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Multi-objective optimal design of fuzzy logic controller using a self configurable swarm intelligence algorithm

A. Rama Mohan Rao *, K. Sivasubramanian

Structural Engineering Research Centre, CSIR Campus, Taramani, Chennai 600113, India

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ABSTRACT

This paper presents a multi-objective fuzzy logic controller (PSO–FLC) for active vibration control of seismically exited buildings by combining a new self configurable multi-objective PSO (particle swarm optimisation) algorithm with fuzzy logic controller. The rule base of the proposed PSO–FLC is tuned for optimal control performance by simultaneously optimizing displacement, drift ratio, acceleration and average control force. In addition, the proposed PSO–FLC algorithm also optimises the number as well as the optimal locations of the actuators. Six and 10 storey framed structures subjected to seismic excitations are considered as numerical examples to demonstrate the superior performance of the PSO–FLC algorithm over other control algorithms.

1. Introduction

Protecting civil engineering structures from environmental loads such as strong winds and severe earthquakes can save lives and building contents. Passive, semi-active, and active control schemes are becoming an integral part of structural systems over the past two decades [1]. Particularly, the concept of semi-active and active control has been widely accepted and has been frequently applied to civil structures for the past two decades [2,3]. Despite some obvious problems in the implementation of active control strategies for structures subjected to earthquake excitations, there has been an intensive research in the area of active control of structures in the recent past because of achieving higher control of response when compared to passive controllers. Moreover control algorithms developed for active control are directly useful for developing other recent control strategies like semi-active control.

Various control algorithms that demand a high performance of control systems have been developed [1]. Control theories such as linear quadratic regulator (LQR), linear quadratic gaussian (LQG), H_2 and H_∞ optimal control methods are being commonly used for active control of earthquake response of structures. However, all these conventional control theories must first acquire an exact mathematical model for an actual structure and then design the control law. Since civil engineering structures are complex multi degree of freedom systems, it is very difficult to find an exact mathematical model to describe the behaviour of the structure.

The theory of fuzzy sets established by Zaedeh [4] in 1965 has been extensively researched in various fields of engineering for many years. In control engineering, the fuzzy theories are applied to the automatic operator control in steam engine by Mamdani [5], and to civil engineering by Brown and Yao [6], and Juang and Elton [7]. The most attractive feature of fuzzy control is that the controller does not rely on the analysis and synthesis of the mathematical model of the process. By incorporating human expertise into the fuzzy IF-THEN rules, a linguistic FLC can be constructed to control complex structural systems. Expert knowledge is however required for determination of many fuzzy parameters while designing a FLC. Since no fixed process for designing a FLC exists, the design parameters of the FLC have to be chosen on the basis of a trial and error study of the control objective and it is desirable to tune these parameters for optimal control performance.

The FLC algorithms have been investigated earlier for the active control of civil engineering structures by Faravelli and Yao [8], Battaini et al. [9], Naghdy et al. [10] and Al-Dawod et al. [11]. Similarly, Park et al. [12] have proposed an independent modal space fuzzy control algorithm. Most of these works use a rule base with varying size and different combination of input feed back variables like displacement, velocity, acceleration etc. No efforts have been made in the above implementations to solve FLC as an optimisation problem in order to tune the fuzzy parameters for optimal control performance. A few investigations are also reported where genetic algorithms are combined with fuzzy logic control to tune the membership functions [13–15]. However, most of these efforts either use single objective or at most two objectives to optimise

* Corresponding author. Tel.: +91 44 22549183; fax: +91 44 22541508.
E-mail addresses: arm2956@yahoo.com, arm@sercm.csir.res.in (A. Rama Mohan Rao).

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the fuzzy parameters. Moreover, the multi-objective implementations employed in the earlier works are rather outdated and not as effective as the current state-of-the-art algorithms in defining Pareto optimal solutions. In the present work we propose a new multi-objective particle swarm optimisation algorithm for tuning the fuzzy parameters by simultaneously optimising the displacement, drift ratio, absolute acceleration and control force in order to obtain optimal control performance, with constraints on maximum control force and maximum allowable drift ratio.

Another important issue to deal with the design of active control system is to decide upon the number and optimal placement of active control devices. In the present work, we use active tendon mechanism (ATM) as control devices. Reasonable amount of research work has been reported in the literature on the problem of optimal actuator placement [16–25]. Most of the earlier works attempt to use either genetic algorithms (GA) or simulated annealing (SA) to solve the non-linear discrete optimisation problem in order to arrive at the optimal placement of given number of actuators. However, there is not much work reported on simultaneous optimisation of number as well as placement of actuators, while tuning the performance of the control algorithm. A multi level algorithm [26] has recently been proposed for arriving at optimal number and placement of active tendons on tall building frames, while simultaneously optimising the control algorithm. It is appropriate to mention here that the multilevel algorithms are complex to handle as they often require communications between different levels of optimisation. Further, optimal solutions are difficult to obtain. Keeping these things in view, we propose to include both the number as well as actuator locations on the structure as design variables in addition to the design variables related fuzzy control parameters in our optimisation scheme to solve as a single level multi-objective optimisation problem for optimal control performance.

2. Parameters for tuning fuzzy logic controller

The prime objective of active vibration control of tall buildings is to

(i) Minimise the peak lateral displacement, X_{max}.
(ii) Minimise the peak inter-storey drift ratio, defined as $(X_i - X_{i-1})_{max}/h_i$, where h_i represents the height between the ith and $(i-1)$th stories, X_i and X_{i-1} are the displacements at ith and $(i-1)$th stories, respectively.
(iii) Minimise the peak absolute lateral acceleration, $(a + a_g)_{max}$, Where a is the acceleration at any node in the structure and a_g is the ground acceleration.
(iv) Optimise the average control force requirement defined as $\frac{1}{t}\int_{t_i}^{t_f} (u^{T}u)^{1/2}dt$, where u is the control force vector.

Among these four criteria considered, (i) and (ii) are directly related to structural safety, and (iii) serves as an indicator of human reactive feeling. The fourth objective related to control force, reflects the efficiency of the installed active control system.

3. Fuzzy logic controller design

Fuzzy logic, introduced by Zadeh [4], enables the use of linguistic directions as a basis for control. A FLC can be incorporated into a closed-loop control system similar to conventional controllers. The most widely used fuzzy control inference R is the "if-then" rule (Mamdani type model), which can be written as follows, when two input data are used in their antecedent parts

$$R^i: \text{if} \quad X_1 = A_i \quad \text{and} \quad X_2 = B_i \quad \text{then } Y = C_i, \tag{1}$$

where i is number of control rules, X_1 and X_2 are variables of the antecedent part and Y is a variable of the consequent part. A_i, B_i, and C_i are linguistic values of the fuzzy variables. FLC essentially consists of four components namely, *fuzzification, rule base, decision making* and *defuzzification*. *Fuzzification* maps the measured crisp inputs into fuzzy linguistic values using fuzzy reasoning mechanism. *Rule base* consists of a collection of the expert control rules needed to achieve the control goal. *Decision making* is the fuzzy reasoning mechanism, which performs various fuzzy logic operations to infer the control action for a given fuzzy input. *Defuzzification* converts the inferred fuzzy control action into the required crisp control value.

The fuzzy controller uses crisp data directly from a number of sensors. These data are then converted into linguistic or fuzzy values through the fuzzification process. In the present work, the absolute acceleration and velocity have been used as input fuzzy variables [27] to FLC in order to determine the required control force, which is the output variable. Each of the input and output fuzzy variable is defined in the fuzzy space in the form of seven linguistic values namely NL (negative large), NM (negative medium), NS (negative small), ZE (zero), PS (positive small), PM (positive medium), PL (positive large). It is however appropriate to mention here that the input and output fuzzy variables need not be defined using the same number of linguistic values. However, detailed parametric studies conducted on FLC [27] suggest that equal number of linguistic values for both input and output fuzzy variables, to define fuzzy space are generally effective. A generalized bell shaped membership function is used in the proposed PSO–FLC controller. The shape of the generalized membership function is defined by the parameters 'a', 'b', and 'c', where 'a' is the half-width of the membership function at 0.50 membership grade; 'b' is the slope of the membership function and 'c' is the position of the centre of the membership function. It can be easily verified that almost all other types of membership functions can be derived from the generalized bell shaped membership function by appropriately defining the above three parameters.

$$\mu_x = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}. \tag{2}$$

The membership functions for both the input and output variables are shown in Fig. 1. The details of the inference rules employed in the present work are shown in Fig. 2. The fuzzy controller will couple the point-valued MAX–MIN fuzzy inference engine product rule to combine the membership values for each rule (Mamdani type), and the centre of area (COA) defuzzifier scheme to obtain the crisp value.

As mentioned earlier, determination of fuzzy parameters to design a FLC requires expert knowledge. Since no fixed process for

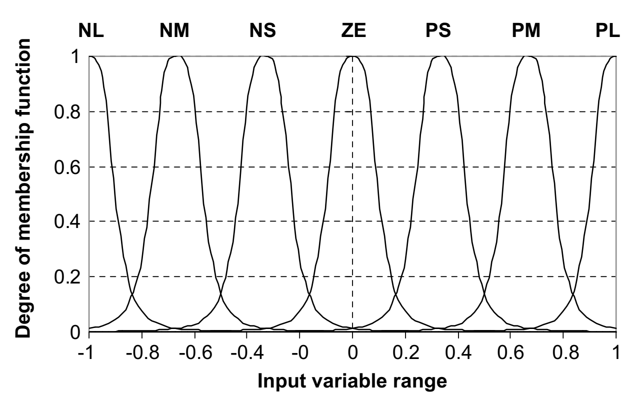

Fig. 1. Membership functions used for input and output variables of the proposed FLC.