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HYBRID CONTROL USING EVOLUTIONARY TUNED FUZZY CONTROLLER TECHNIQUES – A STUDY

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Abstract: Due to the increasing global demand for energy, and the potential dangers of relying too heavily on our fossil fuel reserves, more and more research is being directed towards alternative, and preferably reusable or sustainable forms of energy supply. Many of these real world systems have operating regions or regimes that exhibit varying degrees of non-lineararity. An example of this are the significant variations in the dynamic characteristics of a distributed collector field within a solar power plant. Here a gain-scheduled controller using pole placement with feedforward was chosen to control the more linear operating regimes of the plant. A study was then carried out to find the best-suited and most efficient evolutionary-tuned fuzzy logic based controller, for exclusive and concentrated use on the plant's more non-linear regions. *Copyright © 2002 IFAC*

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1. INTRODUCTION

Recent research has demonstrated that a gain scheduling approach, Johansen, *et al*. (2000), can be used to control a solar power generation plant successfully, over a large part of its operating range. However, the results of this type of control deteriorate somewhat when the plant is operated in its more nonlinear regimes. It is therefore proposed in this work to combine this type of controller with controllers best suited to the more nonlinear operating regimes. Previous work on controllers that fit these requirements include the fuzzy PD, Malki and Chen (1994), the fuzzy PI, Loebis (2000) and the fuzzy PI+D controller, Tang *et al*. (2001). The PI and PI+D controllers were combined in turn with the gain scheduler to find the best hybrid controller for the plant. The fuzzy tuning was implemented using a multiobjective genetic algorithm (MOGA), developed by Fonseca and Fleming (1998), and implemented within a hierarchical structure, developed from Tang, *et al*. (1996).

Tang, *et al*. (1996), demonstrated how a hierarchical chromosome structure could be employed in the search for parsimonious fuzzy controllers, i.e. ones with a reduced fuzzy set and rule base. This approach has also been successfully applied in Ke, *et al*. (1998), and shown to offer acceptable control and the possibility of a simple hardware realisation. In this work, this idea is extended by considering the use of the MOGA with the hierarchical chromosome structure to design the fuzzy controller to meet a set of performance criteria at different points in the operating regime. 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 controller, and 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. 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 ^oC and an outlet temperature of 290 ^oC.

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^{o}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

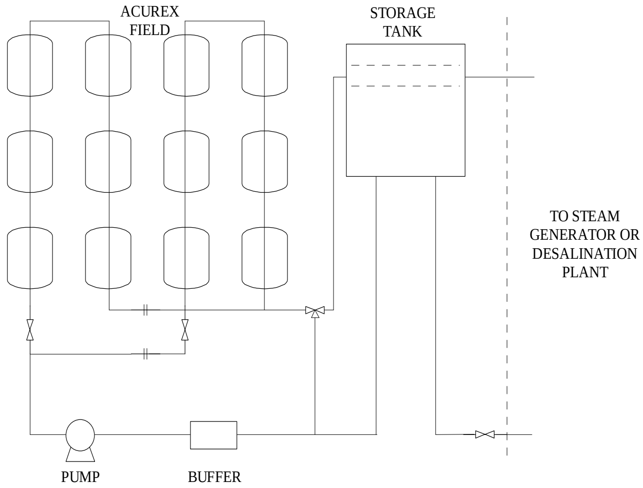


Fig. 1. Schematic representation of the solar plant

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 ^oC. If the difference is higher than 100 ^oC, 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, couldn't 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.*, (2000), 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 (1997). 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

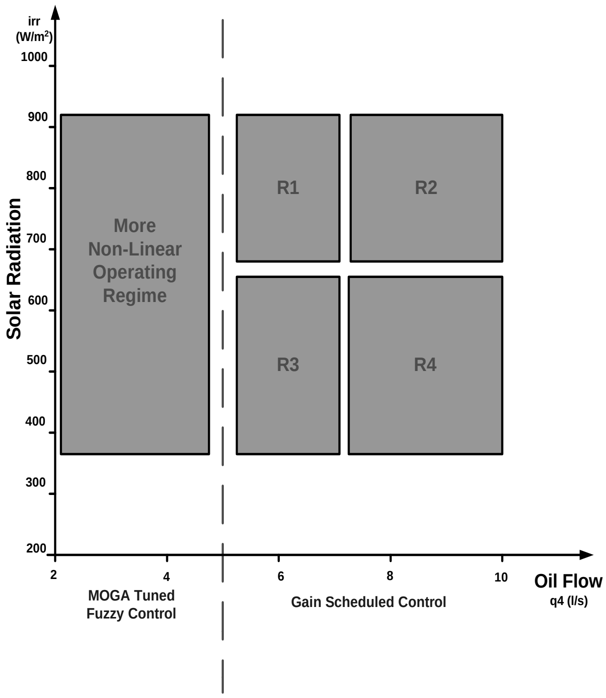


Fig 2. The plant's operating regimes.

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 √2 wrong. The decomposition of the proposed hybrid controller into its operating regimes, including those of the gain scheduler is shown in Fig. 2.

Two local linear models presented by Hunt and Johansen (1997), were identified from experimental data, using locally weighted regression as described by Johansen, *et al.* (1998). 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, by reducing the gain by a factor of 5/8, generated two new local models corresponding to a solar radiation of 500 W m^{-2}. 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 400W m^{-2}.

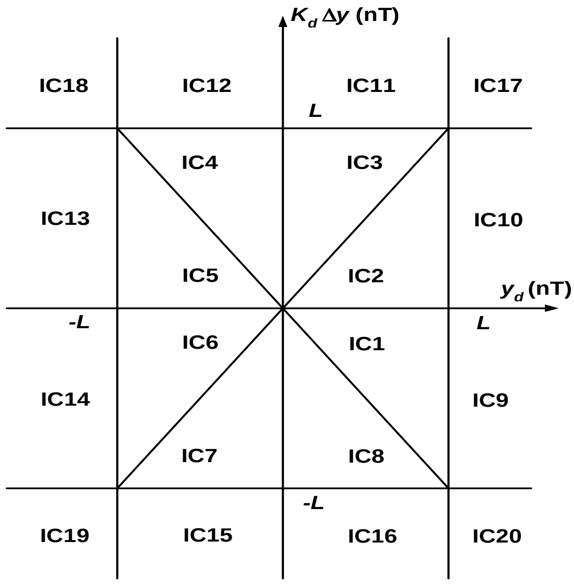
In Johansen, *et al.* (1998), it was also shown that the performance of the gain-scheduled controller was not ideal at the lower flow rate of 4 l s^{-1}, with significant overshoot and some oscillation of the control signal. Here, the authors will demonstrate that this may be improved by refining the models in this regime with an improved PRBS test signal. Furthermore, the nonlineararities 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 controller to improve these flow rates.

4. FUZZY CONTROLLER CHOICE

In the work developed by Malki and Chen (1994), the fuzzy PD controller was shown to have the edge over traditional controllers, particularly when the system to be controlled is nonlinear.

This work was extended further by Tang, *et al.* (2001) where the defuzzification of the fuzzy D controller, Fig. 3, was developed to realise a fuzzy PI+D controller, Fig. 4, which again achieved improved results when controlling nonlinear plants. The additional defuzzification required for the PI controller section is similar to that of the D except that the input signals in this case are different.

Also work by Loebis (2000) used a MOGA tuned fuzzy PI controller with feedforward to obtain good results when controlling a solar power plant, Fig. 5.



$$\Delta u_D(nT) = \begin{cases} \dfrac{L[Ky_d(nT) - K_d\Delta_y(nT)]}{2(2L - |y_d(nT)|)} & \text{in IC 1, 2, 5, 6} \\ \dfrac{L[Ky_d(nT) - K_d\Delta_y(nT)]}{2(2L - K_d|\Delta_y(nT)|)} & \text{in IC 3, 4, 7, 8} \\ \frac{1}{2}[-K_d\Delta_y(nT) + L] & \text{in IC 9, 10,} \\ \frac{1}{2}[y_d(nT) - L] & \text{in IC 11, 12,} \\ \frac{1}{2}[-K_d\Delta_y(nT) - L] & \text{in IC 13, 14,} \\ \frac{1}{2}[y_d(nT) + L] & \text{in IC 15, 16,} \\ (0) & \text{in IC 17, 19,} \\ (-L) & \text{in IC 18} \\ (L) & \text{in IC 20} \end{cases}$$

Fig. 3. Fuzzy D controller input-combination values with their formulas.

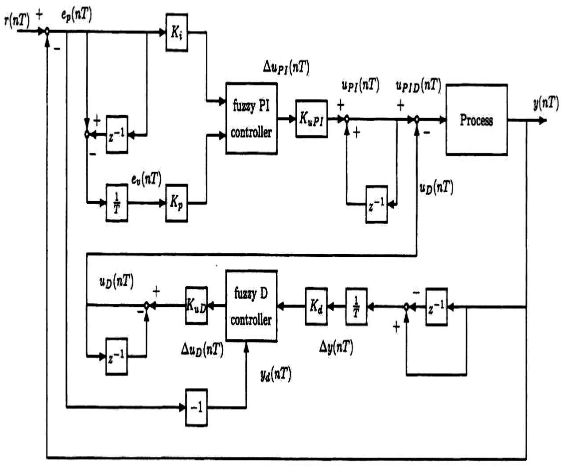


Fig 4. Fuzzy PI+D control system.

The work in this paper adds Hierarchical MOGA tuning and feedforward to the PI and PI+D fuzzy controllers mentioned above, and attempts to find the most suitable controller for the more nonlinear regimes of the solar power plant. Only the improved fuzzy PI tuning is described next as the PI+D tuning is similar.

5. TUNING THE FUZZY PI CONTROLLER WITH A HIERARCHICAL MOGA

In an initial study by Loebis (2000), a fuzzy PI type controller was designed for better control of the solar plant's low flow rates. This offered an improved performance compared with the standard PI controller. A MOGA was used to optimise the rule-base and membership functions for the controller against two performance criteria; rise time, for each portion of the set point (due to each step input having a different step time, initial value and final value), and covariance (for all portions), giving ten objective functions in all.

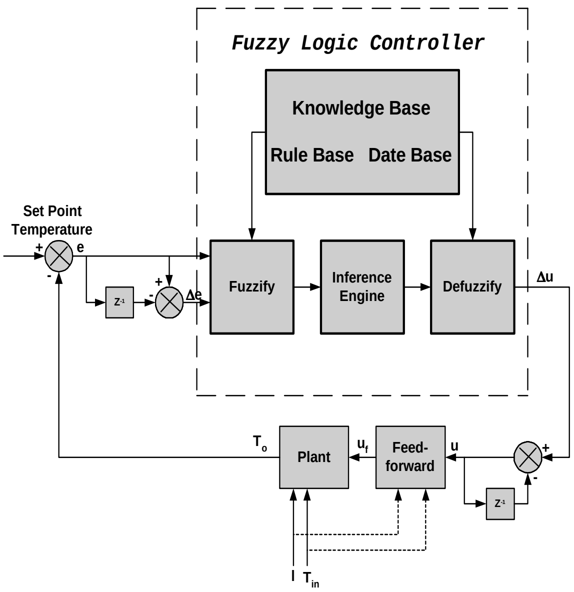


Fig 5. A Fuzzy PI controlled Solar Power Plant.

In the work presented here, the following improvements to the work of Loebis (2000) were developed 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 was under 5 l s^{-1}.
- A hierarchical MOGA (HMOGA) was designed in order to obtain the optimum number of membership functions and fuzzy rules.

Further, the multiobjective GA could be designed to allow more control objectives to be employed such as settling time and steady-state error. This is possible because there are no step changes inside the more nonlinear regions.

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.

The fuzzy logic PI controller (FLC) proposed here, defines the error (e) as the difference between the plant's 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.

The HMOGA is utilised to optimise the fuzzy membership functions, while an evolution process to obtain an optimal set also governs the fuzzy rules. 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. The control scheme for the Fuzzy PI controller is depicted in Fig. 6. An example of one particular fuzzy set within a chromosome is shown in Fig. 7.

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

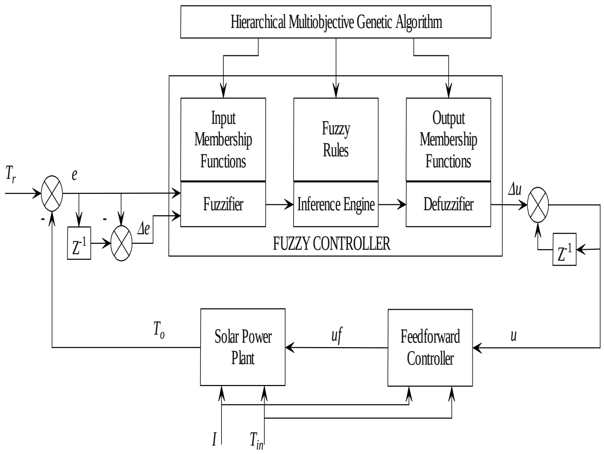


Fig. 6. The solar power plant fuzzy PI control scheme using HMOGA tuning

a special delta shift form of mutation was designed for this purpose, Ke, *et al*. (1998). When decoding the chromosomes to phenotypic values, a remedial procedure was performed to ensure that there was 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 (1998) to determine fitness on the basis of non-dominance of the individuals.

The criteria used to assess the performance of the fuzzy controllers and their transition from the fuzzy mode to gain scheduled is:

i. integral of the absolute value of the error multiplied by a variable penalty factor, Ke, *et al*. (1998)
ii. overshoot
iii. rise-time
iv. settling time
v. covariance
vi. oil flow rate

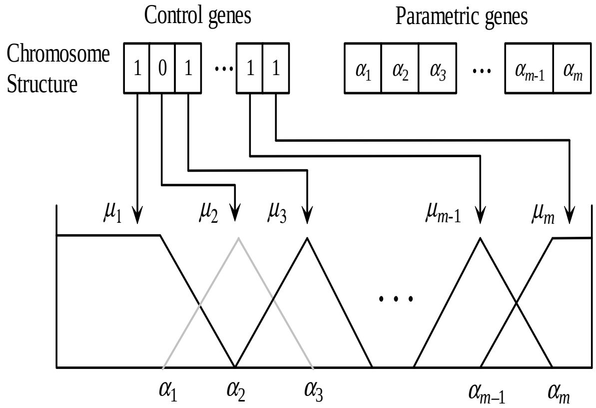


Fig. 7. HMOGA chromosome structure

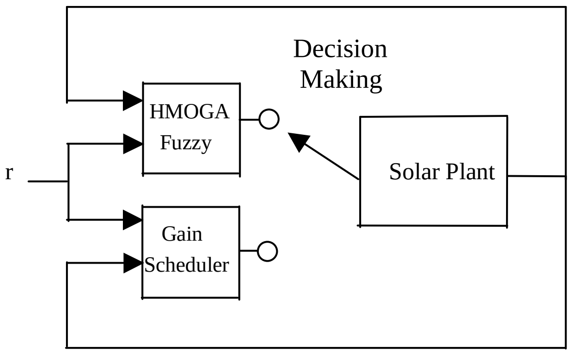


Fig. 8. The combined controller

6. THE COMBINED CONTROLLER

The decision making for the combined controller, Fig. 8, is determined by the oil flow rate. The HMOGA tuned Fuzzy controllers only being implemented at flow rates below 5 l s^{-1}.

7. RESULTS

Figs. 9 and 10 show a typical response for the outlet oil temperature tracking for the combined controllers, i.e. fuzzy-PI and PI+D with the gain scheduler, respectively. In the figures, each discrete step point change corresponds to a separate design objective for ii, iii, iv and v. 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.

A typical set of reduced subsets (3×5×5) for fuzzy membership functions obtained by the HMOGA are

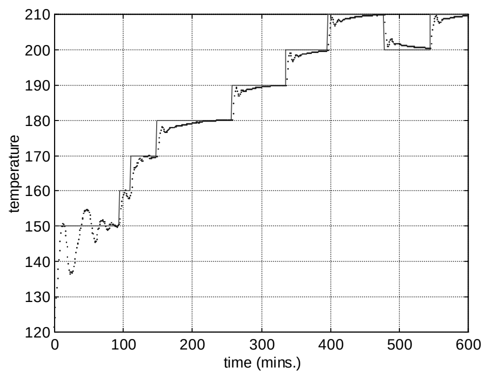


Fig. 9. Typical simulation results for the fuzzy PI

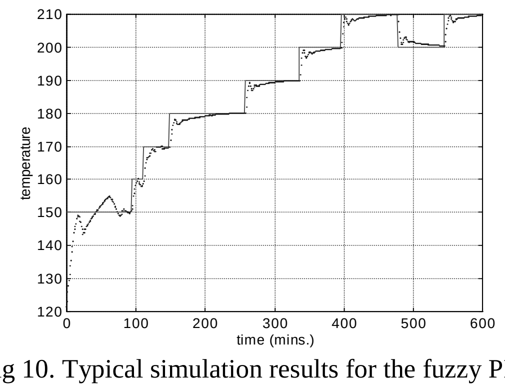


Fig 10. Typical simulation results for the fuzzy PI+D

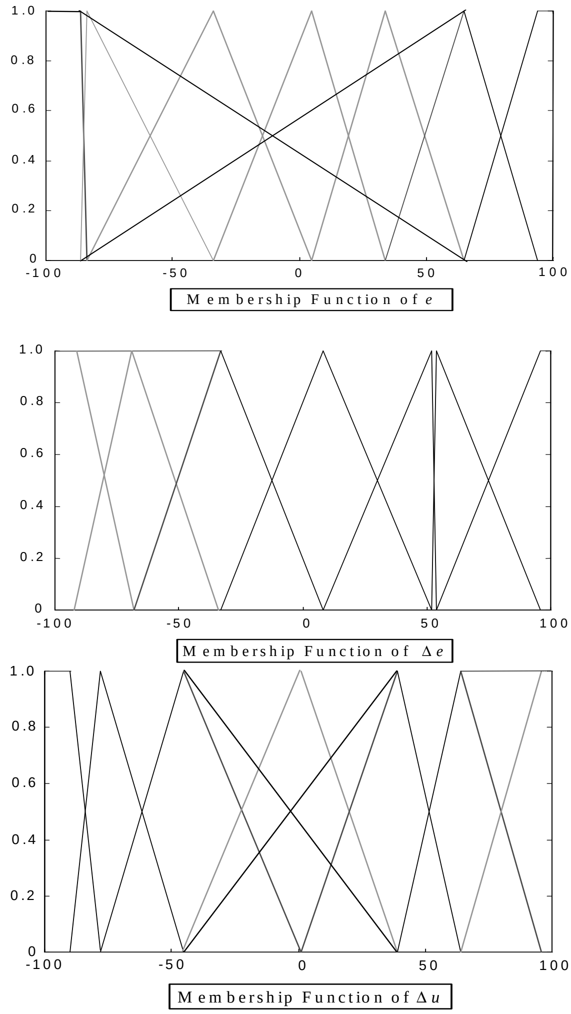


Fig. 11. Typical fuzzy subsets and membership functions for the solar power plant

shown in Fig. 11. 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 systems engineer could therefore make the choice of the final solution, 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.

8. 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.

Allowing the fuzzy controller to operate only in the regions of higher non-lineararities:

- Reduced the search space, which in turn permitted the MOGA to produce a set of non-dominating solutions at a much faster rate.
- Improved control by allowing a wider choice of performance criteria.
- Increased the operating range at low oil flow rates, which allows the plant to function in environments where local solar radiation conditions have always been regarded as marginal.

The reduction in the size of the fuzzy controllers is attractive because it is simpler to both understand and validate, and also easier to implement in hardware.

Although both HMOGA-tuned fuzzy controllers perform well in controlling the more nonlinear regimes of the solar power plant, it is felt that the hybrid controller using the fuzzy PI+D has more potential regarding nonlinear control.

9. ACKNOWLEDGEMENTS

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