GENETIC MODELLING AND CONTROL OPTIMISATION OF CRYOGENIC COOLING PLANT

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ABSTRACT: Multi objective optimisation techniques based on genetic algorithms were used to optimise the rule-base and membership functions of a fuzzy logic controller for controlling a cryogenic plant. The plant is used for cooling process for electrical characteristics of high temperature superconducting devices. A neuro-fuzzy model of the plant was developed based on experimental operating data. The complete system consists of a temperature set-point scheduler, fuzzy logic controller and the simulated plant neuro-fuzzy model. GAs were used to optimise the fuzzy logic controller parameters using different breeding and ranking techniques, the best method being identified via simulation.

KEYWORDS: Fuzzy logic control, neuro-fuzzy modelling, genetic algorithms, cryostat process.

INTRODUCTION

Fuzzy logic was invented over 25 year ago by Zadeh (1965). Initially it found few applications but later its commercial potential has been realised to provide embedded control systems in a wide range of consumer appliances. Fuzzy logic acts as a mean of translating uncertain, qualitative, non-statistical linguistic statements such as small, large, hot and cold, into precise mathematical language. Fuzzy control was first demonstrated by Mamdani (1976) using a subset of fuzzy logic. It allows vague, imprecise instruction to be combined and manipulated to provide rules and procedures based on general principles and expert knowledge which lead to a non-linear mapping of the input/output transition functions. However, the design of the membership functions and the rule-base to generate a model for mapping input/output data still needs an optimisation technique such as neuro-fuzzy systems or genetic algorithms.

In a previous study, multi-objective genetic algorithms (GA) were used to optimise the performance of a self-organising fuzzy logic controller (Mahfouf et al, 1998). In this paper, different GA methods have been tested, such as the breeding type, and multi-objective ranking, for optimising the fuzzy rules and membership functions of a fuzzy logic controller for controlling the cooling rate of an industrial cryogenic process. Results show that the GA can optimise successfully the controller parameters to achieve high accuracy.

GENETIC ALGORITHMS

GAs are exploratory search and optimisation methods that were devised on the principles of natural evolution and population genetics (Holland, 1973). Unlike other optimisation techniques, a GA does not require mathematical descriptions of the optimisation problem, but instead relies on a cost-function, in order to assess the fitness of a particular solution to the problem in question. Possible solution candidates are represented by a population of individuals (generation) and each individual is encoded as a binary string containing a well-defined number of chromosomes (1's and 0's). Initially, a population of individuals is generated and the fittest individuals are chosen by ranking them according to an *a priori*-defined fitness-function, which is evaluated for each member of this population. In order to create another better population from the initial one, a mating process is carried out among the fittest individuals in the previous generation, since the relative fitness of each individual is used as a criterion for choice. Hence, the selected individuals are randomly combined in pairs to produce two off-springs by *crossing over* parts of their chromosomes at a randomly chosen position of the string. These new off-springs are supposed to represent a better solution to the problem. In order to provide extra excitation to the process of generation, randomly chosen bits in the strings are inverted (0's to 1's and 1's to 0's). This mechanism is known as *mutation* and helps to speed up convergence and prevents the population from being predominated by the same individuals. All in all, it ensures that the solution set is never empty. A compromise, however, should be reached between too much or too little excitation by choosing a small probability of mutation. There are four well-known reproduction techniques, Generational Replacement (GR), Steady-State (SS), Generational Gap (GG), and Selective Breeding (SB), plus a more recently developed Stud GA.

MULTI-OBJECTIVE GENETIC OPTIMISATION TECHNIQUE

In problems that have multi-objective formulation, objectives are often combined by means of an aggregation function. Combining the objectives to obtain an optimised solution has the advantage of producing a single solution, which requires no interaction with the decision-maker. However, if the solution found is not acceptable, tuning of the aggregation function is required followed by a new run of the optimiser until a suitable solution is found. The aggregation functions can be as simple as the weighted sum to a target vector. The method functions by generating an initial population which is evaluated to determine the performance of each individual, then an off-spring is generated which in turn is evaluated according to the performance of each individual. The last step is to select the best individual from both generations. Several popular methods exist for producing a single solution to a multi-objective optimisation operation as explained below and their respective performances may differ depending on the problem at hand. However, in this paper comparison will only be made between the average ranking method and the pareto-ranking method.

BREEDING METHODS

There are many breeding methods used in GAs, the most popular being steady state and selective breeding. The former method is more likely to find a solution which is not the best, as it has a small tendency to make big changes in the generations. On the other hand, selective breeding is more active in terms of generating new individuals to make the search reach wider selections, therefore it is more likely to find the best solutions.

The Selective Breeding reproduction method is designed to overcome some of the deficiencies in the other methods. In the steady-state breeding method, a sampling error still occurs in selecting the parents and deletion of individuals from the population, and often good individuals can appear and be deleted without a chance of recombination. Selective breeding introduces determinism in order to eliminate stochastic sampling error in deletion of candidates. The method consists of the following: if the initial population is of size ‘*n*’, then another population of the same size ‘*n*’ is produced through the mating process. The two populations are combined together to form a population of size ‘*2n*’ which will be ranked in the usual manner to produce a population of ‘*n*’ best individuals. This method has been found to converge more quickly that most of the others.

A recently introduced breeding method is “stud breeding”, which has a wider range of search and is more active in terms of finding new solutions (Khatib et al, 1998). This methods does not rely on cross-over, rather, it uses mutation and shuffling. In each generation, the best individual is selected and copied to replace the whole generation, then for each individual, mutation and bits shuffling is carried out to create new individuals from the best. It is claimed that this method has better search qualities than the other methods, including that of speed.

RANKING METHODS

There are many ranking methods for multi-objective genetic algorithms. Basically, the ranking is based on the fitness function of each individual with respect to the different objectives. Then, the fitness functions of each objective are combined together to generate a single fitness function for each individual, which is ranked to get the final generations. Two methods has been used in this investigation, *average ranking*, and *pareto ranking*.

The average multi-objective optimisation approach is based on ranking the population according to each objective individually, then a new overall rank can be generated by taking the average of the newly ranked populations. Finally, ranking the new vector is used to produce the final generation.

Pareto ranking is a different approach for multi-objective optimisation which is based on ranking according to the actual concept of pareto *optimality*. The method guarantees equal probability of reproduction to all non-dominated individuals. If both objectives have the same priority, all the satisfying individuals (the ones which meet their goal) are preferable and have a lower rank (higher fitness) than the remaining ones.

CRYOGENIC PLANT

The cryogenic plant in this study is used for cooling process for assessment of electrical characteristics of high temperature superconducting devices. The system consists of a dewar flask filled with helium and a stepper motor to lower and raise a probe in the dewar (Figure 1). This probe contains the superconducting device as well as the sensor for measuring the temperature. The stepper motor is mounted on top of the dewar and is controlled by a PC which calculates the number of step required to obtain a specific cooling rate profile (Johnston, 1998).

PLANT MODELLING

The Adaptive Network Based Fuzzy Inference System (ANFIS) learning architecture is based on a fuzzy inference system implemented in a framework of an adaptive network (Jang, 1993). Using a hybrid learning procedure, ANFIS can learn an input-output mapping relating to human knowledge (i.e. in the form of if-then fuzzy rules). The ANFIS architecture has been employed to model non-linear functions, identify non-linear components on-line in a control system, and predict a chaotic time series. ANFIS performs the identification of an input-output mapping, available in the form of a set of N input-output examples, with a fuzzy architecture, inspired by the Takagi-Sugeno modelling approach. The fuzzy architecture is characterised by a set of rules, which are properly initialised and tuned by a learning algorithm.

The cryogenic plant characterised by its is non-linear dynamics, and there is no physical model available. Therefore, a neuro-fuzzy model of the plant was developed based on input-output data collected from characterisation experimental runs on the process. The data consists of the temperature of the probes, and the stepping motor change rate. At each experiment the probe is lowered to 306 steps, and then the controller takes over by changing the stepping rate of the motor to keep the temperature close to the desired trajectory. The results of 24 experiments were included in the learning process. The variables chosen for the model are the probe position, the rate of change in the probe position, the probe temperature, and the last change in the temperature, while the output is one step ahead change in the temperature. The neuro-fuzzy system was trained for 500 epochs. The final model if the system is tested on one of the experiments, and the error in the model is shown in Figure 2.

FUZZY LOGIC CONTROLLER DESIGN

A fuzzy logic controller has been designed to track a desired rate of change in temperature. This trajectory is calculated by a scheduler which uses the measured probe temperature to produce an initial desired rate with a continuous change to the final desired rate. The fuzzy logic controller is designed with 9 rules, the inputs being the error and change in error, while the output is the change in the stepping rate to either lower or raise the probe. Gaussian fuzzy membership functions where selected. The fuzzy controller is designed to track the set-point produced by the set-point scheduler, by changing the stepping rate which is fed to the simulated model of the process as shown in Figure 3.

The set-point scheduler is designed to change the desired rate from the initial value to the slower final value rate as the temperature approaches the range where the experiment characterisation of the device is to be carried out. The first step involves lowering the temperature as fast as possible (200 mK/s) to around 140K, then slowing the cooling rate to 100 mK/s in the range between 140-100K. Then, for the last stage at bellow 100K the cooling rate is slowed to 10 mK/s. This rate is maintained through the transition temperature at which the sample becomes superconductive (95-97K) and down to a predetermined temperature of about 90K.

GA PARAMETERS OPTIMISATION

The GA optimisation is based on 2 objective functions, namely, the integral square error (ISE) and the integral time absolute error (ITAE). The input variables were the rules positions and the membership function shape, each of which has 5 bit resolution. The generation size was chosen to be 10 for faster simulation. The simulation length was set to 200 epochs.

The initial rule-base was set to default, as shown in Table 1, all the membership functions being the same. The optimisation algorithm is set to change the position of the rules and the membership function width. In order to avoid generating a rough control surface, a constrained parameters modification technique was chosen. There are two constraints, the first is not to allow linguistic labels to be changed (e.g. negative to positive or zero), while the second is the membership function width, not to allow it to go very narrow, or too wide. Narrow membership functions tend to make the controller to behave like a relay, while wide membership functions make the sets to overlap too much which makes the controller less sensitive to small input changes.

Table 1: Fuzzy controller rule-base.

	change in error		
error	N	Z	P
N	N	N	Z
Z	N	Z	P
P	Z	P	P

Simulation runs were conducted for two breeding methods, each of them with two ranking methods, average and pareto. Table 2 summaries the simulation results for the four GA optimisation methods. Comparing the performance of each case, it is shown that the selective-pareto ranking gives the best results. Figure 4 shows a simulation run using selective breeding and pareto ranking. The figure consists of: (a) the simulated system time response of the probe temperature and (b) the final 3D shape of the rule-base. The rule-base surface has been tuned to achieve a non-linear controller with smooth control surface.

Table 2: GA optimisation simulation results

Case	Type	ISE	ITAE
1	stud-average	44.700	2111.9
2	stud-pareto	47.512	2214.7
3	selective-average	47.157	2380.5
4	selective-pareto	42.076	2355.2

CONCLUSIONS

It is widely recognised that in multi-objective optimisation, the concept of optimality becomes absolute as a number of potential best candidates are proposed rather than only one best candidate for the optimisation problem. As a result, a number of ranking methods and breeding have been proposed, among them pareto-ranking, distance and average ranking methods, which have one common feature, being to decide which candidate is the *best*. In this paper different breeding and multi-objective ranking methods have been tested for tuning a fuzzy logic controller for an industrial cryogenic plant. The selective breeding and pareto ranking has achieved good accuracy compared to the nontuned controller. The optimisation methods can be extended to include more objectives.

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REFERENCES

1. Holland JH, 1973. "Genetic algorithms and the optimal allocation of trials", SIAM J. Comput., Vol. 2, pp 89-104.
2. Jang JR,1993. "ANFIS: Adaptive-network, based fuzzy inference system". IEEE transaction on Systems, Man, and Cybernetics, Vol. 23, No. 3, pp. 665-685.
3. Johnston R, 1998. "Fuzzy logic for high performance control". Measurement and Control, Vol. 31, pp. 73-79.
4. Khatib W, Fleming PJ, 1988. "Evolutionary Collaborative Optimisation Architectures". RAeS Int. Conference on Multi-Objective Optimisation., London, November, pp. 8/1-8/8.
5. Mahfouf M, Abbod MF and Linkens DA, 1998. "Multi-objective genetic optimisation of the performance index of self-organising fuzzy logic control algorithm using a fuzzy ranking approach". EUFIT'98. Aachen, Germany, September 8-12.
6. Mamdani EH, 1976. "Advances in the linguistic synthesis of fuzzy logic controllers". Int J. Man Mach Stud, Vol. 8, p 669.
7. Zadeh LA, 1965. "Fuzzy sets". Information and Control, Vol. 3, pp. 338-353.

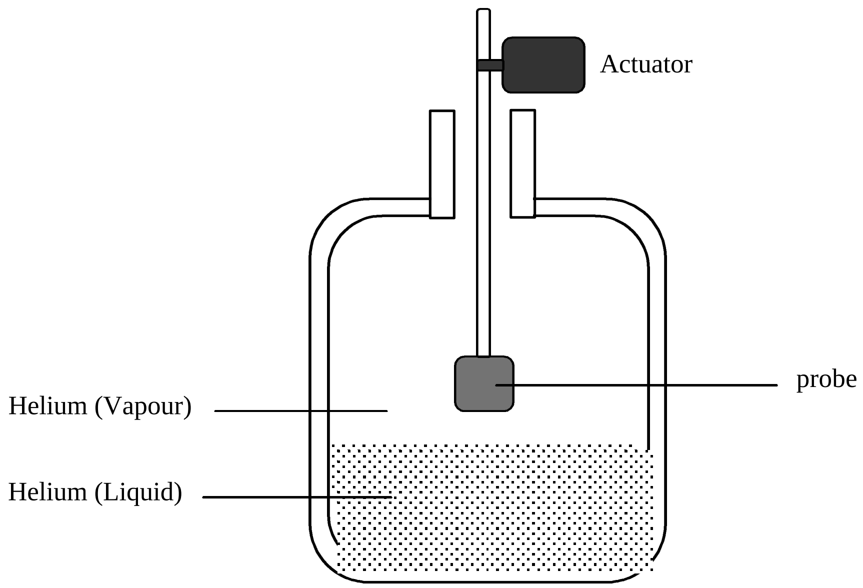
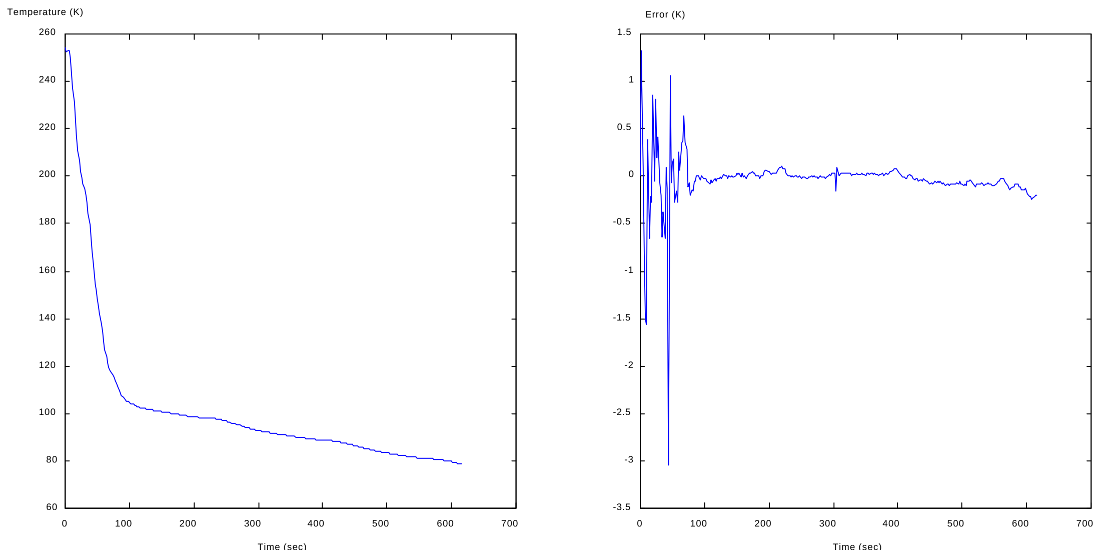


Figure 1: Schematic diagram of the cryogenic plant.



(a) experimental validation data

(b) model validation error

Figure 2: Neuro-fuzzy model validation.

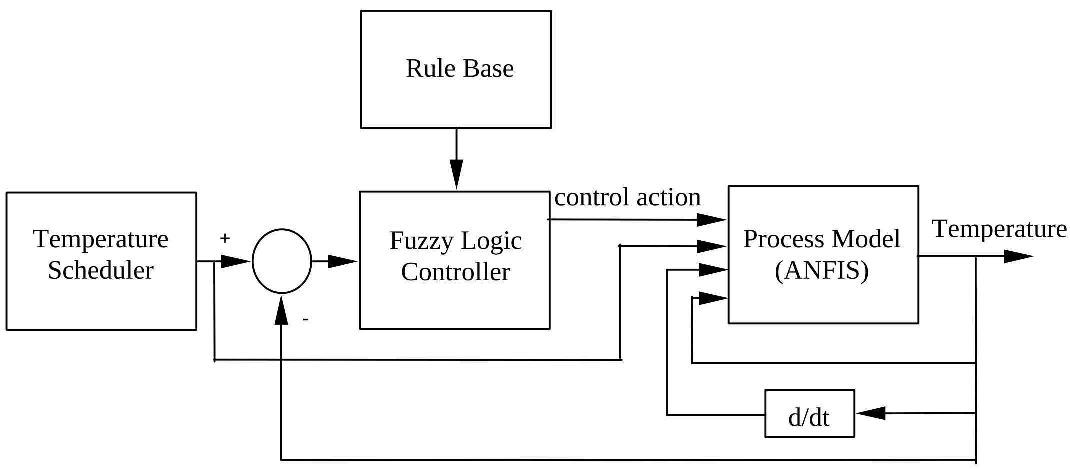
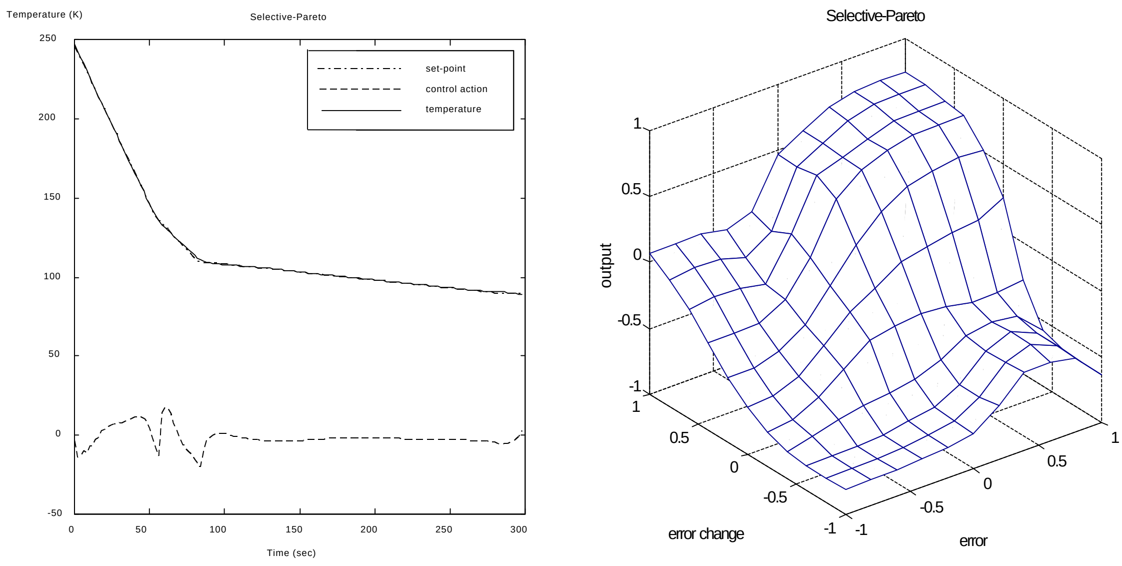


Figure 3: Block diagram of the control system.



(a) Time response (b) rule-base 3D surface

Figure 4: Simulation run of an optimised controller using selective-pareto ranking.