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A COMPOSITE SELF TUNING STRATEGY FOR FUZZY CONTROL OF DYNAMIC SYSTEMS

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Abstract - The feature of self learning makes fuzzy logic controllers [1,2] attractive in control applications. This paper proposes a strategy to tune the fuzzy logic controller on-line by tuning the data base as well as the rule base. The structure of the controller is outlined and preliminary results are presented using simulation studies.

1.0 Introduction

Fuzzy logic control is usually implemented using lookup tables that are derived off-line. Most of the commercial products currently employ this approach. Several researchers though have been studying approaches to incorporating learning into the fuzzy control architecture. Most of these algorithms are, however, heuristic and subjective and there is no systematic procedure to design and analyze self-tuning fuzzy controllers. Along these lines, a self-tuning strategy was presented by Wu et al. [3,4] to tune the data base for a nonlinear time varying system. They also report successful on-line implementation on an experimental setup. This paper extends the study using a controller with more degrees of freedom.

System Description

Figure 1 show a four-bar linkage system considered, which is representative of a common type of transmission system in several machines. The governing equations for the load is given by Eq.1,

$$M(\theta)\ddot{\theta} + V(\theta)\dot{\theta}^2 + G(\theta) = T(t) \qquad (1)$$

where θ is angular position of link 2, M and V are complex nonlinear functions of θ representing the reflected inertia and the centrifugal and coriolis force terms respectively, and T is the torque applied by the motor. The system becomes a time invariant one when $M(\theta)$, $V(\theta)$ and $G(\theta)$ are constants. The model nonlinearities in this case are primarily motor friction, both viscous and coulomb. Figure 2 shows that the variation of M as a function of the angular position of link 2 is significant. The control objective is to maintain the speed of link 2 constant.

2.0 Composite Algorithm

A 'velocity' type fuzzy logic controller (Figure 3) is used in this study. The error (e) and change of error (Δe) are used as the control variables of the system and are defined as

$e(k) = s(k) - y(k)$ where k: present time

$\Delta e(k) = e(k) - e(k-1)$ k - 1: previous sampling instant

s(k): setpoint at instant k

y(k): output of plant at instant k

Triangular and trapezoidal membership functions are used to interpret term sets of linguistic variables. Based on this interpretation, the term sets in the data base can be represented by functions of the position of the fuzzy sets heights as

$$E = E(0, s_e, m_e, b_e),\ \Delta E = \Delta E(0, s_{\Delta e}, m_{\Delta e}, b_{\Delta e}),\ \Delta U = \Delta U(0, s_{\Delta u}, m_{\Delta u}, b_{\Delta u})$$

The maximum overlap of membership functions of two adjacent fuzzy sets is 0.5 and three fuzzy sets do not overlap. This is found to be the optimal arrangement for 'completeness'[7].

The controller proposed consists of two parts, FLC_d, based on data base tuning, and FLC_r, based on rule base tuning. Contributions from both the FLCs are added to get the actuating signal (Figure 3). In the reported study, the data base is tuned first, and then the rule base.

Data Base Tuning

A tuning factor α is introduced to modify the support of every fuzzy set of the term set simultaneously, keeping the same completeness, as

$$F' = F\ [0, \alpha s, \alpha m, \alpha b]$$

where F can be any fuzzy term set of E, ΔE and ΔU, and F' is the modified fuzzy term set (Figure 4). Note that the rule base does not change in this case. This algorithm can be briefly stated as follows :

1. set all factors $\alpha_i = 1$
2. select linguistic variable F_i to be tuned
3. start the control program and obtain ISE_o
4. modify α to α-0.1 and get the new membership functions
5. start control program to get ISE_i
6. if $0 \leq \alpha$ goto 4
7. get the minimum ISE_i and select the corresponding value of α_i as optimal
8. go to 2 for the next linguistic variable F_i until all are complete
9. repeat (2) through (8) until $\alpha_i(new) = \alpha_i(old)$.

Tuning of the Rule Base

This part of the algorithm is implemented on-line after time > 4^*t_r, where t_r is the system rise time. The algorithm is structured as follows :

if $\Delta ISE(t+\Delta t) > \Delta ISE(t)$ then

if $\omega_2 > \omega_d$, reduce predominant consequent term set by one level

if $\omega_2 < \omega_d$, increase the predominant consequent term set by one level

If $\Delta ISE(t+\Delta t) \leq \Delta ISE(t)$, no changes are made. ISE is the integral squared error calculated from $4*t_r$ to t. The term 'predominant' refers to the antecedent sets with $\mu(x) > 0.5$. In our case, they are $\mu_e(x) > 0.5$ and $\mu_\theta(x) > 0.5$. The contribution from FLC_r has arbitrarily been scaled at present to provide small correction inputs based on θ, the position of link 2.

3.0 Results and Discussion

The original rule base and the data base of this fuzzy system is based on designer's knowledge which is heuristic and subjective. The sampling rate for the simulation control program is 150 Hz. The simulation is implemented using the Advanced Continuous Simulation Language (ACSL) and run on a CRAY computer. The membership functions are used directly rather than by lookup tables. Figures 5 and 6 depict the variation of output speed for the two control configurations. For the FLC_d only case, the error is ISE=0.185, while for the composite controller, i.e., FLC_r and FLC_d the error was found to decrease to 0.156. The data base tuning was accomplished in three passes through the loop, i.e. steps 2 to 8 in the data base tuning algorithm above. The rule base tuning was performed only for 10 seconds (approximately 16 rotations of the four bar linkage). At present we only report that the architecture gives good results and has promising qualities. The controller should learn to reduce the error better after longer training periods.

A controller architecture is proposed which is capable of learning the periodic time varying dynamics of a nonlinear system and compensating for the repetitive dynamics. This compensation is provided by an additional input from the FLC_r part of the controller. In the system considered the periodic variation in load inertia results in a continuous fluctuation of load speed. Data base tuning by itself does not suffice since it does not capture the spatial variation effects. Appropriate rule base modification based primarily on the input angle θ is found to be effective. It should be noted that the fuzzy logic controller allows for the inclusion of this information in a simple way as compared to the classical ones. MRAC controllers have also been designed for the system, but the complexity in its design is much more as compared to the fuzzy case [5]. The results presented are of a preliminary nature but seem to show definite trends as far as convergence and suitability of the proposed architecture. Real time implementation and experimental studies will be reported in forth coming publications.

4.0 Acknowledgments

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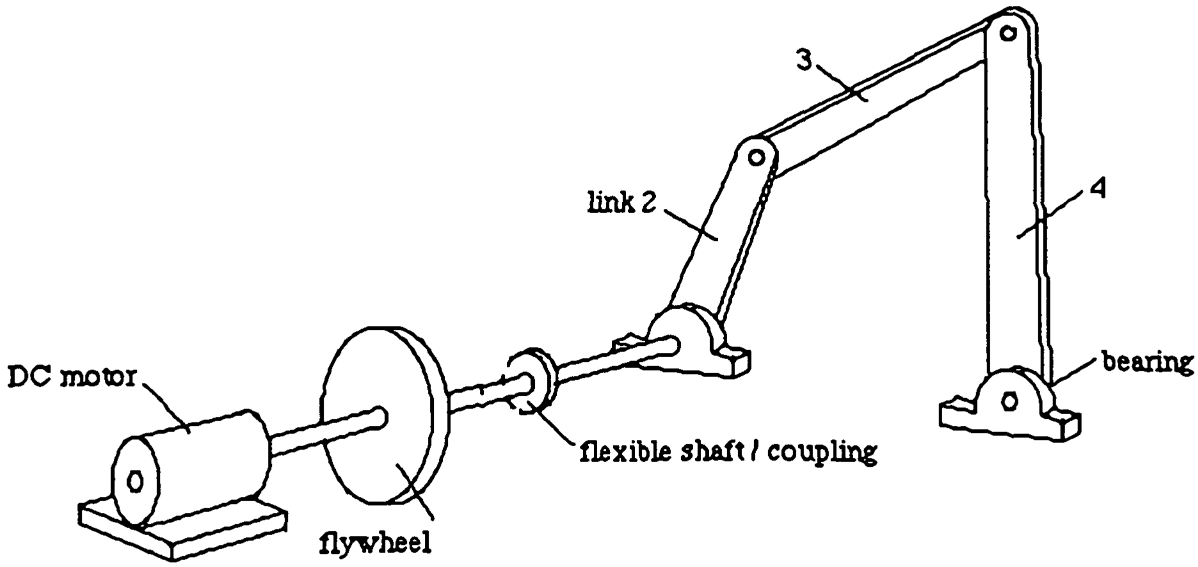

Figure 1 . Nonlinear periodically time varying system

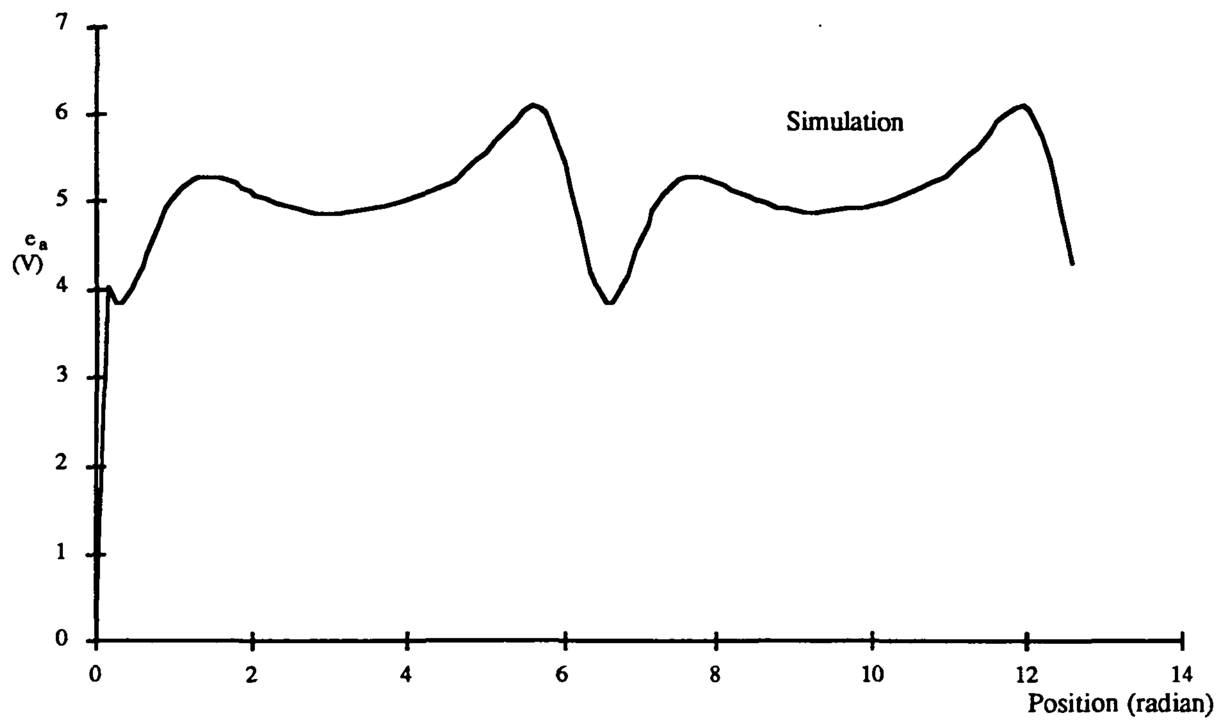

Figure 2. Load characteristics (a). Motor voltage required for constant speed

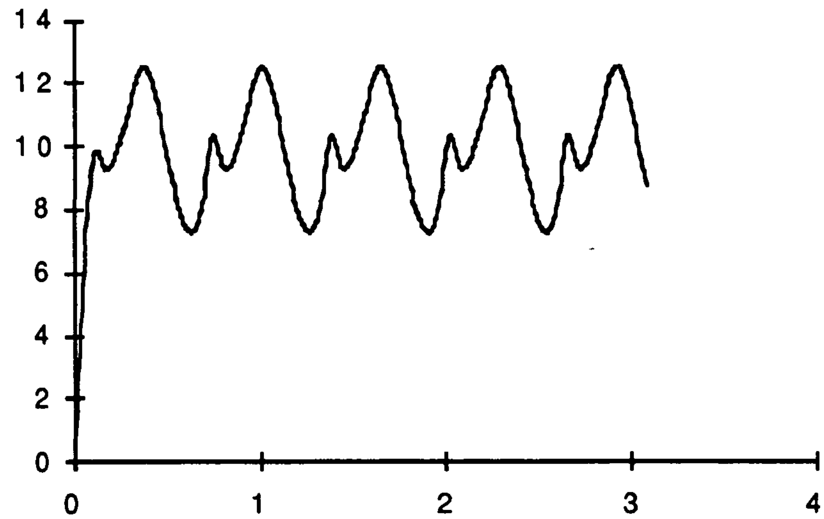

Figure 2. (b). Variation of speed at a constant motor voltage

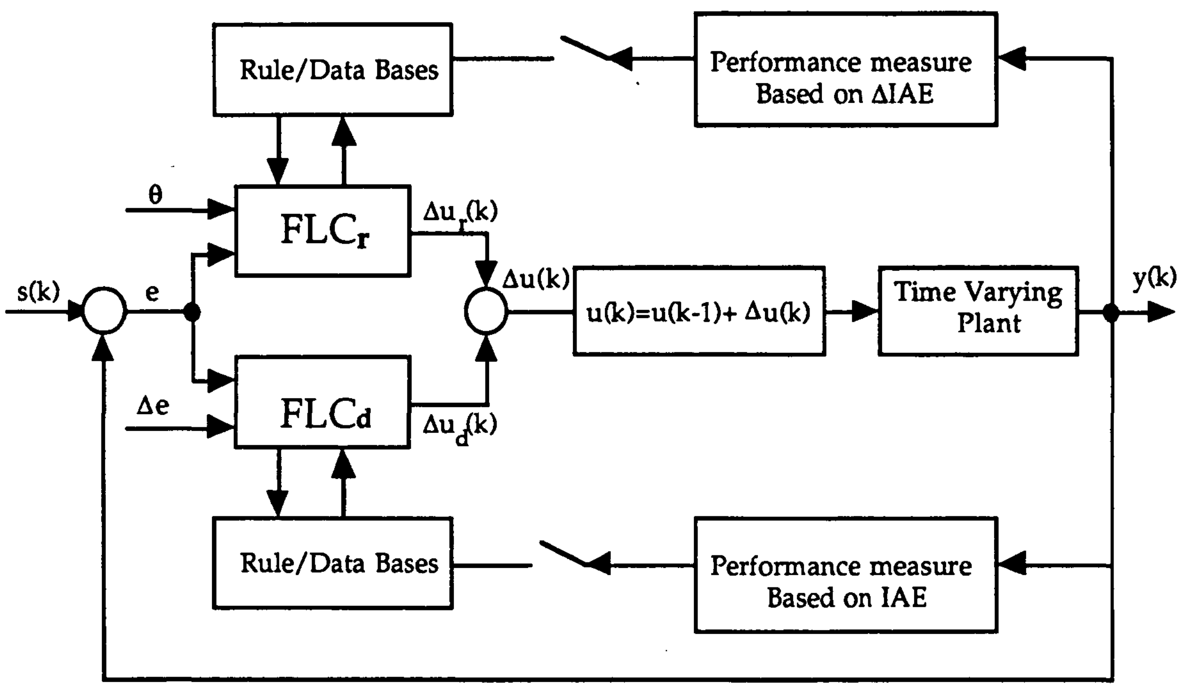

Figure 3. Composite fuzzy logic controller

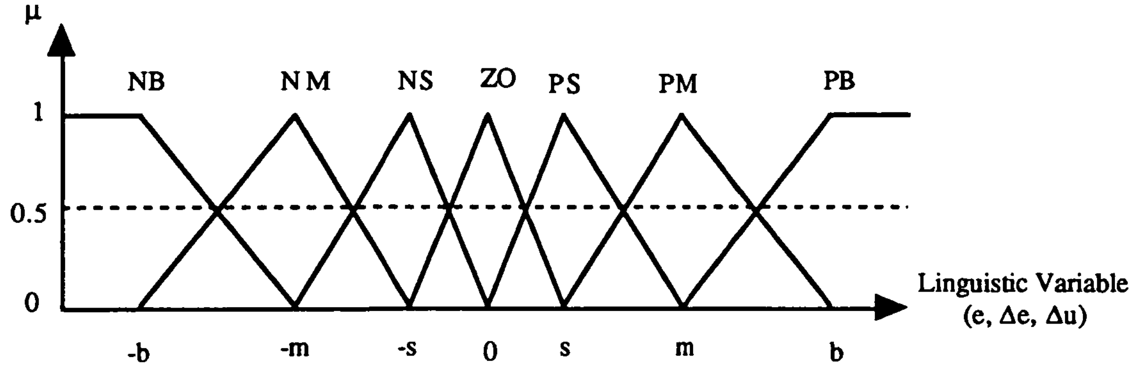

Figure 4. Membership functions for fuzzy term sets

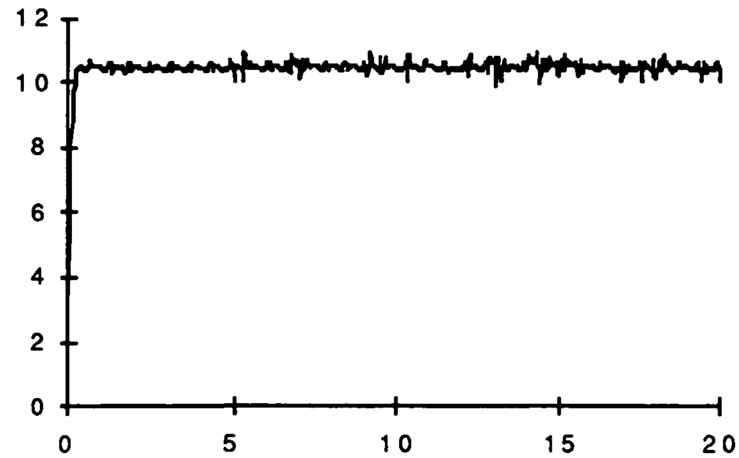

Figure 5. Fuzzy control with only data base tuning FLC

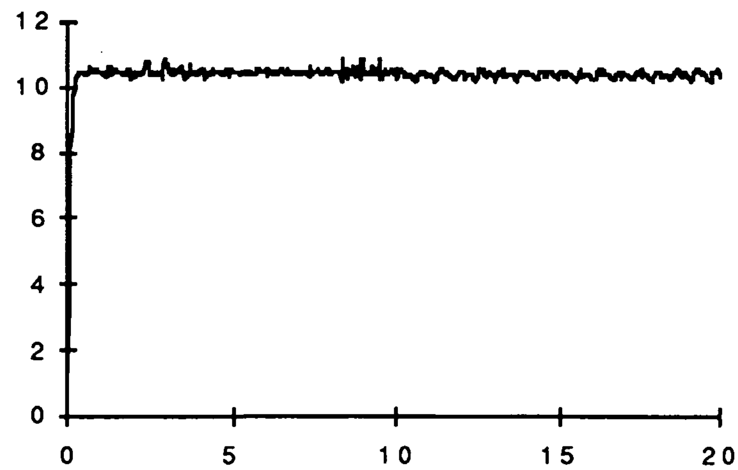

Figure 6. Fuzzy control with both data base and rule base tuning FLCs