GAIN-SCHEDULED CONTROL OF A SOLAR POWER PLANT USING A HIERARCHICAL MOGA-TUNED FUZZY PI-CONTROLLER

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ABSTRACT

In order to regulate the significant variations in the dynamic characteristics of a distributed collector field in a solar power plant, various control techniques including feedforword control, gain scheduling and fuzzy control have been considered in the past. This paper develops some of these previous approaches by considering the operating conditions of the plant and the desired controlled responses. The result is a control scheme that employs a fuzzy PI controller, with feedforward, for the highly nonlinear part of the operating regime and gain scheduled control over the more linear part of the operating envelope. In order to satisfy performance characteristics for the plant at different points in the operating regime, a multiobjective genetic algorithm is used to design the parameters of the fuzzy controller. To reduce the size of the search space and the resulting fuzzy controller, a hierarchical encoding is employed with the multiobjective genetic algorithm. The resulting controller is shown to both satisfy the desired performance criteria and have a reduced number of terms compared with a conventional design approach.

1. INTRODUCTION

In previous work, Tang et al [1] have demonstrated how a hierarchical chromosome structure can be employed in the search for parsimonious fuzzy controllers, i.e. ones with a reduced fuzzy set and rule base. This approach has been successfully applied to the control of a nonlinear system, a solar power generation plant [2], and shown to offer acceptable control and the possibility of a simple hardware realisation. In this work, we extend this idea by considering the use of a multiobjective genetic algorithm (MOGA) [3] with the hierarchical chromosome structure to design the fuzzy controller to meet a set of performance criteria at different points in the operating regime.

However, other researchers have demonstrated that the solar plant can be controlled well over a large part of its operating range using a gain scheduling approach [4]. So, we consider the use of the fuzzy controller for control within the regions of high nonlinearity of the solar power plant and to make more effective use of a gain-schedule controller by allowing it to operate only in the more linear regions of the system. The overall effect of this approach will be to reduce the search space for the hierarchical MOGA, which itself will further reduce the number of membership functions and rule-base required for fine-tuning. This greatly improves the processing time when tuning the fuzzy-PI controller, and also improves control within the highly nonlinear regions of the plant.

2. PLANT DESCRIPTION

The ACUREX-field, Plataforma Solar de Almeria (PSA), is located in the southern part of Spain. The field is composed of 480 distributed solar parabolic collectors, arranged in 10 parallel loops and is outlined in schematic in Fig. 1. A collector uses the parabolic surface to focus the solar radiation onto a receiver tube, which is placed in the focal line of the parabola. The heat-absorbing oil is pumped through the receiver tube, causing the oil to collect heat, which is transferred through the receiver tube walls. The thermal energy developed by the field is pumped to the top of the thermal storage tank, whereupon the oil from the top of the storage tank can be fed to a power-generating system, a desalination plant, detoxification plant or to an oil-cooling system if needed.

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The oil outlet from the storage tank to the field is at the bottom of the storage tank.

For the initial start-up of the plant, the system is provided with a three-way valve, which allows the oil to be circulated in the field until the outlet temperature is adequate to enter the storage tank. The oil pump, which pumps the oil from the storage tank, through the collector tubes and into the top of the storage tank is located at the field inlet. To ensure that the collectors give optimum solar absorption, every collector row has a sun tracking system fitted to it.

A data acquisition system for the plant provides the following data: the solar intensity, inlet temperature to the field, outlet temperature of each loop and two other outlet temperatures between the field and storage tank, the current oil pump flow and requested value, and the tracking status of the collectors. The plant can generate 1.2 MW of peak power with beam solar radiation of 900 W m^{-2}. The oil-storage tank has a capacity of 140 m^3, which allows for storage of 2.3 thermal MWh for an inlet temperature of 210 °C and an outlet temperature of 290 °C.

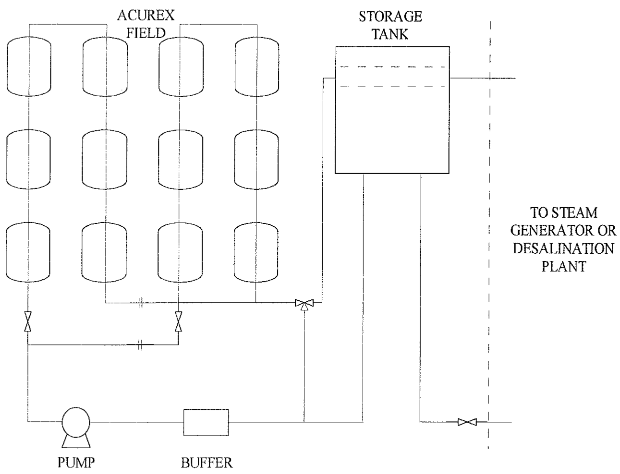

Figure 1: Schematic representation of the solar plant

The operation limits for the oil pump are between 2.0 and 10.0 l s^{-1}. The minimum value is there for safety and to reduce the risk of the oil being decomposed, which happens when the oil temperature exceeds 305 °C. The consequence of exceeding the maximum oil temperature is that all the oil may have to be changed leading to plant down-time and loss of power generation. Another important restricting element in this system is the difference between the field's inlet and outlet oil temperatures. A suitable, or normal, difference is around or less than 70 °C. If the difference is higher than 100 °C, then there is a significant risk of causing oil leakage due to high oil pressure in the pipe system.

A control system for this plant has the objective of maintaining the outlet temperature (in this case the average outlet temperature of all the parallel loops) at a desired level in spite of disturbances like solar irradiation (clouds and atmospheric phenomena), mirror reflectivity and inlet oil temperature. The oil flow rate is manipulated by the control system through commands to the pump. It should be noted that the primary energy source, solar radiation, cannot be manipulated. The performance measures of the control system are to keep the oil outlet temperature close to its set point, and to avoid oscillations in the oil pump flow rate.

3. GAIN-SCHEDULED CONTROL

In previous work, Johansen *et al* [4] employed a traditional gain-scheduling approach for the solar plant. This used a set of local linear controllers, each designed by pole-placement, based on local linear ARX models that were identified using the methods and software described in Hunt and Johansen [5]. A feed-forward block was also placed in the controller from the solar radiation input (I), to improve disturbance rejection. The linear models were designed for control in the more linear regions of the oil-flow (q), i.e. above 5 l s^{-1}.

Their decomposition was carried out in the operating range of, $0 \leq I \leq 1000$ W m^{-2} and 5 l s^{-1} $\leq q \leq$ 10 l s^{-1}. This decomposition was selected such that the gain and time constant of the linearisation of the simple model varies with less than a factor of 2 between any neighbouring regimes. Thus, assuming the local models are exactly correct at the centre points of their corresponding regimes, the interpolated model gain and time constant are never more than a factor of $\sqrt{2}$ wrong.

Two local linear models presented in [5] were identified from experimental data, using locally weighted regression as described in [6]. These correspond to the operating points with oil flow rates at 6 and 8 l s^{-1} respectively. The plant was perturbed with PRBS signals of amplitude 0.5 l s^{-1} around both of these operating points. Also, the gain of the local linear models was corrected using the average solar radiation during each PRBS test such that they corresponded to a solar radiation of 800 W m^{-2}. Furthermore, two new local models corresponding to a solar radiation of 500 W m^{-2} were generated by reducing the gain by a factor of 5/8. This gives a total of four local models corresponding to the four operating regimes. The plant does not normally operate in steady state at solar radiation levels below 400 W m^{-2}.

In [6] it was also shown that the performance of the gain scheduled controller was not ideal at the lower flow rate of 4 l s^{-1}, with significant overshoot and some oscillation of the control signal. Here, the authors will demonstrate that this may be improved by refining the models in this regime with an improved PRBS test signal. Furthermore, the nonlinearities were more pronounced at low flow rates. Thus, a finer decomposition into operating regimes may be desirable as q becomes smaller. In view of the uncertainties and difficulties of control at low flow rates, the method chosen in this study was to use a hierarchical MOGA tuned fuzzy PI controller to improve these flow rates.

4. TUNING THE FUZZY PI CONTROLLER WITH A HIERARCHICAL MOGA

In an initial study [7], fuzzy PI type controllers were designed for low flow rates that offered an improved performance compared with the standard controller. A MOGA was used to design the rule-base and membership functions for the controller against a number of performance criteria including rise time, overshoot and stability. In the work presented here, improvements to the work of Loebis [7] are developed to reduce the number of membership functions, the size of the rule base and the multiobjective genetic algorithm search space.

The result of this study was to vastly reduce the processing time required to tune the fuzzy PI controller. The search space was reduced by allowing the fuzzy PI controller to operate only in the high nonlinear areas of the system, i.e. where the oil flow is under 5 l s^{-1}. A hierarchical MOGA (HMOGA) was also designed in order to obtain the optimum number of membership functions and fuzzy rules. Further, the multiobjective GA was designed to allow more control objectives to be employed such as settling time and steady-state error. The HMOGA is designed in such a way that the genes of the chromosome are classified into two different types. One type of gene (*control*) affects the activation of the other type of genes (*parametric*). The effectiveness of this genetic formulation enables the fuzzy subsets and rules to be reduced while maintaining the system performance at the desired level.

A PI fuzzy logic controller is proposed were the error (e) is defined as the difference between the plant output temperature (T_O) and the set point signal (T_r). The error and its increment (Δe) are considered to be the inputs for the fuzzy controller and the output variable (Δu) is the increment to the control signal. A feed-forward term was added after the FLC to improve the disturbance rejection caused by variations in the solar radiation. This control scheme is depicted in Fig. 2.

The HMOGA is utilised to optimise the fuzzy membership functions, while the fuzzy rules are also governed by an evolution process to obtain an optimal set. The HMOGA is inspired by the hierarchical structure of DNA in biological systems. There are two types of genes, the control genes and the parametric genes, constructed in a hierarchical manner. The control genes govern the activation states of the parametric genes. Different activation states of the parametric genes can result in different structures in the phenotypes and therefore different membership function sets. An example of one particular fuzzy set within a chromosome is shown below in Fig. 3.

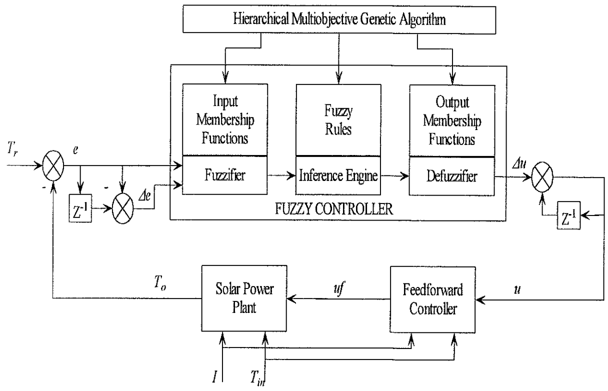

Figure 2: Solar power plant control scheme (nonlinear regimes)

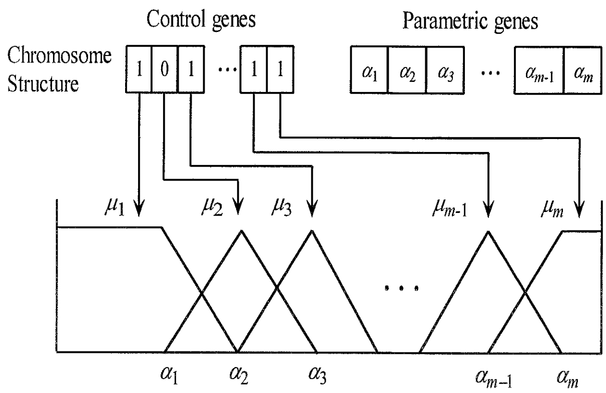

Figure 3: HMOGA chromosome structure

Three fuzzy sets are required for the solar plant FLC, namely e, Δe, and Δu and these were encoded into such a hierarchical chromosomes. The control genes, in the form of bits, determine the membership function activation, whereas the parametric genes are in the form of real numbers to represent the membership functions. The domain of all the fuzzy variables was normalised into the range of [-100, 100]. The fuzzy rules for each chromosome were classified, as the fuzzy subsets may vary from one chromosome to another. Also to allow each fuzzy rule table to evolve a special delta shift form of mutation was designed for this purpose [2]. When decoding the chromosomes to phenotypic values, a remedial procedure was performed to ensure that there were no undefined regions represented by the fuzzy membership functions, i.e. that invalid fuzzy sub-sets could be bypassed and the valid subsets enlarged to cover all the undefined regions.

The HMOGA uses the same Pareto-optimality criteria as Fonseca and Fleming [3] to determine fitness on the basis of non-dominance of the individuals. The criteria used to assess the performance of the fuzzy-PI controller and its transition from the fuzzy mode to gain scheduled are:

i. integral of the absolute value of the error multiplied by a variable penalty factor [2]
ii. rise-time (at each operating point change)
iii. overshoot (at each operating point change)

5. THE COMBINED CONTROLLER

The decision making for the combined controller, Fig. 4, is determined by the oil flow rate. The HMOGA tuned Fuzzy PI only being implemented at flow rates below 5 l s^{-1}.

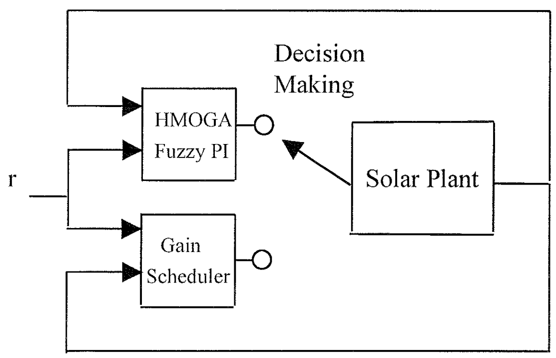

Figure 4: The combined controller

6. RESULTS

Fig. 5 shows a typical response for the outlet oil temperature tracking for the combined controller, i.e. fuzzy-PI and gain scheduled. In the figure, each discrete step point change corresponds to a separate design objective for both ii and iii. The design of the final controller is therefore a compromise that offers good performance across the operating range and also minimises that set point tracking error.

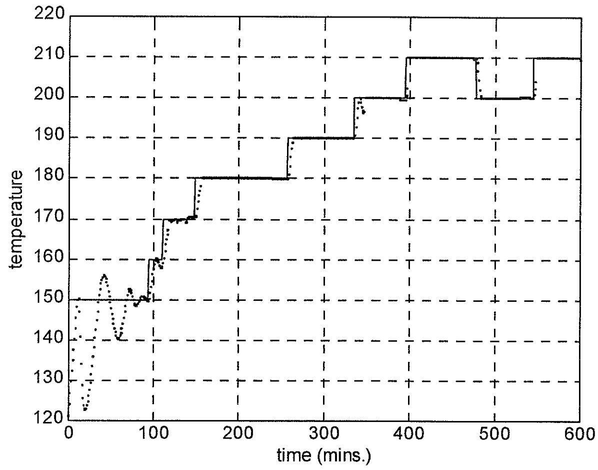

Figure 5: Typical simulation results

A typical set of reduced subsets (3 × 5 × 5) for the fuzzy membership functions obtained by the HMOGA are shown in Fig. 6. It should be noted that the reduced subsets do not degrade the system performance and are generally comparable with those obtained using conventional fuzzy design methodologies. However, as HMOGA is a Pareto-based approach there will not be one single 'best' solution. Rather, there will be a family of solutions that offer different trade-offs over the design objectives. The choice of the final solution could therefore be made by the control and/or systems engineer on the basis of performance criteria rather than the algebraic properties of a weighting function as is generally the case with single objective design techniques.

7. CONCLUDING REMARKS

The combined control of the solar plant was shown to be more effective than that of using fuzzy or gain scheduled control alone. It was also demonstrated that the size of the fuzzy controller can be reduced, while still allowing it to offer good performance over a set of objectives at a number of different operating points. The reduction in the size of the fuzzy controller is attractive because it is simpler to both understand and validate, and also easier to implement in hardware.

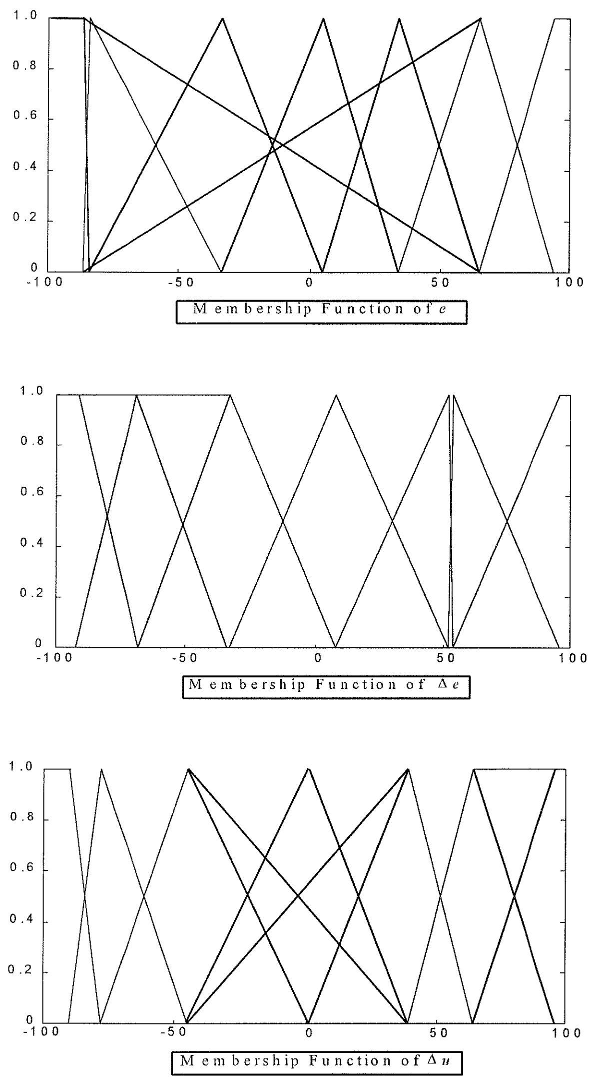

Figure 6: Typical fuzzy subsets and membership functions for the solar power plant

In future work, it is proposed to demonstrate the application of this approach to situations where the plant is subjected to external environmental changes, for example during a brief period of cloud cover. In such circumstances, there are wide variations in oil temperature and flow rates in the system need to be adjusted accordingly. The highly nonlinear region, below 5 l s^{-1}, maybe better controlled by the fuzzy controller at these operating points.

8. ACKNOWLEDGEMENTS

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