, 2000). Multi-agent systems have several properties that make them particularly attractive for use with large, complex systems (Lesser, 1999). The first, and usually most important in critical systems, is a high level of reliability. Modularity and scalability are also attractive features of multi-agent systems. Software agents often produce different solutions to the same problem. *Solution multiplicity* arises when several agents, using completely independent methods, arrive at different conclusions based on the presented data. Negotiation between agents, in the form of sharing state and decision information, is therefore required to resolve the situation (Tatara *et al.*, 2003*a*). Siirola *et al.* (2003) have demonstrated that agent-based collaboration for optimization problems outperforms stand-alone optimization methods because the agents are able to effectively combine the results of multiple optimization techniques.

The agent-based control system architecture consists of several sub-systems, each of which are highly modularized (Figure 1). At the process level, network elements such as reactors and valves

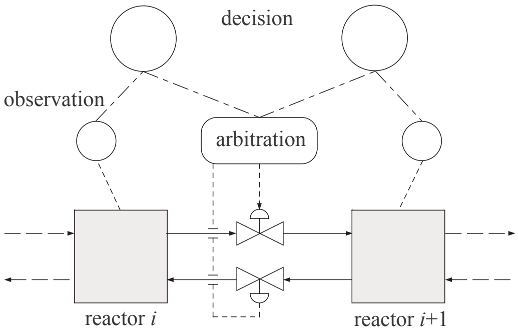

Fig. 1. Control agent architecture.

interface with the higher-level agents via low-level agents. The lowest level of agents in the control system hierarchy include observation and actuation agents. Each reactor is monitored by an *observation* agent that is responsible for sampling data requested by other agents as well as storing the data in a history for some specified time. The interconnection flow rates are manipulated by *actuation* agents (not shown) that receive commands from control arbitration agents. Arbitration agents may be local (focusing on the operation of a few adjacent reactors) or global (focusing on arbitration for all reactors.)

The next layer in the control hierarchy is the *local decision* layer. Local decision agents are responsible for monitoring control functions and proactively improving the overall performance of the network based on the control objectives of the individual agents and the reactor network as a whole. Due to the number of control responsibilities of decision agents, each agent may use subagents. For example, the local control decision agent requires information regarding the state of the process. A sub-agent is therefore tasked with checking the state of a reactor or one of its neighbors.

During network operation, local decision agents attempt to satisfy their individual control objectives, for example to change the dominant autocatalytic species concentration from one species to another. However, in many cases, a decision agent may never fully reach its desired objective due to potential conflicts with other agents' control objectives. If an agent desires to modify the interconnection flow rate between a reactor and its neighbor in order to meet a control objective, the adjacent reactor will be affected as well. Naturally, disputes will arise as to the value of the interconnection flow rates between neighboring reactors.

Arbitration agents serve both as a communication channel between decision agents as well as a means to resolve disputes between agents. The arbitration agents receive requested operational procedures from the local decision agents and then presents a solution to them. For example, a decision agent must modify the residence time of the reactor to flush out an undesirable species by manipulating the interconnection flow rate. The decision agent sends a set of acceptable values for the manipulated variables to the arbitration agent which then tries to match the desired operational values for neighboring decision agents.

Finally, *supervision* agents function as the topmost layer in the control system hierarchy. This layer is responsible for setting the desired global operating conditions for the entire network, for example the spatial distribution of autocatalytic species in the network.

Considering the nonlinearity of reactor networks, it is difficult to predict how the behavior of the system changes when the system parameters are manipulated. Consequently, one cannot easily predict how to change operating conditions of the network by manipulating the flow rates. Decision agents are given the task of changing the dominant autocatalytic species in their reactor by manipulating the interconnection flow rates between neighboring reactors. Various methods are used to guide the decision agents in planning their control strategies including dynamic exploration of the parameter space, rule-based heuristic models, or first-principles based models.

Decision agents may exploit a model of the reactor network, say by knowing the precise location of stable branches and oscillatory regimes. For example, the complete bifurcation structure for a particular system would be quite valuable to decision agents in formulating a control strategy. However, since the number of steady states increases exponentially with the size of the system, this method is not scalable to larger systems. An effective solution is provided via rule-based heuristic models coupled with dynamic exploration techniques.

A heuristic model of the reactor network consists of rules that describe how the manipulated variables affect the system behavior. For example, the stable steady states occupy only certain portions of the diagram, or only certain spatial patterns of species concentration are stable. This information is provided to the decision agents in the form of rules to guide their control actions. Furthermore, the decision agents are allowed to "probe" the system by making small, temporary changes to the manipulated variables and observing the resulting system behavior. This dynamic exploration provides additional flexibility to the decision agents when the generalized heuristic model cannot explain system behavior.

The software agents have been developed in G2 (Gensym, 2003), which is a graphical knowledge-based system development environment for creating intelligent real-time applications. G2 provides a suitable platform for the development of agent-based monitoring and control systems. Software agents are developed using the object-class structure and the heuristics are expressed using class methods and rules. The ordinary differential equations that describe the autocatalytic reactions in each CSTR are solved numerically using the CVODE solver (Cohen and Hindmarsh, 1994). The solver code is written in C and linked to the G2 agent-based system via a custom software bridge.

The reactor class definition in G2 is designed such that the reactor objects have the same attributes as defined in the ODE model. For example, the feed rate to any particular CSTR object is mapped to the specific array location in the ODE solver. When the simulator is initialized, the user may specify the size of the reactor network, initial conditions and inputs. The appropriate number of reactor objects are automatically created by the agent-based system and the reactor objects are modified to include the initial conditions. The CVODE solver simply requires the initial states and parameters to describe the system. The solver then dynamically creates the appropriate equations internally and returns the output to G2, where the states are then mapped back to the reactor objects.

3. REACTOR NETWORK MODEL

A network of I interconnected isothermal CSTRs (Figure 2(a)) is modeled by specifying the mass balance for an individual reactor (Figure 2(b)) at spatial position i in the network, where $i = 1..I$. The cubic autocatalytic reaction for N autocatalytic species is

$$R + 2P_n \xrightarrow{k_n} 3P_n \tag{1}$$

$$P_n \xrightarrow{k_{dn}} D \tag{2}$$

where R is the resource, P_n is the n^{th} species, and D is a dead (inert) species. Reaction rate constants k_n and k_{dn} characterize the growth and death rates of the n^{th} species.

The rates of change of the resource and species concentrations for a reactor i in network of I identical reactors of constant volume can be written as

$$\begin{aligned} V\frac{dR_i}{dt'} &= -\sum_{n=1}^{N} Vk_nR_iP_{ni}^2 + F(R_0 - R_i) \\ &\quad + G(R_{i-1} + R_{i+1} - 2R_i) \qquad (3) \\ V\frac{dP_{ni}}{dt'} &= Vk_nR_iP_{ni}^2 - P_{ni}(F + Vk_{dn}) \\ &\quad + G(P_{n,i-1} + P_{n,i+1} - 2P_{ni}) \qquad (4) \end{aligned}$$

where R_0 is the resource concentration in the feed, R_i is the resource concentration in reactor i, P_{ni} is the n^{th} species concentration in reactor i, F is the feed flow rate, G is the interconnection flow rate and V is the reactor volume. Note that the feed stream to each reactor is identical and contains only resource. The state equations can be written in dimensionless form as

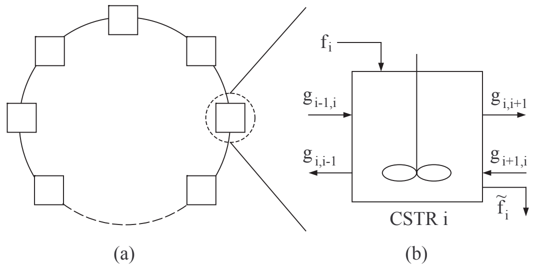

Fig. 2. CSTR network diagram.

$$\begin{aligned} \frac{dr_i}{dt} &= -\sum_{n=1}^{N} k_nr_ip_{ni}^2 + f(1 - r_i) \\ &\quad + g_{i-1,i}(r_{i-1} - r_i) + g_{i+1,i}(r_{i+1} - r_i) \qquad (5) \\ \frac{dp_{ni}}{dt} &= k_nr_ip_{ni}^2 - p_{ni}(f + d_n)) \\ &\quad + g_{i-1,i}(p_{n,i-1} - p_i) + g_{i+1,i}(p_{n,i+1} - p_{ni}) \qquad (6) \end{aligned}$$

by redefining the variables as $r_i = R_i/R_0$, $p_{in} = P_{ni}/R_0$, $f = F/(VR_0^2)$, $g = G/(VR_0^2)$, $d_n = k_{dn}/R_0^2$, and $t = R_0^2t'$.

Since the complexity of the system grows geometrically with the number of species and the number of reactors in the system (Tatara *et al.*, 2004*c*; Tatara *et al.*, 2004*b*), for a network size of $I > 3$ with two or more species, analytical solutions become practically intractable, although a single trivial steady state ($r_i = 1$, $p_{in} = 0$) exists for all i for every combination of model parameter values. This trivial steady state is always stable and will always pose a threat to control efforts as it represents total extinction of the autocatalytic species in the system.

In the control examples detailed in the next section, the interconnection flow rates are treated as manipulated variables. The system is operated with constant volume, thus, constraint equations are formulated on the reactor flow rates to ensure that material is conserved. The reactor flow inputs include the reactor feed and the interconnection flows from the neighboring reactors. Outflow rates from each reactor include the interaction outflows to neighboring reactors as well as the drain. The constraints include a lower bound such that all flow rates are non-negative and an upper bound that ensures the equality of total inflow and total outflow. The implication for a controller scheme that manipulates interconnection flow rates is that the total outflow surplus (ie the reactor drain) must be checked before the control move is permitted. If the reactor drain is 0 and the controller tries to increase one of the interconnection outflow rates, then the other outflow rate must be decreased accordingly to maintain constant volume.

4. CASE STUDY: CONTROL OF CHEMICAL SPECIES FRONT IN NETWORKS

The performance of the control system is demonstrated in a case study to control the distribution of autocatalytic species in a network of five reactors hosting two species using the interaction flow rates as the manipulated variables. The two species that populate the reactor network are characterized by identical growth and death rates, given as $k = 25$ and $d = 0.1$, respectively. Initially all feed flow rates $f = 0.008$ and all interconnection flow rates $g = 0.001$ are uniform for all reactors. When a particular interaction flow rate is manipulated, the outflows of the corresponding reactors are adjusted using constraint equations on the flow rates, thus keeping the volume of each reactor constant.

Moving the system from different initial spatial configurations to different final configurations requires individualized control strategies. Although it is a difficult control problem for conventional controllers, an agent-based architecture can achieve spatial state transitions as illustrated below. The case study involves moving the network boundary between two competing species, each established in one half of the network. The control system is given the desired final spatial configuration and must decompose this task into a set of smaller sub-tasks. One such subtask solution process is demonstrated here.

Starting with the spatial configuration shown in Figure 3a in which Species 1 is established in reactors one through three and Species 2 in reactors four and five, the control objective is to shift the network boundary between species, resulting in the spatial configuration shown in Figure 3d in which Species 1 is established in reactors one and two and Species 2 in reactors three through five. The control system makes its first attempt by increasing the interaction flow rate from reactor 4 to reactor 3, though ultimately failing (Figure 3b). Species 1 is resident in the reactor 3 which prevents Species 2 from establishing itself there. The local controller on reactor 4 attempts to increase the interaction flow rate from reactor 4 to reactor 3 to 0.009 but is constrained by the available inflow to the reactor. As a solution, the control system requests additional flow from reactor 5 and again increases the interaction flow rate from reactor 4 to reactor 3 to 0.017 which is sufficient to allow Species 2 to overtake Species 1 in reactor 3 (Figure 3c). The interaction flow rates are reset to

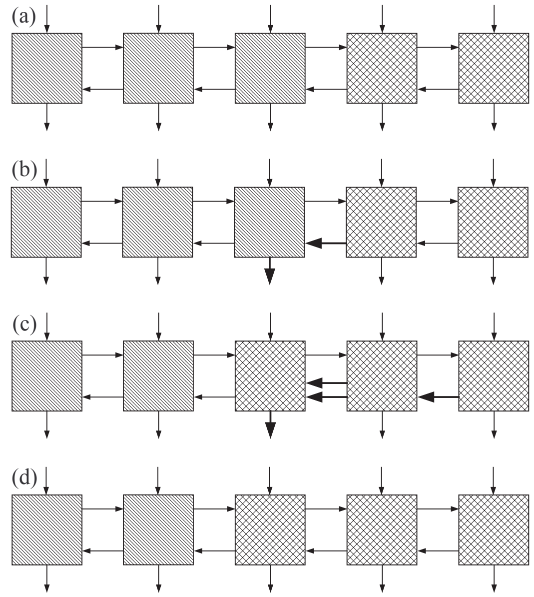

Fig. 3. Moving species front in a network of reactors.

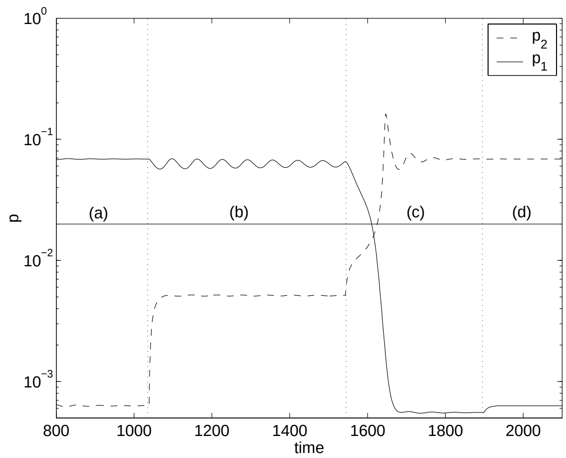

Fig. 4. Species concentration profiles for CSTR 4.

the initial network conditions $g = 0.001$ resulting in a new stable network configuration (Figure 3d). The species concentration profile for reactor 3 is shown in Figure 4.

5. CONCLUSIONS

An adaptable, intelligent agent-based control systems has been implemented to control the spatial distribution of autocatalytic species in a reactor network by manipulating the interconnection flow rates. This methodology has been proposed as a real-time alternative to traditional nonlinear control schemes involving predetermined controller configurations or computationally expensive optimization techniques. Controlling the spatial distribution of autocatalytic species in a network of reactors requires simultaneous manipulation of interconnection flow rates within the system. The multi-agent control system is able to explore the parameter space of the network and intelligently manipulate the network flow rates such that the specified goal is achieved.

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