Genetic Tuning of Fuzzy Inference System for Furnace Temperature Controller

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***Abstract** – Since last two decades Fuzzy Control has emerged as a novel methodology in the industrial process control. It is mainly due to ability of Fuzzy Logic to handle non-linearity that exists in the industrial process and develop non-mathematical model of complex process. Fuzzy Systems appears to be straight forward and simple to design and implement. However this is not true. In fact they inevitably need tuning. Different methods exist for tuning the Fuzzy Systems, and Genetic Algorithm is one of them. The present paper presents the tuning of Fuzzy Inference Process (FIS) design for Small-Scale Furnace Temperature Control. The MATLAB source code is created for off-line tuning of input membership of FIS. The tuned FIS is embedded in the Simulink Fuzzy Logic Furnace Temperature Controller. The results demonstrate the significance of tuning in Fuzzy Systems.*

***Keywords** – Furnace, Fuzzy Logic, Process Control, Tuning, Genetic Algorithm*

I. INTRODUCTION: GENETIC TUNING OF FIS MODEL

Fuzzy models can be categorized in two broad classes: those in which the underlying fuzzy sets represent the semantics of the model and those in which the underlying fuzzy sets represent an arbitrary partitioning of the data space for each variable. Fuzzy control system is a good example that overlaps the two categories. Because fuzzy models are highly dependent on the term sets underlying each variable as well as the method fuzzy inference, though easy to design they are often difficult to tune [1-3]. In the present project an attempt is made to explore the off-line genetic tuning algorithm for optimizing the Fuzzy Inference System (FIS) through membership function amendment.

II. GENETIC TUNING PROCESS

The genetic tuning algorithm aims to optimize FIS fuzzy model by creating the population of range values of membership function. The range values are encoded in the chromosome as real numbers representing the membership function. Each chromosome represents spread of fuzzy membership function. Fig.1 schematically depicts the overall functional flow of genetically tuning process of FIS desired for controlling the furnace temperature [4].

A. Implementation of Genetic Algorithm

The initial phase of the Genetic Tuning Algorithm involves the design and implementation of a chromosome population to represent a set of parameters for creating and evaluating membership function for input variables, viz. *'et'* and *'cet'*. The fuzzy model that computes the change in count has *'cc'* as output variable. In present study only the input membership functions are tuned genetically to get desirable *'cc'* output when FIS that attempts to control the temperature of the Furnace. The output membership functions are hand tuned before FIS is executed in the run process of Genetic Tuning Algorithm. Table I, Table II and fig.2 show how the chromosome appears in the parameter population for input membership functions. For each input variable the chromosome specifies the amendable left (a_{mn}) and right (b_{mn}) ranges values along with mean value (p_{mn}) [5, 6]. The subscript m=1 and 2 are for input fuzzy sets, while m=3 for output variable. The partitions of fuzzy sets for input variables are signified by n =1, 2 and 3. The partitions of fuzzy sets for output variable are signified by n =1, 2, 3, 4 and 5. The fuzzy sets and their range values, peak values with their labels are shown in the table III.
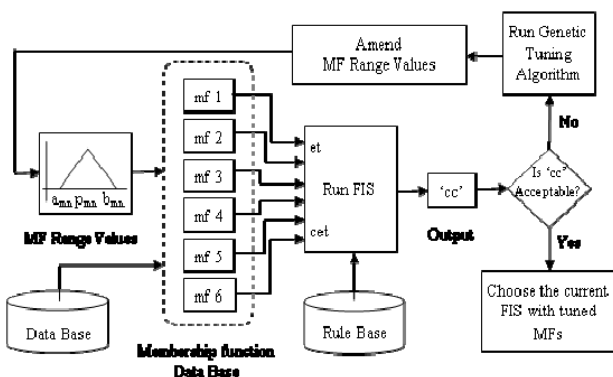

Fig.1. Functional Flow of Genetically FIS Tuning

TABLE I
CHROMOSOME OF INPUT MEMBERSHIP FUNCTION FOR 'ET'

Error in Temperature (*et*)								
N (Negative)			Z (Zero)			P (Positive)		
Left Range	Mean Value	Right Range	Left Range	Mean Value	Right Range	Left Range	Mean Value	Right Range
'a₁₁'	'p₁₁'	'b₁₁'	'a₁₂'	'p₁₂'	'b₁₂'	'a₁₃'	'p₁₃'	'b₁₃'

TABLE II
CHROMOSOME OF INPUT MEMBERSHIP FUNCTION FOR 'CET'

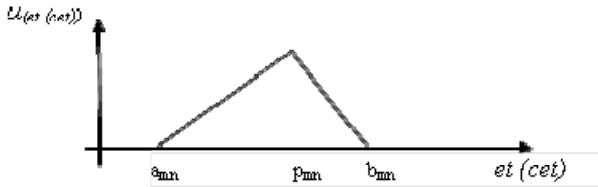| Error in Temperature (*et*)								
N (Negative)			Z (Zero)			P (Positive)		
Left Range	Mean Value	Right Range	Left Range	Mean Value	Right Range	Left Range	Mean Value	Right Range
'a₂₁'	'p₂₁'	'b₂₁'	'a₂₂'	'p₂₂'	'b₂₂'	'a₂₃'	'p₂₃'	'b₂₃'

Fig.2: Membership function parameters

TABLE III DETAILS OF FUZZY SETS

Input / Output Variable	Name of Variable	Label of Fuzzy Set	Left Range	Right Range	Peak Value
Input	et	N	a_{11}	b_{11}	p_{11}
		Z	a_{12}	b_{12}	p_{12}
		P	a_{13}	b_{13}	p_{13}
	cet	N	a_{21}	b_{21}	p_{21}
		Z	a_{22}	b_{22}	p_{22}
		P	a_{23}	b_{23}	p_{23}
Output	cc	NB	a_{31}	b_{31}	p_{31}
		N	a_{32}	b_{32}	p_{32}
		Z	a_{33}	b_{33}	p_{33}
		P	a_{34}	b_{34}	p_{34}
		PB	a_{35}	b_{35}	p_{35}

The set of rules mapping the inputs over output are as given in table IV [9].

TABLE IV RULE BASE OF FIS

IF	N	*et*	is	*AND*	*cet*	N	*THEN*	is	*cc*	is	PB
IF	N	*et*	is	*AND*	*cet*	Z	*THEN*	is	*cc*	is	P
IF	N	*et*	is	*AND*	*cet*	P	*THEN*	is	*cc*	is	N
IF	Z	*et*	is	*AND*	*cet*	N	*THEN*	is	*cc*	is	P
IF	Z	*et*	is	*AND*	*cet*	Z	*THEN*	is	*cc*	is	Z
IF	Z	*et*	is	*AND*	*cet*	P	*THEN*	is	*cc*	is	N
IF	P	*et*	is	*AND*	*cet*	N	*THEN*	is	*cc*	is	Z
IF	P	*et*	is	*AND*	*cet*	Z	*THEN*	is	*cc*	is	Z
IF	P	*et*	is	*AND*	*cet*	P	*THEN*	is	*cc*	is	NB

From the chromosome structure a random population of input fuzzy sets pertaining to the range values is created. This forms the initial population of FIS Model. The constraints on overlap and extreme range values can also be included. In the case of underlying FIS optimization model, the objective function is to get the change in count *'cc'* tending almost to zero.

A. Execute the FIS Model

Every chromosome defines a way of representing the meaning of input temperature control variables *'et'* and *'cet'* with specific range values. Genetic Tuning Algorithm is being included in the program routine for FIS. The temperature controlling knowledge is represented with rule set shown in table III. The input variables *'et'* and *'cet'* forms the chromosome, while the output variable *'cc'* is fixed and is allowed to hand tune by the FIS designer before running the tuning algorithm. When the Genetic Tuning Algorithm is executed the FIS is made to run that generates the value of output variable *'cc'*. The desirable value of *'cc'* is almost tending towards zero. Accordingly the Genetic Tuning Algorithm goes through interactions. The iterations are terminated when fitness functions checks the value of *'cc'* and expected value of *'cc'* being achieved. As many as FIS versions are generated equal to the number of iterations. The designer has flexibility to select any FIS

that meet the requirements to optimize the Furnace Temperature control in the Simulink as well as in real time temperature control hardware. Every FIS record and data pertaining to the membership functions are stored in the MATLAB structure files.

B. Genetic Tuning Algorithm (GTA)

Fuzzy membership functions are represented by the set of numbers assigned to left-right range values and peak value labelled by linguistic values. The membership functions are thus the data items (or data objects) in the data set grouped into overlapping clusters given the fact that there are one or more criteria that are influence their formation. This can be qualitative as well as quantitative. The Genetic Tuning Algorithm starts with an initial population, where each individual of the population is a partitioning of the membership functions over underlying universe of discourse generated by different error computing criterion. The algorithm has two computational elements that work together are [7, 8]-

- *The Genetic Algorithm (GA) and*
- *Fuzzy Inference System (FIS)*

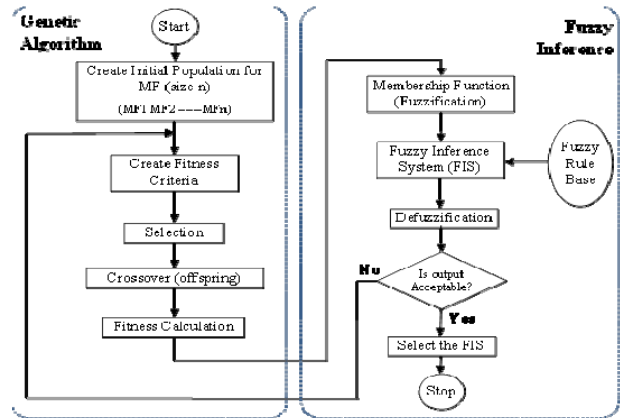The main algorithms GA and the FIS are embedded within the GTA. The flowchart of the GTA is given in fig. 3.

Fig.3 Flowchart of FIS based Genetic Tuning Algorithm

C. The Genetic Algorithm Part

The software implementation of the basic model of a simple genetic algorithm is being consummated by MATLAB code [10]. The five components of a Genetic Algorithm are as follows -

- *A genetic representation for potential solutions to membership function*
- *Method to create an initial population of potential solutions*
- *An evaluation function to rate solutions in terms of their "fitness"*
- *Selection of individuals for the next generation*
- *Genetic operators that alter the composition of the offspring*

For successful run of a GA, the values for the parameters of the GA have to be defined at the beginning such as the population size, parameters for the genetic operators and the terminating condition.

D. Software implementation of Genetic algorithm

The software implementation of Genetic algorithm is accomplished in the canonical form. For reproduction, only crossover operation is performed. The MATLAB code is being created for software approach to off-line tuning of Fuzzy Inference Scheme. The source code for GTA when executed it runs through population-selection-crossover-fitness calculation-generation of new offspring (input membership functions) in iterations set by the user. The sample FIS offspring with 'et', 'cet' and 'cc' are shown in fig. 4.
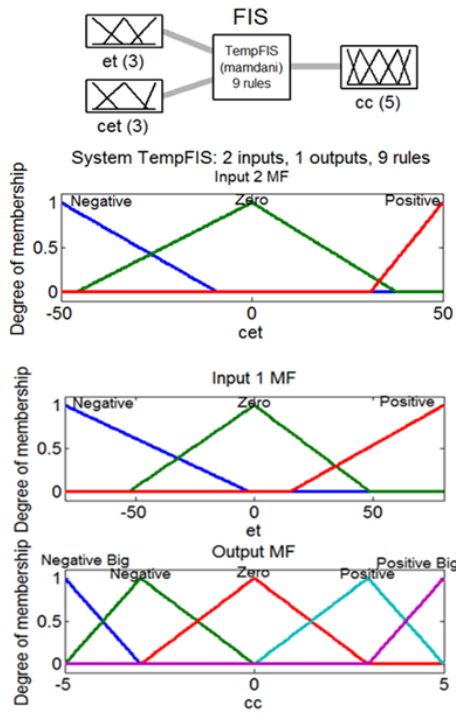

Fig.4 FIS with Offspring MFs

III. TUNING OF MEMBERSHIP FUNCTIONS

Evolution through generations in the membership function performed by Genetic Tuning Algorithm implemented by MATLAB code is shown in the table V. When Genetic Tuning Algorithm is executed, it begins to evolve through number of generations pertaining to the input membership functions for error-in-temperature (et) and change-in-error (cet) in an attempt to produce the output change-in-count (cc) close to zero. The amendment in the membership functions undergone form one generation to next is illustrated in the table V.

The algorithm is efficient as far as the evolution process is concerned, but obtaining the [n]th generation of membership functions for which 'cc' is almost zero is randomly achievable. The GTA has been executed several times and the process of evolution was kept under investigation. Based on the 'best-fit' policy, the FIS of nth generation possessing the tuned membership function for input variables was used in creating Simulink model of Furnace Temperature Control. The GTA is dynamically executed, but the choice of tuned membership function is made 'off-line' by the designer.

TABLE V
EVOLUTION OF MEMBERSHIP FUNCTION BY GTA

Generation Pij	error in temeprature *(e)*	Generation Pij	change in error *(ce)*
P1 1		P2 1	
P1 3		P2 2	
P1 5		P2 4	
P1 6		P2 7	
P1 n		P2 n	

P i j = population with I[st] membership function and j[st] generation
n = genration of offering at desired value of 'cc'

IV. TUNED SIMULINK FUZZY LOGIC FURNACE TEMPERATURE CONTROLLER

The Simulink System setup created for Fuzzy Logic Temperature Controller hosted with tuned FIS is shown in the fig. 5.
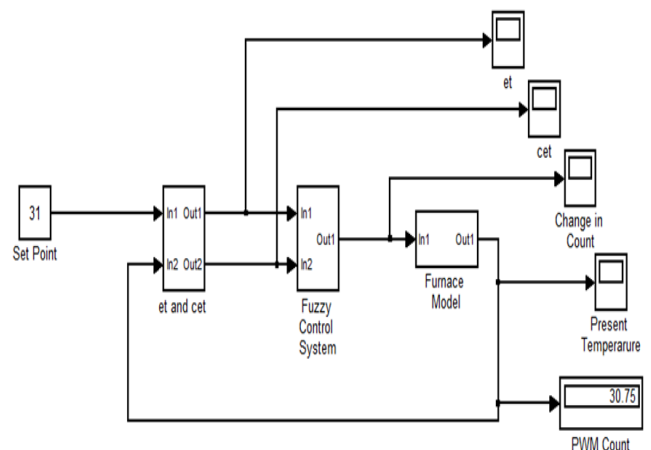

Fig. 5 Simulink Tuned Fuzzy Logic Furnace Temperature Control System

The Fuzzy Inference Systems generated at different generation level during after running the GTA are enlisted in the table VI. The FIS differ in the input membership functions for 'et' and 'cet' with output membership functions for 'cc' and rule set unchanged.

TABLE VI
VARIANTS OF FUZZY INFERENCE SYSTEMS

Sr. No.	Name of FIS	MF = [a_{i1}	p_{i1}	b_{i1}]	
		et	cet		cc
1.	FurnaceControl_FIS_FOUR	N [-80 -80 -40] Z [-45 0 45] P [20 80 80]	N [-50 -50 10] Z [-50 0 50] P [30 50 50]		
2.	FurnaceControl_FIS_THREE	N [-80 -80 -10] Z [-80 0 80] P [-10 80 80]	N [-50 -50 10] Z [-50 0 50] P [-10 50 50]	NB [-5 -5 -3] N [-5 -3 0]	
3.	FurnaceControl_FIS_TWO	N [-80 -80 -30] Z [-50 0 50] P [30 80 80]	N [-50 -50 20] Z [-30 0 30] P [30 50 50]	Z [-3 0 3]	
4.	FurnaceControl_FIS_ONE	N [-80 -80 -20] Z [-60 0 60] P [20 80 80]	N [-50 -50 10] Z [-40 0 40] P [10 50 50]	P [0 3 5] PB [3 5 5]	
5.	FurnaceControl_FIS_TUNED	N [-80 -80 0] Z [-80 0 80] P [0 80 80]	N [-50 -50 0] Z [-50 0 50] P [0 50 50]		

The performance of variant Simulink Tuned Fuzzy Logic Furnace Temperature Control System were studied and tested for different set-point temperatures. The observations made are shown table VII. All variant FIS have shown the inability to reach the set-point temperature except the tuned FIS, which has closely attained the set-point temperature. The results have demonstrated the significance role of tuning of FIS in the furnace temperature control. Table VII illustrates the set-point achievement approximately by second and almost by fifth FIS variant.

TABLE VII
SET POINT TEMPERATURE TRACKING

Set-Point Temperature (^{o}C)	Un-tuned FIS	
	Optimized Temperature (^{o}C)	Steady state Error in Temperature
30.00	59.68	-29.68
34.00	62.33	-28.33
38.00	64.66	-26.66
45.00	50.72	-5.72
49.00	50.06	-1.06

The observation of steady state error in temperatures indicates the ability gained by the Furnace Temperature Control system in successfully tracking the set-points after applying the tuning to the FIS that is being embedded in the Fuzzy Controller block of the Simulink System (Fig. 5). The time-response of set-point tracking and input/output signals are depicted in the fig. 6(a-d).
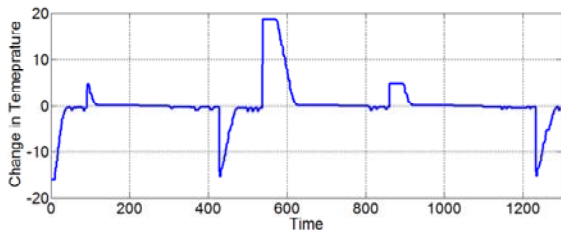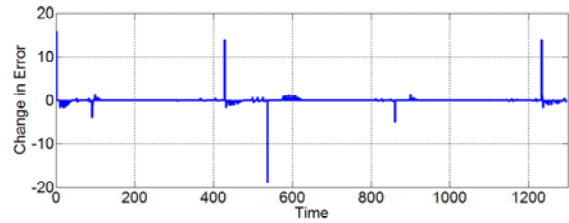

Fig. 6(a) Error in Temperature
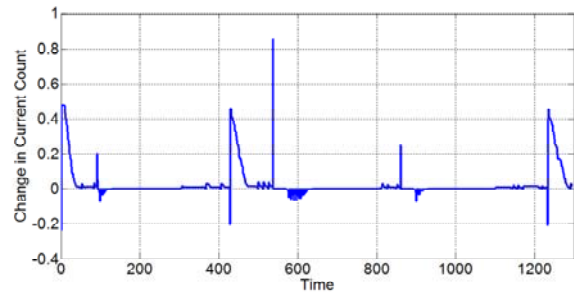

Fig. 6(b) Change in Error
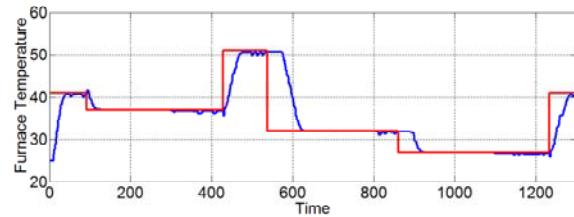

Fig. 6(c) Change in Count

Fig. 6(d) Set-point (red) Tracking (blue)

V. CONCLUSIONS

Designing the Fuzzy Logic Controller appears to be simple and straight forward, but, in fact it demands for high skill Based on the observations made during the simulation study of Simulink Fuzzy Logic Furnace Temperature Controller revealed that the tuning is essential in optimizing the performance of Fuzzy Controller. This is primarily due to the un-tuned FIS entrenched in the FLC block of Simulink System failed to track the set-point temperature. This obviously indicated that the Genetically Tuned Fuzzy Inference System help optimize the performance of Fuzzy Logic Furnace Temperature Controller.

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