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Dynamic switching based fuzzy control strategy for a class of distributed parameter system

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ABSTRACT

In this work, a dynamic switching based fuzzy controller combined with spectral method is proposed to control a class of nonlinear distributed parameter systems (DPSs). Spectral method can transform infinite-dimensional DPS into finite ordinary differential equations (ODEs). A dynamic switching based fuzzy controller is constructed to track reference values for the multi-inputs multi-outputs (MIMO) ODEs. Only a traditional fuzzy logic system (FLS) and a rule base are used in the controller, and membership functions (MFs) for different ODEs are adjusted by scaling factors. Analytical models of the dynamic switching based fuzzy controller are deduced to design the scaling factors and analyze stability of the control system. In order to obtain a good control performance, particle swarm optimization (PSO) is adopted to design the scaling factors. Moreover, stability of fuzzy control system is analyzed by using the analytical models, definition of the stability and Lyapunov stability theory. Finally, a nonlinear rod catalytic reaction process is used as an illustrated example for demonstration. The simulation results show that performance of proposed dynamic switching based fuzzy control strategy is better than a multi-variable fuzzy logic controller.

1. Introduction

A large number of physical and chemical industrial processes, such as tubular chemical reactor [1], curing oven [2,3], and arc welding process [4], are DPSs because their input, output, state, and even parameters vary temporally and spatially. They are usually described mathematically by partial differential equations (PDEs) with boundary conditions and initial condition [5].

Control of DPSs is a difficult and an important problem [6], and many methods were proposed to control DPSs. Those methods can be classified into three kinds, simplification approach, 'early lumping', and 'later lumping' [7]. The popular simplification approach simply regards DPS as a lumped parameters system (LPS). Simplification to LPS is often used by ignoring the spatial variation in many of industrial applications. It has advantage of low cost and may be satisfactory if the requirement is not that high. In order to catch more spatial information, 'early lumping' method is to discretize DPSs into finite ordinary differential equations (ODEs) using finite-difference or finite-element techniques. However, number of the ODEs is often very high, and controllers may be difficult to design. In 'later lumping' method, DPSs are transformed into finite ODEs by using spectral method or time/space separation method [8–11] where some truncation techniques are used [2], such as Galerkin method [12,13], approximate inertial manifold [14–18], or Karhunen–Loéve expansion [19,20], and some controllers can be used directly, such as PID controller [12], optimal control method [21], model based control [13,22], neural network for DPS control [23], model predictive control [24–27] and adaptive seeking control [28]. There are mainly two advantages in this method: (1) number of ODEs usually is less than that of 'early lumping' method especially for parabolic PDEs. (2) Spatial information is contained in eigenfunctions and eigenvalues. However, those controllers may depend much on an accurate model of DPS, and desired control performance may not be obtained due to the following three inaccurate model reasons

(1) There are unknown nonlinearities.
(2) Disturbance is existed in DPSs.
(3) Fast mode of the DPS is neglected.

As an intelligent method, fuzzy logic controller (FLC) is widely used in industrial processes due to its inherent robustness [29–33]. Some traditional FLCs have been used for DPS control [34,35]. However, those traditional fuzzy approaches are inherently designed for simplification method not for later lump method. A three-dimensional (3D) FLC is attempted to process a DPS [36], where

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spatial information is obtained from several sensors. However, finite sensors should only obtain limited spatial information in industrial processes. Design a Takagi–Sugeno (TS) fuzzy system [37] is relatively complex. If traditional FLCs are directly used on DPS control based on later lump method, it needs to design rules and rule bases for different ODEs, and some parameters should be designed in FLCs.

Generally, parameters of a controller will greatly affect control performance. Thus, how to design parameters of a controller is a very important problem, such as many tuning methods are proposed for FLCs. Linear methods are often used to tune FLC parameters [30,38,39]. In modern industrial processes, requirements on quality and control performance are increasing, and linear design method may not satisfy demands. Therefore, a nonlinear design method may be a better choice for control performance, such as designing through an optimal method. There are many optimal methods, among which PSO is a global optimum. An advantage of the PSO is that paradigms can be implemented in a few lines of computer code [40]. Previous testing has found the PSO to be effective in some kinds of problems, such as training of neural network weights and function optimal [41].

Motivated by above discussions, spectral method is used to transform an infinite-dimensional nonlinear DPS into finite-dimensional ODEs in order to get a low order approximation model of the DPS, and spatial information can be contained in eigenfunctions and eigenvalues. Because there are some uncertainties, a multi-variable FLC can be designed to track reference values for the MIMO ODEs. So, a multi-variable FLC is proposed to control a parabolic DPS in a previous work [42]. In that work, the multi-variable FLC is designed based on traditional FLC structure and fuzzy matrix theory, in which fuzzifier, inference and defuzzification are in a multi-variable fashion. However, another FLC can also be constructed through traditional FLS based on dynamic switching. In order to simplify controller design, only one traditional FLS and one rule base is adopted for different ODEs, and MFs are adjusted by input scaling factors because changing scaling factors have the same effect with adjusting MFs. An analytical model of the FLC is deduced inconvenient for designing scaling factors and analyzing stability of the control system. Moreover, for unknown nonlinearity, PSO is used to tune scaling factors in order to get a sound performance. Finally, analytical models of the dynamic switching based fuzzy controller, definition of stability and Lyapunov stability theory are used to analysis stability of the controlled nonlinear DPS. In order to illustrate the proposed control strategy, a nonlinear rod catalytic reaction process is used as a demonstration.

2. Problem formulation

A class of distributed parameter system, such as some thermal processes [12,43] and diffusion equation [44], is used to illustrate that how to design dynamic switching based fuzzy controller and the spatially distributed nature of the process is often described as a nonlinear parabolic PDE.

$$\frac{\partial}{\partial t}y(z,t) = \mathcal{A}y(z,t) + f\left(y(z,t), \frac{\partial^2 y(z,t)}{\partial z^2}, \frac{\partial^3 y(z,t)}{\partial z^3}\ldots\right) + \mathcal{B}u(z,t) \quad (1)$$

subject to some boundary and initial conditions, where, $y(z, t)$ is the state, $t>0$ is a temporal variable, $z \in R$ is a 1-dimensional spatial variable with $z \in [0, z_0]$, $u(z, t)$ is a controller, Differential operator $\mathcal{A}$ belongs to Hilbert space with $\mathcal{A} = g_1 + g_2\partial^2/\partial z^2$, g_1, g_2 are constants, $f(\cdot)$ is a unknown nonlinear function, and $\mathcal{B}$ is a linear operator which descripts distribution of controller in DPS.

By choosing a complete family of smooth global self-adjoint spatial orthogonal basis functions $\{\phi_m(z) \,|\, m = 0, 1, \cdots\}$, $\phi_m(z)$ chosen as spatial basis function is the mth eigenfunction, and then state variable $y(z, t)$ and control $u(z, t)$ can be represented in a separable fashion [12]

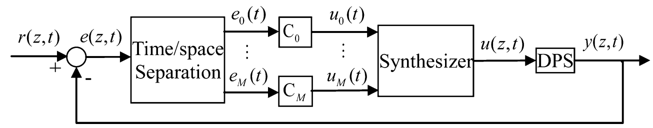

Fig. 1. Traditional control strategy for DPSs.

$$y(z,t) = \sum_{m=0}^{\infty} a_m(t)\phi_m(z),\; u(z,t) = \sum_{m=0}^{\infty} u_m(t)\phi_m(z) \quad (2)$$

where $a_m(t)$ and $u_m(t)$ are temporal coefficients in Hilbert space, $u_m(t)$ is controller of corresponding ODE $a_m(t)$.

Substituting (2) into (1), then, project (1) onto $\phi_m(z)$, and using Galerkin method [2,45], one can obtain dominant dynamic property with ODEs

$$a'_m(t) - (g_1\lambda_m + g_2)a_m(t) - \int_0^{z_0} f\left(y(z,t), \frac{\partial^2 y(z,t)}{\partial z^2}, \frac{\partial^3 y(z,t)}{\partial z^3}\ldots\right) \times \phi_m(z)dz = bu_m(t)(m = 0, \ldots, M) \quad (3)$$

where b is derived from operator $\mathcal{B}$ [43], λ_m is a eigenvalue, $m=0$, ..., M, and unknown nonlinear term in (3) is rewritten as

$$Q_m(t) = \int_0^{z_0} f\left(y(z,t), \frac{\partial^2 y(z,t)}{\partial z^2}, \frac{\partial^3 y(z,t)}{\partial z^3}\ldots\right)\phi_m(z)dz \quad (4)$$

Based on (3), traditional controller C_m is often adopted to control the mth ODE, as shown in Fig. 1. In Fig. 1, $r(z, t)$ is a set point, $e(z, t) = r(z, t) - y(z, t)$ is an error variable of the state, $e_m(t) = r_m(t) - a_m(t)$ is error of the mth coefficient. Reference value $r_m(t)$ is obtained from time/space separation process

$$r_m(t) = \int_0^{z_0} r(z,t)\phi_m(z)dz \quad (5)$$

Above process follows spectral method, and only gets a low order approximation model of a DPS. However, unknown nonlinear part of ODEs (3) and coupling may impact dynamic of DPS. Moreover, disturbance may be also exited in DPS system.

3. Fuzzy control strategy

Because unknown dynamics are existed in DPS, a dynamic switching based fuzzy control strategy is proposed in this paper where only one fuzzy logic system of traditional FLC is adopted for different ODEs as in Fig. 2. k_{em} and k_{dm} ($m=0, \ldots, M$) are input scaling factors, e_m is error of the mth ODE in (3), $\mathcal{G}$ is a differential operator d/dt, $\dot{e}_m$ is change of error of the mth ODE in (3), k_{um} are output scaling factors of the control system, u_m is crisp output of the mth ODE, crisp inputs are defined as

$$R_m = k_{em}e_m,\; E_m = k_{dm}\dot{e}_m \quad (6)$$

and control variables are

$$U_m = k_{um}u_{l_m} \quad (7)$$

In Fig. 2, L_R, L_E and L_u are switches. When L_R, L_E and L_u turn to joints with crisp input R_m, E_m, crisp output u_{l_m}, separately, crisp output u_{l_m} can be obtained, $m=0, \ldots, M$.

In this fuzzy logic system, MF, rule base, rule and inference are all invariable, they are listed as follows:

MF: Input R_m and E_m are classified into seven linguistic labels as positive large (PL), positive middle (PM), positive small (PS), zero (ZR), negative small (NS), negative middle (NM), and negative large