ARTIFICIAL IMMUNE NETWORK APPROACH APPLIED TO OPTIMIZATION OF A DISCRETE INCREMENTAL VARIABLE STRUCTURE CONTROLLER

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Abstract¾ Artificial immune system (AIS) approaches, which are used in this work, are learning and optimization methods that can be applied to find the solution of many types of optimization problems. This paper presents an AIS approach applied to optimize the design of an incremental discrete variable structure controller (VSC) for minimizing the generalized minimum variance (GMV) strategy. Control design and implementation tests are assessed in a nonlinear continuous stirred tank reactor.

Keywords— Artificial immune system, variable structure controller, generalized minimum variance, stability.

1 Introduction

Sliding mode control (SMC) is a special case of variable structure control and it constitutes a nonlinear control technique that provides robustness, fast response and accuracy. Generally, the continuous-time variable structure system approach gives robustness to matched disturbances and system uncertainties. SMC advantages are insensibility to parameter variations, mismatch dynamics and external disturbances.

Recently, the discrete version of the variable structure control based on the input-output transfer function has been received attention in the control research community worldwide (Furuta *et al*., 1989; Furuta, 1993, Pieper and Surgenor, 1993; Corradini and Orlando, 1995; Chan, 1999).

In particular, when the variable structure control has been implemented by using the generalized minimum variance conception, the literature shows different control algorithms to deal with parametric uncertainty and to give a good dynamic for the controlled system. These modifications are based on control design factors such as: i) sliding surface; ii) switching term of the nonlinear part; iii) mathematical representation of the plant (deterministic or stochastic); iv) non-minimum or minimum phase; v) magnitude of the control signal; vi) dynamic for tracking setpoint changes and; vii) stabilization in the presence of disturbances (Furuta *et al*., 1989; Corradini and Orlando, 1995; Chan, 1999).

These early control methodologies have some characteristics such as: i) implement a positional algorithm; ii) zeros of the open-loop plant must be stable; iii) control weighting polynomial defined in the surface must be zero in the steady-state phase to ensure zero offset. On the other hand, the discrete variable structure control conception proposed in this paper, is overcoming these design conditions and it is based on the RST control structure connected to the generalized minimum variance control in order to simplify the control design and to improve the performance of the control system (Coelho and Sumar, 2001).

The performance of this control approach depends not only on the control structure but also on the values of the controller parameters, mainly in control of nonlinear systems. Conventionally, these parameters are manually tuned by the designer, who attempts to find an acceptable controller solution. However, this relies on an adhoc approach to tuning, which depends on the experience of the designer. If the designer is not experienced, this process can become tedious and time consuming. In either case, there is no guarantee that the designed solution will perform satisfactorily as the tuning process depends on the qualitative judgment of the designer. A solution to this problem is to use optimization techniques that tune such parameters automatically (Alfaro-Cid *et al*., 2005).

Evolutionary algorithms and swarm intelligence systems have been widely applied to different methods to tune variable structure control (Chow *et al*., 2003; You *et al*., 2004; Alfaro-Cid *et al*., 2005; McGookin and Murray-Smith, 2006).

So, in this paper, the design of the incremental Variable Structure Controller (VSC) is optimized by an Artificial Immune System (AIS) for a nonlinear Continuous Stirred Tank Reactor (CSTR). The merits of AIS lie in immune recognition, reinforcement learning, feature extraction, immune memory, diversity, robustness, pattern recognition and memorization capabilities.

Design and optimization aspects, in order to show the effectiveness and the potentiality of the incremental VSC, are shown.

This paper is organized as follows. The design idea of the incremental VSC design is derived in section 2. Fundamentals of AIS are shown in section 3. Application in CSTR plant and conclusion are given in sections 4 and 5, respectively.

2 Incremental VSC Design

A discrete input-output transfer function is representing the following monovariable plant where u_k is the input and y_k is the output:

$$A(q^{-1})y_k = q^{-d}B(q^{-1})u_k \qquad (1)$$

Polynomials $A(q^{-1})$ and $B(q^{-1})$ have no common terms, q denotes the shift operator defined by $q^{-1}y_k = y_{k-1}$ and d is the time-delay of the plant. $A(q^{-1})$ and $B(q^{-1})$ are assumed unknown (case of a nonlinear plant) and given by

$$A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_{na} q^{-na}$$
$$B(q^{-1}) = b_o + b_1 q^{-1} + b_2 q^{-2} + \ldots + b_{nb} q^{-nb}$$

Roots of $A(q^{-1})$ and $B(q^{-1})$ are not assumed to be in the unit disk. So, looking at the structure of the open-loop plant, the controller can deal with stable/unstable and minimum/non-minimum phase systems.

The control objective is to minimize the variance of the controlled variable s_{k+d}, to give the control input satisfying

$$s_{k+d} = T(q^{-1})e_{k+d} + P(q^{-1})Du_k = 0 \qquad (2)$$

where $e_{k+d} = y_{k+d} - r_{k+d}$, $\Delta u_k = (1-q^{-1})u_k$ is the incremental control, and the polynomials

$$P(q^{-1}) = p_o + p_1 q^{-1} + p_2 q^{-2} + \ldots + p_{nb-1} q^{-nb+1}$$
$$T(q^{-1}) = t_o + t_1 q^{-1} + t_2 q^{-2} + \ldots + t_{na} q^{-na}$$

must be selected in order to guarantee a stable closed-loop system and they must satisfy the following Lemma (Corradini and Orlando, 1994):

Lemma 1. *The necessary and sufficient condition that the output making $s_{k+d} = 0$ stable is that all roots of*

$$A(q^{-1})Q(q^{-1}) + B(q^{-1})T(q^{-1}) = 0$$

are inside the unit disk and $(Q,T),(A,T),(B,Q)$ have no common roots outside of the unit disk, where $Q(q^{-1}) = DP(q^{-1})$.

The incremental control input to satisfy Eq. (2) is

$$R(q^{-1})Du_k = \left[T(q^{-1})r_{k+d} - S(q^{-1})y_k\right] \qquad (3)$$

where

$$R(q^{-1}) = E(q^{-1})B(q^{-1}) + P(q^{-1})$$

and $E(q^{-1})$ and $S(q^{-1}) = s_o + s_1 q^{-1} + s_2 q^{-2} + \ldots + s_{nd} q^{-na}$ are polynomials satisfying the identity

$$T(q^{-1}) = E(q^{-1})\Delta A(q^{-1}) + q^{-d}S(q^{-1})$$

The control input applied to the plant is given by

$$u_k = u_{k-1} + \Delta u_k$$

Observation 1: The control structure, Eq. (3), can be represented in the RST form, as shown in Fig. (1).

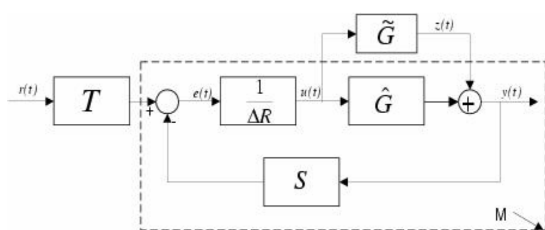

Fig. 1. RST structure with additive uncertainty.

In order to ensure stability for the closed-loop system, it is possible to analyze the effect of tuning parameters on the robust stability under the presence of plant mismatch by using the small gain theorem (Banerjee and Shah, 1995). Applying the small gain theorem in the system of Fig. 1, the following sufficient condition for stability can be derived:

$$\left|\tilde{G}(e^{-jw})\right| < \left|\frac{1}{M(e^{-jw})}\right| \quad \forall w \in [0, p]$$

where

$$M(e^{-jw}) = M(q^{-1}) = \frac{S(q^{-1})}{\Delta R(q^{-1}) + \hat{G}(q^{-1})S(q^{-1})}$$

Thus, the existence of at least one set of polynomials $R(q^{-1})$, $S(q^{-1})$ and $T(q^{-1})$ can be derived in order to guarantee a stable GMV control.

The performance of the control law, Eq. (3), can be improved by adding an auxiliary input obtained by connecting the incremental GMV control with VSC (Corradini and Orlando, 1995). The incremental discrete control algorithm is based on the following theorem:

Theorem 1. *Given a system S of the form Eq. (1), the following incremental control law:*

$$R(q^{-1})\Delta u_k = T(q^{-1})r_{k+d} - S(q^{-1})y_k + s_k + v_k \quad (4)$$

guarantees the achievement of a stable discrete sliding motion on the hyperplane $s_{k+d} = 0$*, if* v_k *is chosen as*

$$v_k = \begin{cases} -2se/s_k & se\ |s_k| \geq \sqrt{e} \\ -2se/s_k & se\ |s_k| < \sqrt{e} \end{cases}$$

where e *and* s *are positive scalars, with* $0 < s < 1$.

Proof. Proof is omitted due to space limits. See Coelho and Sumar (2001) for details.

Observation 2: The choice of the parameters s and e affects the duration and the shape of the initial transient of the control and output variables. Hence, their settings can be done according to the "best" tradeoff between acceptable initial control efforts and satisfactory transient duration. In this work, an AIS is employed to optimize the parameters s and e. AIS is also utilized to optimize the parameters of polynomials $P(q^{-1})$, $R(q^{-1})$, $S(q^{-1})$ and $T(q^{-1})$. In this work, the total of estimated parameters using AIS is equal to 11.

3 Artificial Immune System

Artificial immune systems (AIS) are learning and optimization methods that can be used for the solution of many different types of optimization problems (Dasrupta, 1999; De Castro and Timmis, 2003).

A meta-heuristic optimization approach employing artificial immune network called opt-aiNET algorithm to optimize the design of incremental VSC is proposed in this paper. The aiNET algorithm is a discrete immune network algorithm based on the artificial immune systems paradigm that was developed for data compression and clustering (De Castro and Von Zuben, 2001), and was also extended slightly and applied to optimization to create the algorithm opt-aiNET (De Castro and Timmis, 2002). Opt-aiNET, proposed in De Castro and Timmis (2002), evolves a population, which consists of a network of antibodies (considered as candidate solutions to the function being optimized). These undergo a process of evaluation against the objective function, clonal expansion, mutation, selection and interaction between themselves.

Opt-aiNET is capable of performing local and global search, as well as to adjust dynamically the size of population (Campelo *et al*., 2006). Opt-aiNET creates a memory set of antibodies (points in the search space) that represent (over time) the best candidate solutions to the objective function. Opt-aiNET is capable of either unimodal or multimodal optimization and can be characterized by five main features: (i) the population size is dynamically adjustable; (ii) it demonstrates exploitation and exploration of the search space; (iii) it determines the locations of multiple optima; (iv) it has the capability of maintaining many optima solutions; and (v) it has defined stopping criteria. The steps of opt-aiNET are summarized as follows (Coelho and Alotto, 2007):

Initialization of the parameter setup

The user must choose the key parameters that control the opt-aiNET, i.e., population size (M), suppression threshold (s_s), number of clones generated for each cell (N_c), percentage of random new cells each iteration (d), scale of affinity proportion selection (b), and maximum number of iterations allowed (stop criterion), N_{gen}.

Initialization of cell populations

Set iteration t=0. Initialize a population of i=1,..,M cells (real-valued n-dimensional solution vectors) with random values generated according to a uniform probability distribution in the n dimensional problem space. Initialize the entire solution vector population in the given upper and lower limits of the search space.

Evaluation of each network cell

Evaluate the fitness value of each cell (in this work, the objective of the fitness function is to maximize the cost function).

Generation of clones

Generate a number N_c of clones for each network cell. The clones are offspring cells that are identical copies of their parent cell.

Mutation operation

Mutation is an operation that changes each clone proportionally to the fitness of the parent cells, but keeps the parent cell. Clones of each cell are mutated according to the affinity (Euclidean distance between two cells) of the parent cell. The affinity proportional mutation is performed according to equations (5) and (6), given by:

$$c' = c + a \cdot N(0,1) \quad (5)$$

$$a = r^{-1} e^{-f^*} \quad (6)$$

where c' is a mutated cell c, N(0,1) is a Gaussian random variable of zero mean and unitary standard deviation, r is a parameter that controls the decay of the inverse exponential function, and f^* is the objective function of an individual normalized in the interval [0,1].

Evaluation the fitness of all network cells

Evaluate the fitness value of all network cells of the population including new clones and mutated clones.

Selection of fittest clones

For each clone select the most fit and remove the others.

Determination of affinity of all network cells

Determine the affinity network cells and perform network suppression.

Generate randomly d network cells

Introduce a percentage d of randomly generated cells. Set the generation number for $t = t + 1$. Proceed to step of *Evaluation of each network cell* until a stopping criterion is met, usually a maximum number of iterations, t_{max}. The stopping criterion depends on the type of problem.

4 Case Study and Simulation Results

4.1. Continuous Stirred Tank Reactor (CSTR)

The case study consists of an unstable nonlinear CSTR as shown in Fig. 2. Discrete dynamic equations for the reactor are given by (Cheng and Peng, 1997):

$$x_1(k+1) = x_1(k) + T_s \cdot \left[-x_1(k) + D_a \cdot (1 - x_1(k)) \cdot e^{\frac{x_2(k)}{1 + x_2(k)/g}} \right] \quad (7)$$

$$x_2(k+1) = x_2(k) + T_s \cdot \left[-(1-ß) \cdot x_2(k) + B \cdot D_a (1 - x_1(k)) \cdot e^{\frac{x_2(k)}{1 + x_2(k)/g}} + ß \cdot u_k \right] \quad (8)$$

$$y_k = x_2(k) \quad (9)$$

where x_1 and x_2 represent the dimensionless reactions concentration and reactor temperature, respectively, and the control input, u, is the dimensionless cooling jacket temperature. The physical parameters of the CSTR model equations are: D_a, g, B and b which correspond to the Damköhler number, the activated energy, the heat of reaction and the heat transfer coefficient, respectively. Nominal system parameters are: $D_a = 0.072$, $g = 20$, $B = 8$, $b = 0.3$ and T_s is the sampling time (0.2 seconds).

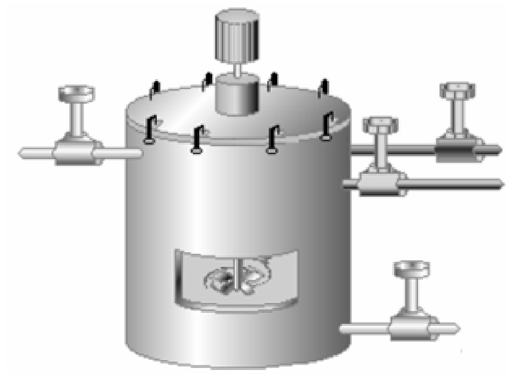

Fig. 2. CSTR plant.

4.2. Simulation Results

This section presents the simulation results for the tuning procedures described in section 3 for the incremental VSC. The procedure has been applied to the nonlinear CSTR plant in reference tracking (servo behavior).

The objective function (to be minimized) by op-aiNET is calculated using the expression of f given by:

$$f = \sum_{k=1}^{N} |e_k| + l \cdot \sum_{k=1}^{N} (\Delta u_k)^2 \quad (10)$$

where $|e_k|$ is the absolute value of elements of error signal, N was 400 samples. The objective function was choice for $\lambda=0.3$ in CSTR plant. The process input u_k is constrained in range [-5,5]. The control objective is to keep the process output as close as possible to the reference.

The opt-aiNET algorithm was implemented in Matlab© (MathWorks). In this work, 30 independent runs were made for each of the optimization methods involving 30 different initial trial solutions (parameters of VSC) for the opt-aiNET.

The setup of opt-aiNET algorithm used was: suppression threshold = 50, percentage of newcomers: d=50%, scale of the affinity proportional selection using a linear reduction of b with initial and final values of 5 and 100, respectively, and the number of clones generated for each cell is N_c=14. The population size N was 20 and the stopping criterion, t_{max}, was 200 generations for the opt-aiNET algorithm.

Table 1 shows the maximum, minimum, mean, and standard deviation of objective function achieved by the op-aiNET for the VSC design.

Table 1. Convergence of op-aiNET for 30 runs.

objective function, f			
minimum	maximum	mean	standard deviation
50.21	59.05	53.20	1.95

As indicated in Table 1, the best result of opt-aiNET was f = 50.21. In this context, for the VSC/GMV, the optimized parameters were:

$$e = 7.1732$$
$$s = 3.1141$$
$$P(q^{-1}) = 0.3544$$
$$R(q^{-1}) = 6.8602 + 0.0316q^{-1}$$
$$S(q^{-1}) = 12.4653 + 57.5699q^{-1} - 66.9559q^{-2}$$
$$T(q^{-1}) = 3.5545 + 2.0054q^{-1} - 2.4348q^{-2}$$

Response for the best servo simulation (30 runs by op-aiNET) is given in Fig. 3. For analysis of this behavior, the reference signal is changing such as: $y_r = 1$ (from sample 1 to 100), $y_r = 3$ (from sample 101 to 200), $y_r = 5$ (from sample 201 to 300), and $y_r = 6.5$ (from sample 301 to 400).

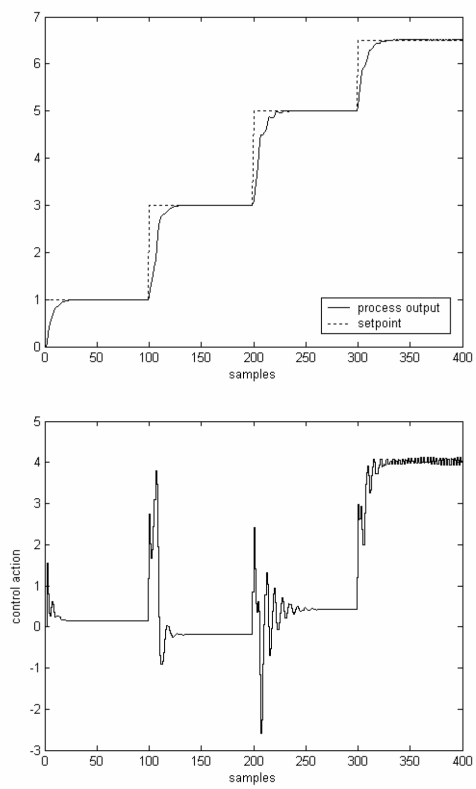

Fig. 3. Servo response of the CSTR using VSC design based on op-aiNET.

Best simulation result shows that the VSC/GMV controller presents good performance in reference tracking and provides a small control variance.

The best design for servo response (Table 1) is validated in a simulation of regulatory response. For analysis of the regulatory behavior, the reference signal is changing of servo analysis such as: $y_r = 1.5$ (from sample 1 to 100), $y_r = 4$ (from sample 101 to 200), $y_r = 5.5$ (from sample 201 to 300), and $y_r = 6$ (from sample 301 to 400). The regulatory behavior is also based on the rejection of additive disturbances in the process output when: (i) sample 50: $y_k = y_k + 0.3$; (ii) sample 140: $y_k = y_k - 0.3$; (iii) sample 230: $y_k = y_k + 0.5$.

The response of VSC/GMV design is given in Fig. 4. Performance of VSC/GMV design was affected by nonlinearity of CSTR. Furthermore, the optimized VSC/GMV design obtained fast response, reasonable control activity, and good ability of perturbation rejection. VSC/GMV ensures steady-state behavior with offset-free for servo and regulatory cases.

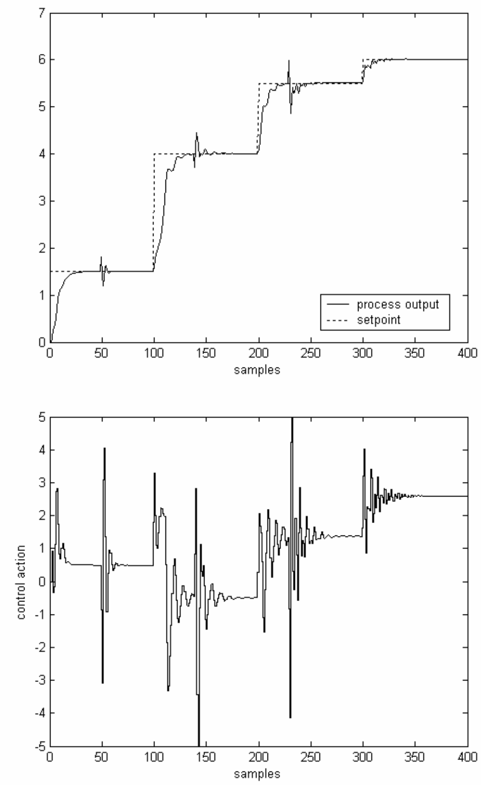

Fig. 4. Regulatory response of the CSTR using VSC design based on op-aiNET.

5 Conclusion

An incremental VSC design based on opt-aiNET optimization method was developed in this paper. VSC/GMV control was assessed in a nonlinear CSTR plant. Simulation results showed that the VSC/GMV controller was able to present a robust performance for the case study.

The good performance in CSTR plant, indicated by the VSC/GMV using opt-aiNET approach, confirms the usefulness and robustness of the proposed method in nonlinear control for practical applications.

Further studies are needed to compare the opt-aiNET algorithm with other evolutionary algorithms in optimization of model-based control methodologies.

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