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Innovative Migrants' Operators for Improved Genetic Optimization of Fuzzy Logic Controller

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Abstract: The Fuzzy Logic Controller (FLC) is very much useful in more complex situations which cannot be dealt mathematically. By providing the knowledge about the complex system, Fuzzy logic controller (FLC) can be developed and formed into a number of fuzzy rules. Since, FLC needs more human approach to control, Genetic algorithm is introduced for the purpose of the design and optimization of fuzzy rule base. But due to some problems like messy overlapping of membership functions and redundant rules, simple GA is not enough. To overcome the above situations, it is better to introduce the migrants' formation which is the movement of individuals between subpopulations. In this study, migrants are introduced in 3 populations (7×7, 5×5 and 3×3) for a second order process and verified the improvement in the genetic optimization of the process.

Key words: Fuzzy logic controller, Genetic algorithm, migrants operators, well-developed fuzzy sets and rule bases

INTRODUCTION

The fuzzy logic controller based technology to describe a complex non linear system. Fuzzy logic (Lee, 1990) based modeling is one of the most significant areas of application of computational intelligence approaches and generally, it is inherently robust with respect to plant parametric variations and measurement uncertainty.

A fuzzy logic controller can have a set of IF-THEN rules and which is more useful in operator controlled plants (Takagi and Sugeno, 1985).

In general IF -THEN rule structure is expressed as follows:

$$\begin{aligned}&\text{Rule 1: IF } x_1 \text{ is } A_1 \text{ THEN } y_1 \text{ is } B_1\\&\text{Rule 2: IF } x_2 \text{ is } A_2 \text{ THEN } y_2 \text{ is } B_2\\&\ldots\\&\text{Rule n: IF } x_n \text{ is } A_n \text{ THEN } y_n \text{ is } B_n\end{aligned} \quad (1)$$

In the above mentioned rule structure, IF part is said to be Antecedent and THEN part is said to be Consequent. The collection of rules is called as Rule base. Figure 1 shows FLC based process control.

In an FLC based process control (Ross, 1990), based on the deviation from the set point and the process variable of the process, FLC takes action according to the control strategy.

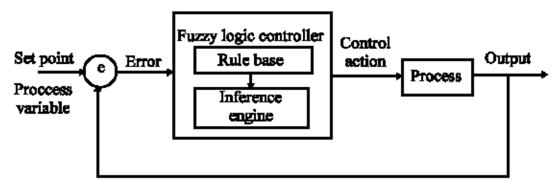

Fig. 1: FLC based process control

variable of the process, FLC takes action according to the control strategy.

Nowadays the design of FLC' membership functions and the rule based have been automated by the use of Genetic Algorithm (GA) which is a powerful optimization technique. But sometimes GA alone is not enough to produce the optimal FLC due to some problems like non-uniformed overlapping of fuzzy sets and redundant rules in the fuzzy rule base. Figure 2 shows the well formed membership function and messy overlapped membership function of an input variable.

For any selected input variable, the fuzzification module produces the membership of one or 2 fuzzy sets. From Fig. 2a, when the input variable assumes a value that is directly under the apex of one of the triangles, the membership of one fuzzy set can be obtained. In such a

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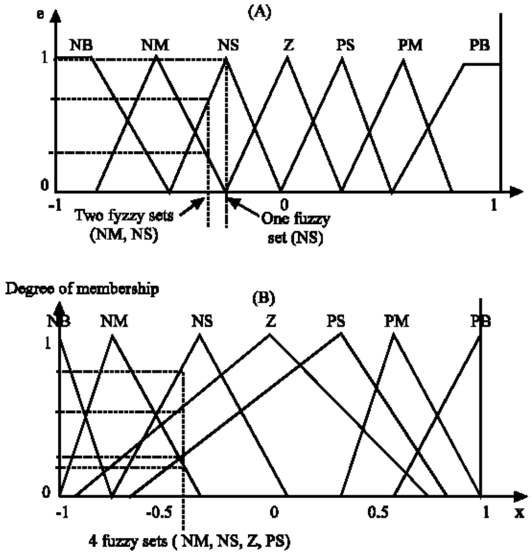

Fig. 2: Well formed and messy overlapped membership functions

case, the membership value is 1.0 for that particular fuzzy set and 0.0 for the other 2 overlapping fuzzy sets. If the input value assumes any other value, then membership of 2 fuzzy sets will result. For a 2-inputs FLC, the number of rules to be fired is 4 (most of the time) or less.

For the messy overlapped fuzzy set shown in Fig. 2a and b, the input variable produces membership of 4 fuzzy sets and the number of rules to be fired is 16. So, because of the high number of fuzzy sets overlapping each other, messy fuzzy sets cause a high number of rules to fire at any one time. This will finally lead to increase the computational speed.

If we consider the uniformly overlapped (well-formed) membership function of one input variable and the corresponding well-developed rule base shown in Fig. 3a, for the selected value of the input variable, fuzzification is to be made easily by firing of minimum number of rules. But many times, the use of individual GA for the purpose of FLC optimization will result into confused rule base containing some nonsense rules shown in Fig. 3b and this will result in increased error instead of decreasing it. Even though the incorrect individual rules in the confused rule base may not affect the overall FLC output, it is difficult for knowledge acquisition.

The FLC output is dependent on the formation of the rule base and the number of rules to be fired at one time according to the assumed value of the input variable. So, our aim is to minimize the number of rules to be fired at one time than to minimize the number of rules in the rule base.

Error \ Change in error	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PB	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	PS	PM	PB	PB	PB	PB

Error \ Change in error	NB	NM	NS	ZE	PS	PM	PB
NB	PB	PM	ZE	PM	NS	PM	NS
NM	PM	PM	NS	ZE	PS	NB	PM
NS	PB	NM	ZE	PB	PS	PS	PB
ZE	PM	PS	NS	PS	PM	PS	NB
PS	NM	PS	NS	NS	ZE	NM	PS
PM	NS	PM	NM	PB	PM	NM	NB
PB	PS	PS	PS	PS	NS	ZE	PB

Fig. 3: Rule bases

In this study, an intensified genetic algorithm (Goldberg, 1989) is proposed to confine the optimization of the fuzzy logic controller which will result well-developed fuzzy sets and rule base. To improve the chances of optimization of FLC, innovative migrants (Cheong and Lai, 2000) have been created between 3 numbers of populations namely 7×7, 5×5 and 3×3. Instead of evolving the 3 populations sequentially; they have been evolved in parallel with migration of individuals between the populations. A second order process is taken here as an application for our purpose.

INNOVATIVE MIGRANTS' OPERATORS AND THEIR CREATION

With respect to Genetic Algorithm, Migration is a process of replacing the worst individuals from one subpopulation by best individuals in another population and the operators involved in this process are called as 'migrants'.

The parameters to be considered for migrants' formation process are:

- Direction of the migrants.
- Migration Interval.
- Migration Fraction.

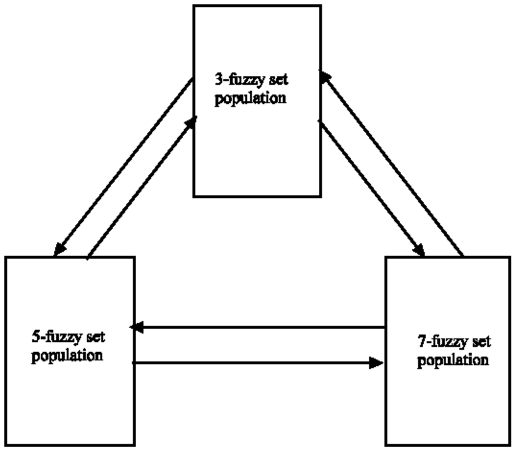

Fig. 4: Model of a migration process

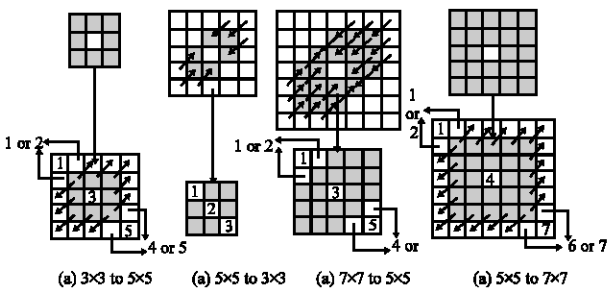

Fig. 5: Migrants creation in the rule base

The process of migration can take place in one (forward or reverse) or both the directions. If the direction is chosen as ‘forward’, migration takes place toward the last subpopulation. That means, the n^{th} subpopulation migrates into the $(n+1)^{th}$ subpopulation. If the direction is chosen as ‘Both’, the n^{th} subpopulation migrates into both the $(n-1)^{th}$ and the $(n+1)^{th}$ subpopulation.

The migration Interval can be utilized to specify the number of generation pass between migrations. The number of individuals’ movement between subpopulations can be specified by Migration Fraction. Figure 4 illustrates the model of a migration process.

Figure 5 shows the procedure (Cheong and Lai, 2000) to convert 3×3-5×5, 5×5-7×7 fuzzy set membership functions and vice-versa. To convert from 3×3-7×7 fuzzy-set membership functions and vice-versa, 5×5 fuzzy-set membership functions have to be used as intermediary.

While, expanding the smaller rule base into larger one, for example 3×3 into 5×5 or 5×5 into 7×7, there are 2 problems were encountered. First, due to mismatching of the ranges of smaller rule base and larger rule base, codes corresponds to the output have to be mapped to a greater range. Next, for the expanded rule base, it is necessary to create extra cells in then rule base. To generate output values for the extra cells, adjoining cells are copied along the diagonal of the rule base as shown by the arrows in Fig. 5a and d. The conversion of larger into a smaller rule base involves copying cells at the same locations in the bigger rule base, except for the extremities and the center of the rule base which will contain fixed values from derived as before. This is shown by the arrows in Fig. 5b and c.

OPTIMIZATION OF FLC USING GENETIC ALGORITHM

Genetic Algorithm (GA) is a powerful problem solving tool (Coley, 1999) which attempts to mimic the natural selection process and evolution in order to find the optimal solution to a given problem. Due to its simplicity, close analogy with biological evolutionary systems and its domain independent representation via bit-strings, GA is likely to be used very much. It is a mathematical method which is motivated by the concept of survival of the fittest in biological evolution.

The first step of Optimization of Fuzzy logic control functions is the creation of population of fuzzy membership functions (Karr, 1991). The fuzzy membership functions can be created randomly, or they can be created as random perturbations around some nominal functions. In that, each member of the population is represented as a binary string. Among many types of membership functions, if triangular membership function is preferred, then each member of the population should have enough genetic information in its binary string to represent 3 parameters $\{a_1, b_1$ and $a\}$ mentioned in Fig. 6.

After generation of population of fuzzy membership functions (each member of the population represented by a bit string), the fitness of each member of the population is evaluated according to some predetermined method.

Then, after the evaluation of the fitness of each member of the population, the weakest members are discarded. The fittest members are now preferred in the reproduction. During crossover, 2 members of the population join with each other to form an offspring which is a combination of the 2 parents. For instance, if each member has k bits of information, then perhaps bits 1-r of parent A and bits r+1-k of parent B could be copied into the offspring, where the number r is randomly generated.

Finally, there is a small but nonzero probability of mutation in the offspring. Mutation is used to re-feed the genetic information which may have been lost in the current generation. A cycle of fitness evaluation, reproduction and mutation is called as a generation (Haupt and Haupt, 1998).

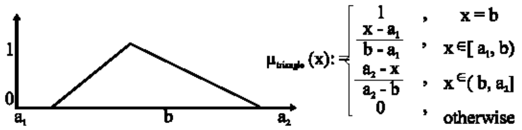

Fig. 6: Triangular membership function

APPLICATION OF MIGRANTS OPERATORS FOR IMPROVED OPTIMIZATION

Consider the following second order process transfer function as an application example.

$$G(s) = \frac{2}{(s^2 + s + 2)} \tag{2}$$

For the above process, error (e) and change in error (ce) are considered as inputs and process variable (pv) as an output.

Figure 7 shows the fuzzy inference system of the process.

The membership function diagrams of the inputs and output of the process are shown in Fig. 8a-c.

Second, genetic optimization of the process was performed without the creation of migrants. Next, to improve the genetic optimization, migrants which are the movement of individuals between subpopulations were introduced in 3 populations such as 7×7, 5×5 and 3×3. Figure 9 shows the block diagram of the process optimization with migrants.

The performance of the Fuzzy logic controller in Fig. 7 was determined by using unit step response. Genetic optimization with 3 fundamental operators namely, Reproduction, Cross over and Mutation was utilized for optimization (Whitfield *et al*., 2003) of the Fuzzy logic controller which is of 3 sizes 7×7, 5×5 and Fig. 10 shows the well-formed rule base of the Fuzzy logic controller.

The response of the fuzzy logic controller is assessed by integral-of-time-multiplied absolute error (ITAE) criterion which is used as an objective function for GA based optimization (Whitfield *et al*., 2003).

$$\text{ITAE} = \int t\left|e(t)\right| dt \tag{3}$$

As per the guide lines for migration creation given in Fig. 5, 5×5 and 3×3 rule bases have been created and shown in Fig. 11.

Here, 3 populations (7×7, 5×5 and 3×3) are evolved in parallel with migrations of individuals between the populations. Migrants' operators have the ability to avoid the premature convergence to local minimas. At every end

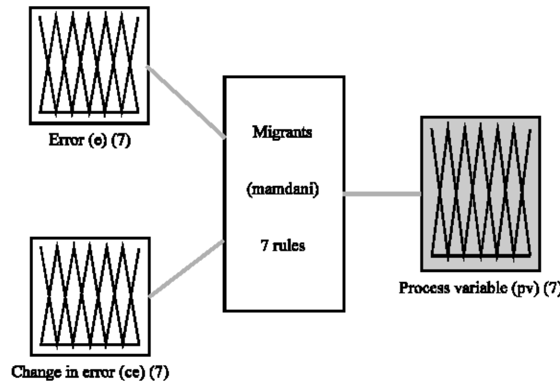

Fig. 7: Fuzzy inference system of the process

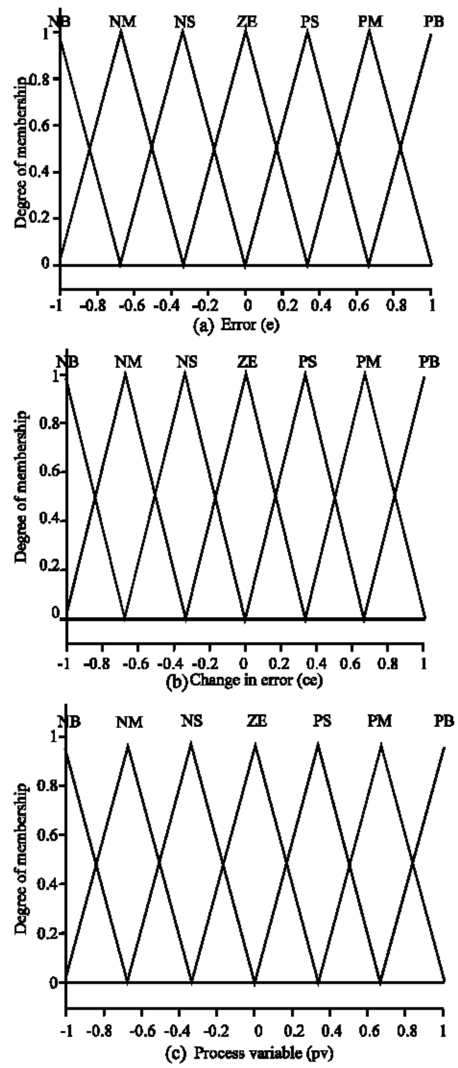

Fig. 8: Membership function diagrams of I-O

of population, 5 numbers of best individuals have been selected and migrated them to other populations.

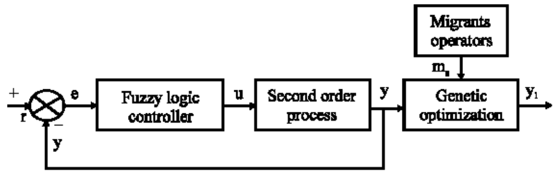

Fig. 9: Process optimizations with migrants

Error \ Change in error	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NM	NB	NM	NS	NM	ZE
NM	NB	NM	NM	NS	NS	NS	PM
NS	NB	NM	ZE	NM	NS	PM	PB
ZE	NM	NB	NM	ZE	ZE	PM	PM
PS	NM	NM	ZE	ZE	PM	PM	PM
PM	NS	ZE	ZE	PM	ZE	PB	PB
PB	ZE	ZE	PS	PS	PB	PB	PB

Fig. 10: Well-formed rule base (7×7) of FLC

NB	NM	NB	NS	NS
NM	NM	NS	NS	ZE
NS	NM	NS	NS	PS
NB	ZE	NS	PS	PS
NS	PS	ZE	NS	PS

NB	NM	NS
NB	NM	NM
NM	PS	NS

Fig. 11: Rule bases with migrants

Table 1: Comparison performance of the GA based system responses with and without migrants operators

System response	Peak amplitude	Overshoot (%)	Settling time (sec)	Rise time (sec)
Without GA	1.3	30.4 at 2.33 sec	7.74	1.0
With GA and Migrants in 7×7 population	1.07	7.42 at 0.36 sec	0.737	0.147
With GA and Migrants in 5×5 population	1.04	3.54 at 0.29 sec	0.55	0.103
With GA and Migrants in 3×3 population	1.00	0.00784 at 3.58 sec	0.193	0.0849

Figure 12a-c show the responses of the selected process with respect to step input with and without migrants' operators in 3 populations.

The comparison performance of the above responses of the process is listed in Table 1.

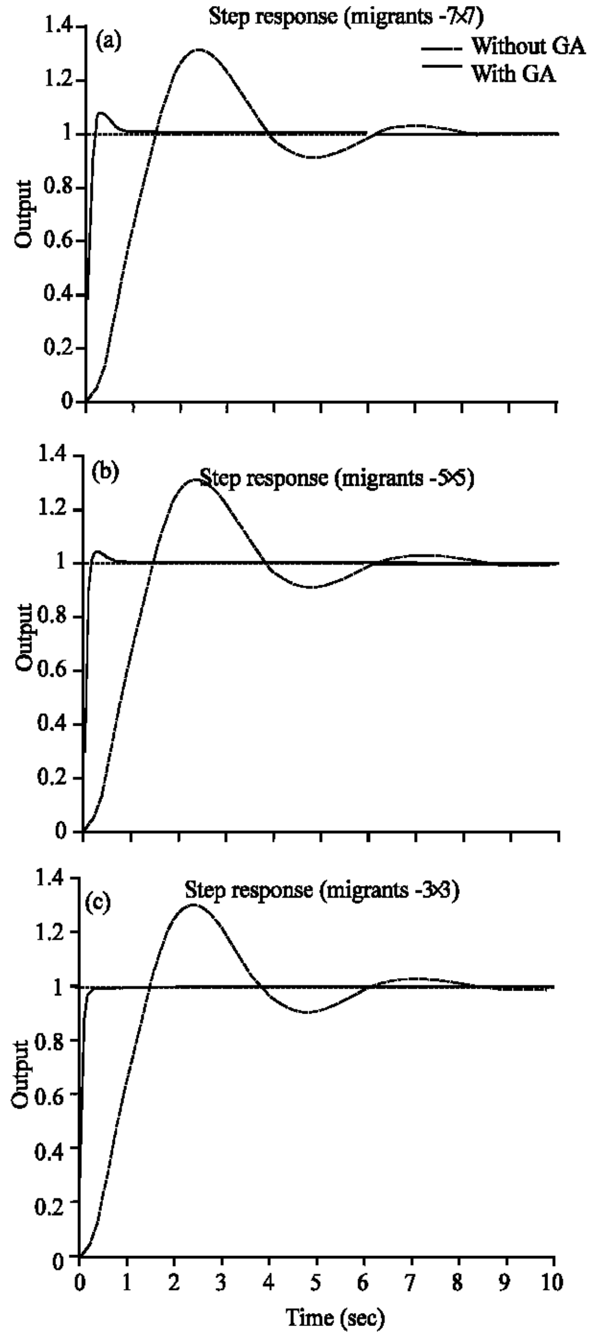

Fig. 12: (a) Step response of second order process with and without GA in 7×7 Population (b) in 5×5 Population (c) in 3×3 Population

CONCLUSION

In this study, the necessity of well-formed fuzzy sets for minimum number of rules' firing and well-developed fuzzy rule bases for better understanding was discussed. The role of novel migrants' operators and the procedure to create them were dealt in detail.

For the chosen second order process, a fuzzy logic controller with 3 well-formed rule bases of 7×7, 5×5 and 3×3 sizes was developed. Next, Genetic algorithm was applied for optimization of FLCs. The inability of GA due to mismatching in different sizes of FLCs, the migration strategy was utilized and observed the improved optimization of the chosen process.

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