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FUZZY CONTROLLERS FOR ACTIVE MAGNETIC BEARINGS

G.M. Allan, P. Schroder and P.J. Fleming

Department of Automatic Control and Systems Engineering
The University of Sheffield, Mappin Street, Sheffield S1 3JD, UK.

Abstract: The design of a fuzzy logic controller for a magnetic bearing is presented. Parameters defining the controller are selected with the aid of a multiobjective genetic algorithm. Unexpected results are discovered which show that novel controllers emerge from what is described in this paper as an 'unconstrained' search technique. This leads to questioning of the conventional guiding principles in problem-solving, of correctness, consistency, justifiability, and certainty, which are seen as not entirely helpful when dealing with technologies like fuzzy logic and genetic algorithms. It is demonstrated that controllers derived from the 'unconstrained' search have unique properties that can be exploited. *Copyright © 2000 IFAC*

Keywords: Fuzzy logic, multiobjective optimisations, genetic algorithms, magnetic bearings, nonlinear control.

1. INTRODUCTION

As economic and commercial pressures push engineering applications to limits of performance and reliability, embedded 'intelligence' becomes an essential feature of new products. It also becomes a key advantage in an increasingly competitive marketplace. These products rely heavily on the multidisciplinary engineer and also often on the implementation of novel control strategies.

Industry has been interested in the application of active magnetic bearings (AMBs) - a good example of a modern mechatronic product - for some years. Examples of industry-sponsored research involving PID and H∞ controllers is described in Schroder (1998). There are good reasons for considering fuzzy controllers for this application. The system is highly non-linear, complex, and difficult to model.

Conventionally, the guiding principles in problem solving are of correctness, consistency, justifiability, certainty, and orderliness. It is difficult to feel comfortable with other approaches. There is an inherent conservatism in engineering. A lifelong training that focuses on a particular way of thinking which renders instinctive certain ideas does not easily adapt to violations of fundamental principles. Genetic programming challenges all our basic ideas about problem solving, the solution process is seemingly random and chaotic. Fuzzy logic asks us to move our focus from 'precision' to 'significance'. However, if it can be accepted that there is also structure within uncertainty and imprecision, then there are other potentially useful approaches to problem solving. If in addition, the problem can be unconstrained and a computer aided design approach exploited, a powerful and flexible tool is enabled with a propensity for generating a range of entirely new solutions.

2. BACKGROUND

2.1 Magnetic Bearings

Active magnetic bearings (AMBs) represent an interdisciplinary area of engineering. They are composed of mechanical components combined with electronic elements, such as sensors and power amplifiers. They have a controller that is usually in the form of a microprocessor, and the software determines the 'intelligence' of the product. The problems with these systems are that they are complex, inherently unstable, highly non-linear, and, as there is typically a large software component, reliability and safety are expensive to ensure.

Fig. 2.1 shows a conventional AMB configuration. A sensor measures the position of a rotor, feeds this to a microprocessor running a control algorithm which calculates a control signal representing the current desired in the magnet coil. The signal is sent to power amplifiers that generate a current in each electromagnet in the bearing. The magnets are arranged equidistantly in rings around the rotor and are usually operated in a differential driving mode.

Here, a bias current is maintained in each magnet and the magnets controlled in pairs, the control signal is added to the bias current in the upper magnets and subtracted from the lower ones. This arrangement increases the linearity of the system making its behaviour isotropic, this is described in (Schweitzer, 1994). The nature of the control algorithm running on the microprocessor determines the system's stiffness, damping and ultimately stability.

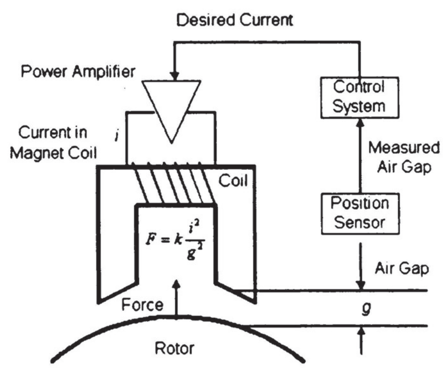

Fig 2.1 AMB configuration for current control

The currents in each magnetic coil are given by the relationship:

$$V = Ri + L\frac{di}{dt}, \qquad (1)$$

where: R = coil resistance,
L = coil inductance,
i = current in the coil and
V = voltage across the coil.

The force generated by the magnets is given by:

$$F = k\frac{i^2}{d^2}, \qquad (2)$$

where: F = force exerted on the rotor,
d = gap between rotor and magnet, and,
k = magnet constant = $\frac{1}{4}\mu_0 N^2 A$.
μ_0 = magnetic field constant of a vacuum,
N = number of turns on the magnet coil,
A = cross sectional area of the magnet.

2.2 Fuzzy Logic

Fuzzy logic was proposed by Zadeh (1965) to provide an approximate yet effective means of describing the behaviour of systems unable to be precisely defined by mathematical analysis. Work in the 70's, most notably by Mamdani, showed fuzzy logic control to be appropriate for the control of complex continuous unidentified or partially identified processes (King and Mamdani, 1977; Mamdani, 1974). More recent work (Koskinen and Virvalo, 1992; Lee, 1990) has shown that although fuzzy logic can be applied to well defined systems, the best results are from systems that are non-linear or ill-defined.

Fuzzy models can be used to describe processes where the underlying physical mechanisms are not completely known and where the understanding of the process is mostly qualitative (Zadeh, 1994). A mathematical model is not needed and implementation is quite straightforward. However, this simplicity also represents a problem.

Fuzzy controllers rely on heuristic knowledge that is subject to the designer's interpretation and choice. There is no generalised method for the formulation of fuzzy control strategies, and design remains a trial and error exercise.

The process of finding appropriate membership functions, their positions, and their rules, is an arduous task. Not surprisingly, there are many ideas for applying learning algorithms to fuzzy systems. The earliest methods, so called 'adaptive' or 'self-organising fuzzy controllers' were developed by Procyk and Mamdani (1979). Later work was put forward by Shao (1988). Neural networks have presented further possibilities and there has been the development of neuro-fuzzy systems (Berenji and Khedkar, 1992; Buckley and Hayashi, 1995; Halgamuge and Glesner, 1994). Genetic algorithms (GAs) offer the most recent, and perhaps most significant, opportunity for automation of parameter selection (Linkens and Nyongesa, 1995a, 1995b). Each method has its associated advantages and disadvantages, and to date there are no clear choices.

2.3 Multiobjective Genetic Algorithms (MOGAs)

Genetic algorithms (GAs) are search techniques that operate without knowledge of the task domain, utilising only the 'fitness' of evaluated individuals. Individuals are, usually, randomly generated bit-strings, and they are 'blind' to their task. A particular implementation of this technique is the multiobjective genetic algorithm (MOGA). This is a global optimisation technique that finds a population of possible solutions rather than one single solution to optimisation problems comprised of multiple objectives.

The MOGA is a proven method used to search across a number of different controller structures and parameters (Dakev, Whidborne, and Chipperfield, 1997) and GAs have previously been used to automate the selection of parameters for a fuzzy logic controller (Linkens and Nyongesa, 1995a; Linkens and Nyongesa, 1995b).

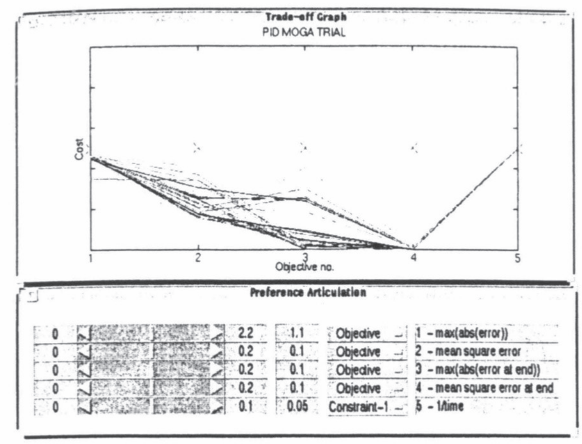

Fig 2.2 Trade-off graph for fuzzy-PID optimisation

AMBs present a demanding control task that require the satisfaction of many, often competing, performance measures and design requirements; disturbance rejection, efficiency, and steady state error all have to be optimised. The performance specifications are used to set objectives for the MOGA. Performance is measured directly from the simulation of each controller on a plant model to increase the accuracy of the information obtained. When the search is terminated, the designer is presented with many different controllers all of which satisfy the specification, see Fig 2.2. A choice is then made by the designer as to which controller offers the best overall performance for the application. In this project this has been implemented using the GA Toolbox for MATLAB (Chipperfield, Fleming, and Pohlheim, 1994), developed in-house, with additional extensions to accommodate multiobjective ranking, sharing and mating restrictions, and an interface which allows the optimisation to be controlled interactively.

2.4 The Application

The AMB application in this case is a turbo-machine destined for marine use. Of particular interest is the ability of the system to resist shock loads. A model of the rotor-bearing system, (Schroder, 1998), has been implemented in Simulink and this model represents a stiff rotor supported by two active magnetic bearings, each constructed of six electromagnets. The limiting transient for the bearings is assumed to be a 30kN sinusoidal disturbance at 4Hz. A schematic diagram of the rotor is shown in Fig 2.3

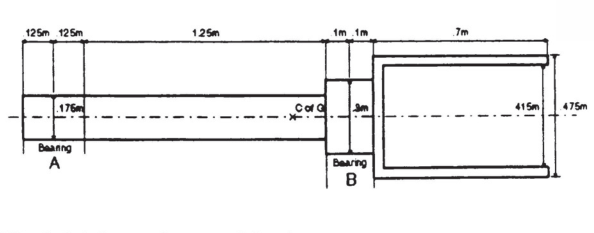

Fig 2.3 The turbo machine's rotor

A small bearing is situated at the left of Fig 2.3, and its electromagnets have a designed maximum load of 6kN. Its purpose is mainly to keep the rotor steady whilst most of the disturbance forces are absorbed by the larger bearing which is situated close to the rotor's centre of gravity and has a designed maximum load of 30kN.

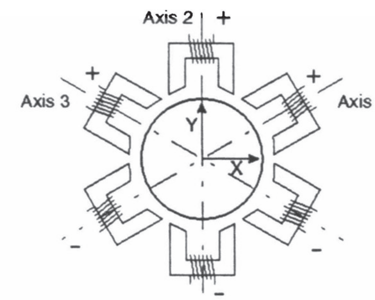

Fig 2.4 The magnetic bearing structure

The magnetic bearings modelled consist of three main stages, a power amplifier model, a model of the coil and a model of the magnet. The AMB configuration chosen is known as current control (Schweitzer, 1992). A bias current is maintained in each magnet in the bearing. The control signal is added to this for the upper magnets, labelled '+' in Fig 2.4 and subtracted from it for the lower magnets, labelled '-'. Treating the magnets in pairs in this way increases the linearity of the system. For a fuller description of the application see Schroder (1998).

For the development of the Fuzzy Controller, a simplified model was considered with two active magnetic bearings, but with each constructed of only two electromagnets. All other parameters and characteristics remained the same.

3. MOGA SELECTION OF A FUZZY PID CONTROLLER

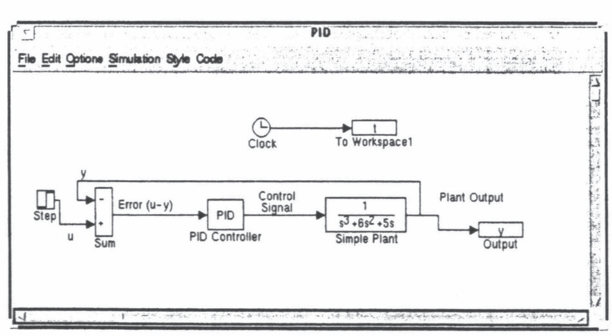

Figure 3.1'Ogata-Model' implemented in Simulink

Before experimenting with the non-linear model of the active magnetic bearing, a simple model was used to prove the method of fuzzy rule selection. The model chosen was as used by Ogata (1997) to illustrate tuning of PID controllers (see Fig. 3.1), and hereafter referred to as the 'Ogata-Model'. A

PID controller model was developed in Simulink using the PID values prescribed by Ogata, then Fuzzy PID controllers were designed using a MOGA to select the positions of suitable membership functions, the rule base and the scaling factors. Two different sets of objectives were used to direct the MOGA search. In the first case (MOGA-1) PID-like objectives were chosen i.e. rise-time, overshoot, settling time, maximum final error, and minimum final error. In the second case (MOGA-2) non-PID like objectives were chosen i.e. maximum absolute error, mean square error, maximum absolute error at end, mean square error at end, and 1/time. The MOGA was configured to treat the simulation time (i.e 1/time) as a constraint, not an optimisation objective, so no attempt was made to reduce it beyond the constraint threshold. Solutions failing to meet this constraint were ranked accordingly. In this way, the search was encouraged to maintain a diverse population whilst moving to a stable controller with good disturbance rejection characteristics. Also the search space was made larger and the problem effectively 'unconstrained'. It was seen that the nature of the search space had a noticeable affect on the characteristics of the controllers that were selected.

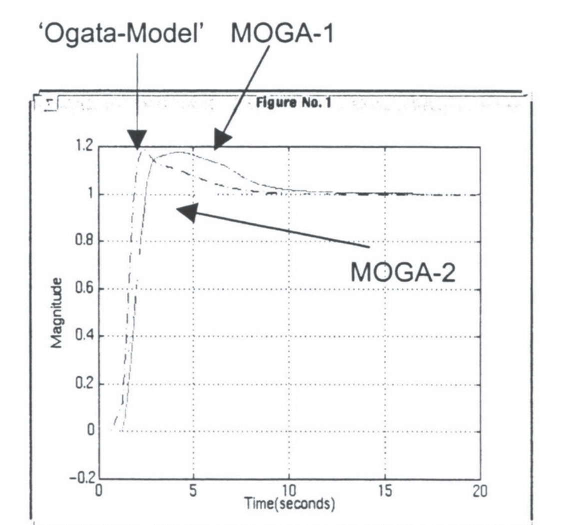

Fig 3.2 Comparison of output for 3 types of controllers.

Fig 3.2 shows the output characteristics of the system responding to a step input with three different controllers, the reference controller - 'Ogata-Model' -, the MOGA-1 controller with fuzzy rules derived from the PID type objectives, and the MOGA-2 controller with fuzzy rules derived from the non-PID type objectives. It can be seen that the MOGA-1 controller has output characteristics similar to the reference controller. The MOGA-2 controller on the other hand shows a different form, but has an equally good performance, in fact better in many respects.

Further investigation of the fuzzy rules surface proves to be most interesting, see Figs 3.3 (a) - (d).

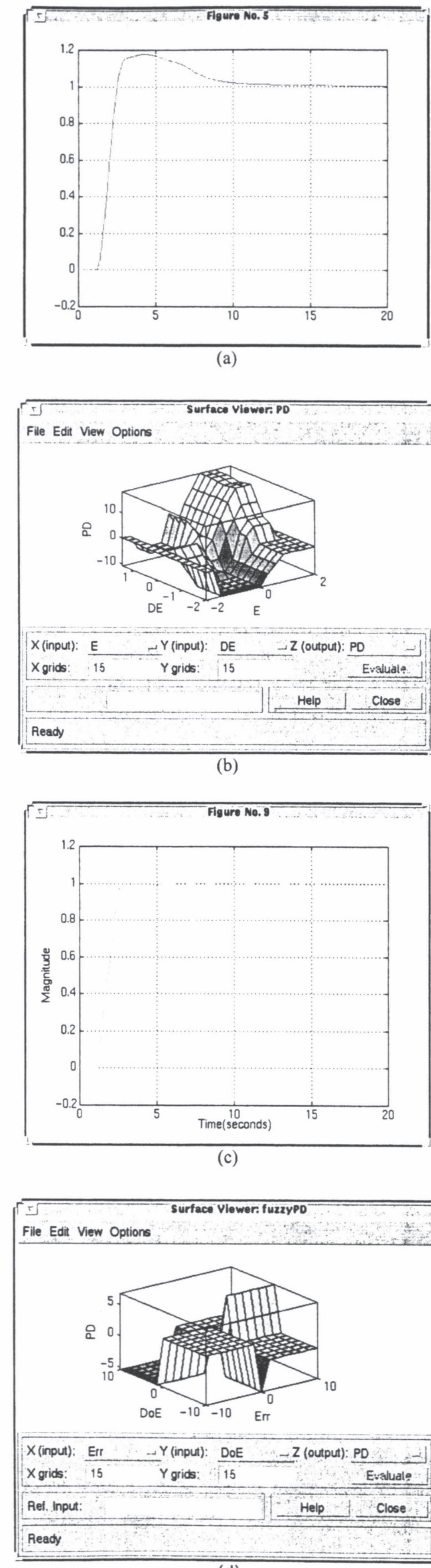

Fig 3.3 Output responses.
(a) MOGA-1; (b) Fuzzy-PD surface - MOGA-1;
(c) MOGA-2; (d) Fuzzy-PD surface for MOGA-2.

In MOGA-1 (Fig 3.3 (a) & (b)) it could be argued that the 'intelligence' of the PID-like controller is reflected in the richness and complexity of the rules surface, and a PID-like output characteristic results. In MOGA-2 (Figs 3.3 (c) & (d)) the surface of the controller does not have this richness, but nevertheless functions well.

When the MOGA is constrained to find PID-type characteristics, with decision objectives commonly used to define the output performance of PID controllers, the result is a controller that behaves very like a conventional PID controller, even although it is a controller based in fuzzy logic. The response exhibits the qualities of that type of controller, and the surface can be thought of as exhibiting the 'intelligence' that is PID theory. The MOGA has done its job. On the other hand, when the MOGA is 'unconstrained' and given decision variables which have less meaning in PID terms, but which more objectively reflect the output desired, the MOGA consistently chooses a controller with rise-time characteristic as good as any of the other controllers, but with no overshoot, and a much shorter settling time. In fact a controller with unique characteristics is selected, and it is interesting to note that there is no great complexity in the surface. It could perhaps be argued that in this case the 'intelligence' was in the computational technique that selected the rules. This seems to highlight an important issue when using computer-aided-design techniques and the question is where to "inbuild" intelligence and where to intelligently search.

4. FUZZY CONTROLLER FOR AN ACTIVE MAGNETIC BEARING

When the methodology outlined above is applied to the selection of a fuzzy controller for the non-linear AMB application, similarly interesting results are achieved. In this case not only must the controller cope with the non-linearity of the system but also the shock loading to the system.

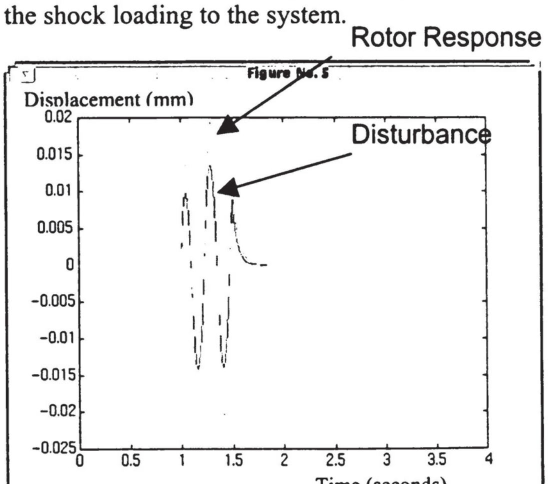

Fig 4.1 Rotor response with fuzzy controller derived from PID type objectives.

Fig 4.1 shows the rotor response from bearing B subject to the shock loading defined. This shows a good performance that is compatible with other well-designed PID controllers.

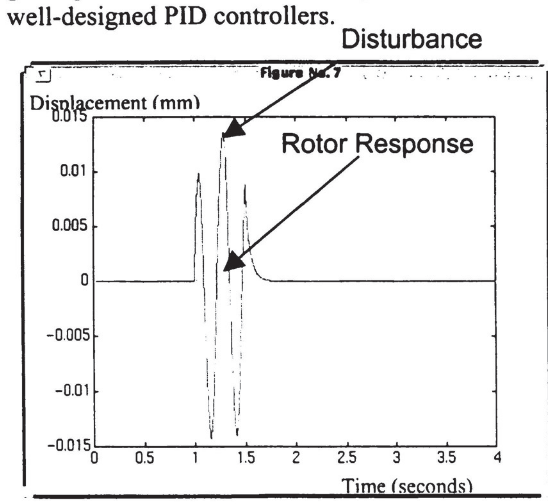

Fig 4.2 Rotor response with fuzzy controller derived from non-PID type objectives.

Fig 4.2 shows the exceptional performance, in terms of ultimate displacement, of the fuzzy logic controller derived from the setting of multiple objectives with 'fitness for purpose' in mind, i.e. minimisation of maximum displacement, mean squared displacement, maximum current, and mean squared current.

The use of the MOGA to select the fuzzy rules had mixed success. A very good controller was found, but results were inconsistent. It was established that unconstraining the problem and driving the solution from the perspective of 'fitness for purpose' had the potential to reveal remarkable solutions, but results were unpredictable. The problem became one of establishing a compromise between directing the solution while still allowing freedom for innovative solutions i.e. the problem was one of deciding how much to constrain the problem and how much to release it.

5. CONCLUSIONS AND FUTURE WORK

There is, it seems, a tendency with all new technologies for them, at first, to be used in ways that conform to established practices. This re-occurring phenomenon can best be illustrated by reference to the industrial monument in Shropshire, England, called "Ironbridge". This first iron bridge, spanning the river Severn, was built in 1777-79. "Halved dovetails with pegs fastened the radial members to the main ribs...etc." (Cossons and Sowden, 1977). This bridge was built with the new technology 'iron', but in a way more suiting wooden construction. The bridge was a great success and is still carrying regular road traffic in 1950, but in reality it did not harness the full potential of the new medium. In fact it takes time to realise the full potential of new technologies.

In this research the initial focus was on the use of a multiobjective genetic algorithm for the selection of fuzzy parameters to a pre-established theoretical domain to mimic a conventional PID controller. This, more or less, represents the conventional route to problem, and is a well-established technique for developing fuzzy controllers. However, it has been argued here, that this does not make best use of genetic algorithms, or of fuzzy logic, and that other methods exist which are more suited to the nature of the technologies being employed, and which fully explore their potential.

An alternative strategy, and the one pursued here, has been to unconstrain the problem space and drive the solution from the concept of, 'fitness for purpose'. The work for the control engineer is then to establish a definition of the optimisation problem, allow the computational activity to be performed, and then use high-level decision skills to choose the most appropriate solution. The responsibility of the engineer is to interpret novel scenarios as potentially rich sources of previously undiscovered solutions, and to find the compromise between the predictable and unpredictable which can drive the problem solving process into new and innovative solutions.

Further work is to research the problem of selecting objectives. This would appear to be part of the overall task of problem definition, and closely linked to the type of genetic algorithm used, and it thus presents a very complex area of investigation. The very nature of these processes defies calibration. There must however be some guide, other than heuristics, for the use of these tools and there needs to be some form of benchmarking exercise performed.

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