

# Design and Analysis of fuzzy PID Controllers using Genetic Algorithm

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**ABSTRACT-** Genetic Algorithms (GAs) are powerful tools to solve large scale design optimization problems. The research interests in GAs lie in both its theory and application. On one hand, various modifications have been made on early GAs to allow them to solve problems faster, more accurately and more reliably. On the other hand, GA is used to solve complicated design optimization problems in different applications.

The main focus of this paper is to find the best Fuzzy PID Controller. We are design four Fuzzy PID Controller (Type-2 FPID, Multistage FPID,GA Type-2 FPID,GA Multistage). We are use GA in both Type-2 & Multistage FPID, then we are analyzing the result on the basis of settling time, Error, Energy consumption and find best fuzzy PID among those. Then we are comparing the result of best Fuzzy PID with Previous paper.

The algorithms are coded with MATLAB and applied on several test functions. The results are compared with the existing solutions in literatures and shows promising results.

### **1.INTRODUCTION**

### (A)FUZZY LOGIC SYSTEMS

FLS is required to map input space to output space using FL. When we talk about uncertainty we usually deal with FL. So, FL is a kind of knowledge which helps us to deal with uncertainty. Traditional logic which deals with either true or false statements. But in the real world problems not every decision is either true or false. So, in order to deal with the real world problems we deal with FL.

## (B)Type-2 FLS

Fuzzy sets models words that are being used in rulebase and inference engine. However, word mean different thing to different people and, therefore, are uncertain. Membership degree of a Type-1 fuzzy set cannot capture uncertainties about the words. Hence, another type of fuzzy set, i.e., Type-2 fuzzy sets came into existence which is capable of handling such uncertainties. For such a fuzzy set membership value corresponding to some crisp input is not a crisp value rather a Type-1 fuzzy set called secondary membership [Karnik and Mendel, 2001b], [Singh and Kakkar, 2014], [Castillo and Melin, 2008]. This concept can be extended to Type-n fuzzy sets. Computations based on Type-2 fuzzy sets are very intensive, however, when secondary membership is assumed unity the computational burden reduces drastically. This is another variant to fuzzy set representation and is known as Interval Type 2 fuzzy sets [Singh and Kakkar, 2014], [Singh and Kakkar, 2014], [Castillo and Melin, 2008].



FIG 1: Block diagram of Type-2 FLS

T2 FLS are an extension of T1 FLS in which uncertainty is represented by an additional dimension. This ancillary third dimension in T2 FLS gives more degrees of freedom for better representation of uncertainty compared to T1 fuzzy sets. T2 FSs are useful in circumstances where it is difficult to determine the exact membership function for a FS. Using T2 FLS provides the capability of handling a higher level of uncertainty and provides a number of missing components that have held back successful deployment of fuzzy systems in human decision making. A T2 FLS includes fuzzifier, rule base, fuzzy inference engine, and output processor as shown in Fig. The output processor includes type-reducer and defuzzifier which generates a T1 FS output (from the type-reducer) or a crisp number (from the defuzzifier). A T2 FLS is characterized using T2 FSs for antecedents and/or consequents and IF-THEN

rules. Block diagram of Type-2 FLS is shown in Fig.3.4. It can be explained as below:

1. Fuzzification: As shown in figure crisp inputs are first transformed into fuzzy sets in the fuzzifier block because it is fuzzy sets and not numbers that activate the rules. Fuzzy sets obtained in this case are Type-2 Fuzzy sets that are three-dimensional.

2. Inference Engine: After measurements are fuzzified, the resulting input fuzzy sets are mapped into fuzzy output sets by the Inference block. This is accomplished by first quantifying each rule using fuzzy set theory, and by then using the mathematics of fuzzy sets to establish the output of each rule, with the help of an inference mechanism. If there are M rules then the fuzzy input sets to the Inference block will activate only a subset of those rules, where the subset contains at least one rule and usually way fewer than M rules. Inference is done one rule at a time. So, at the output of the Inference block, there will be one or more red-rule fuzzy output sets.

3. Outout Processing: The \_red-rule output fuzzy sets have to be converted into a number, and this is done in the Fig. 3.4 Output Processing block. Output processing block consist of two parts, i.e, Type-reduction part where type-2 fuzzy set is reduced to type-1 fuzzy set. There are as many type-reduction methods as there are type-1 defuzzification methods. An algorithm developed by Karnik and Mendel [Karnik and Mendel, 2001a], [Liang and Mendel, 2000] now known as the KM Algorithm is used for typereduction. Although this algorithm is iterative, it is very fast. The second step of Output Processing, which occurs after type-reduction, is called defuzzi cation which is used to obtain crisp output from the fuzzified output.

# (C) Interval Type-2 FLS

Generalized T2 FLSs are computationally more intensive as compared to T1 FLS as former includes Fuzzy sets those are 3-dimensional in nature. Things do simplify when secondary membership functions are considered as interval sets, i.e., the secondary membership values are either 0 or 1 and set are referred as IT2 FSs or simply IT2 FSs. IT2 FSs have received the most investigational interests as thev involve mathematics that is simpler than that of T2 FSs. Therefore. literature generalized available about IT2 FSs is more as compared to that of generalized T2 FSs. Now a days, both kinds of fuzzy sets are being actively investigated by an ever-growing number of researchers around the world. IT2 FSs have widely been accepted as they provide more freedom degree in modeling higher orders of uncertainty than T1 FSs. This property has been the driving force behind more of the advancements in theories and applications of IT2 FSs and FLSs.





## Figure 2: Block diagram of Type-2 FLS

IT2 FSs are represented by upper and lower bounds of uncertainty called Upper Membership Function (UMF) and Lower Membership Function (LMF) as shown in Fig. 3.5. The region between upper and lower bounds of Uncertainty is termed as Footprint of uncertainty (FOU).

## **2. LITERATURE REVIEW**

Ahmet Sakalli, Tufan Kumbasar, M.Furkan Dodurka, Engin Yesil discussed with a simple interval Type-2 Fuzzy PID controller . In this paper analysis the structure of simplest IT2-FPID by using KM algorithm . The structure of ST1T2-FPID is compared with IT2-FPID, T1-FPID and hybrid fuzzy pid on the basis of stimulation result . The outcome of the study shows that, the advantage of the proposed STIT2-FPID structure is related to hybrid nature of the self-tuning structure because it benefits the advantages of the T1-FPID and IT2-FPID controllers by changing the size of the FOU in an online manner .This paper also the work on the tuning the fuzzy PID for enhance the transient state and disturbance rejection performance . This indicate tuning mechanism will improve the result . [2]

Kuldip S. Rattan, Matthew A. Clark, and Jonathan A. Hoffman has Design and Analyze the Multistage Fuzzy PID Controller. The PID is higher order capability fast reaction on change of control input. Tha factor integral and derivative gain in linear PID controller make it difficult to achieve optimal performance . we know that D mode is used when prediction of the error can improve phase load of 900 .PD controller is used

for flying and underwater vehicles .PI Controller will eliminate forced oscillation and steady state error resulting in operation of on-off controller and P controller. By increasing the integral term to decrease steady-state error causes undesired behavior during the transient phase of the system response. The integral term should only be active during the steady-state portion of the response to either reduce or eliminate the steady-state error. This can be achieved by implement a switching multistage PID controller that consists of a first stage PD controller followed by a second stage PI controller. PD controller can not completely eliminate the error. To eliminate this error, the design of a multistage fuzzy PID controller is existing in this paper .[3]

Jouda Arfaoui , ElyesFeki , Abdelkader Mami have Discussed the Genetic algorithm which is generally used in the various best possible problems . This paper propose an another method for designing fuzzy logic controller for temperature control inside the cavity of refrigeration. This paper compare the result of GA FLC with Conventional PID and GA PID with respect to stability ,settling time and energy consumption . The result of this paper shows GA-FLC has good response compare with the other. GA\_FLC reduced the consumption energy of about 1.3401kWh.[4]

## **3.GENETIC ALGORITHM**

Step of GA are;

1) Generate N-Random solution for the given input problem.

2) For each iteration fallow the given step.

a) Find the fitness of each solution (fitness is proportional to error of the solution.

b) Find the mean fitness.

c) If the fitness is less than the mean fitness then pass this solution to the next iteration. (Cross-over)



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d) If fitness is more than mean fitness then discard the solution & replace it with a new random solution (Mutation).

e) Repeat (a to d) for each iteration.

3) At the end of the all iteration we get optimal solution having minimum fitness

# **4.ANALYSIS OF ERROR & SETTLING TIME**

# (A) Type-2 & GA Type-2 Analysis

After design of different fuzzy PID Controller, we are analyze the result, Our Aim is to find best fuzzy PID controller. First off all we are analysis the result of TYPE-2 FUZZY PID with and without Genetic Algorithm .Table-1shows different error and time value for different input and reference temperature . As can be seen from the simulation results GA Base TYPE-2 FUZZY PID has minimum error, but comparatively some time will be increase.

ANALYSIS OF TYPE-2 FUZZY PID AND GA BASE TYPE-2 FUZZY PID					
INPUT TEMP.= 30 REFFERENCE TEMP=20					
	TYPE-2 FUZZY	GA.TYPE-2 FUZZY			
ERROR	12.6	0.5			
TIME	6sec	9sec			
INPUT TEMP.=50 REFFERENCE TEMP=20					
	TYPE-2 FUZZY	GA.TYPE-2 FUZZY			
ERROR	12.6	0.3			
TIME	5sec	9sec			
INPUT TEMP.=20 REFFERENCE TEMP=30					
	TYPE-2 FUZZY	GA.TYPE-2 FUZZY			
ERROR	8.2	0.4			
TIME	5sec	9sec			
INPUT TEMP.= 10 REFFERENCE TEMP=30					
	TYPE-2 FUZZY	GA.TYPE-2 FUZZY			

ERROR	8.2	1.4
TIME	3sec	9sec

TABLE-1: ANALYSIS OF TYPE-2 FUZZY PID AND GA BASE TYPE-2 FUZZY PID

## (B) Multistage & GA- Multistage Analysis

Now we are Analysis the result of Multistage Fuzzy PID with and without Genetic Algorithm, (Table-2) With different input and reference temperature. As can be seen from the simulation results GA Base Multistage FUZZY PID has minimum error, but comparatively some time will be increase.

ANALYSIS OF MULTISTAGE FUZZY PID & GA MULTISTAGE FUZZY PID					
INPUT TEMP.=30 REFFEREMCE TEMP=20					
	MULTISTAGE	GA-MULTISTAGE			
ERROR	10	0.1			
TIME	4sec	9sec			
INPUT TEMP.=50	REFFEREMCE TEMP=20				
	MULTISTAGE	GA-MULTISTAGE			
ERROR	11	0.6			
TIME	4sec 9sec				
INPUT TEMP.=20	REFFEREMCE TEMP=30				
	MULTISTAGE	GA-MULTISTAGE			
ERROR	12.2	0.5			
TIME	3sec	9sec			
INPUT TEMP.=10	TEMP=30	REFFEREMCE			
	MULTISTAGE	GA-MULTISTAGE			
ERROR	12.26	1.5			
TIME	3sec	9sec			

TABLE-2: ANALYSIS OF MULTISTAGE FUZZY PID & GA MULTISTAGE FUZZY PID

Now up to this stage from the analysis we observe that GA is always best with Error & time parameter. Now we compare the result of GATYPE-2 FPID with GA MULTISTAGE FPID, From the fig6.8,which shows



complete graphical analysis , we observe that GA TYPE-2 is best, it has minimum error.



# FIG4: Graphical analysis of all fuzzy pid

**5:ENERGY ANALYSIS** The new approach GA TYPE-2 FPID & GA Multistage FPID reduced the energy consumption compared

FPID reduced the energy consumption compared with the classical TYPE-2 & Multistage FPID control. Energy Analysis Type-2 & GA Type2



#### FIG3:Energy analysis of Multistage and GA-multi 6.COMPARISON WITH PREVIOUS PAPERS

The GA TYPE-2 FLC allowed to reach the desired temperature after about 9 SEC. As for the Conventional GA-PID controller, the internal temperature takes about 1h to achieve the desired temperature. Consequently, the optimal fuzzy controller was more effective than the Conventional PID controller. The Table V summarizes the energy saving, Settling time & Error for the four controllers. So all the parameter will be improved in our proposed work.

#### TABLE-3:Comparison With Previous Papers

	Previous Result		Proposed Result	
	GA-PID	GA-FLC	GATYPE- 2FPID	GA MUL TI- FPID
Settling Time	1 HR	23MIN	9SEC	9SEC
Energy Consump tion(in mj)	1.523196*10 10	$1.183212*1$ $0^{10}$	0.03	0.04
Error			0.60	0.83

#### 7.CONCLUSION

In this project, we are finding the best fuzzy PID controller among the four PID (TYPE-2, Multistage, GA-TYPE2, GA multistage) for Temperature control application. We are use the concept of fuzzy logic and Genetic algorithm. According to the profiling results, the use of above soft-computing techniques resulted in an outputs better dynamic and static characteristics Simulation was carried out using MATLAB to get the output response

of the system. The simulation results were observed and analyze, compared with that of conventional controller, we observe that GA will give excellent result than conventional with respect to settling time, Error & Energy consumption.

The further analysis we observe that GA-Type2 FPID is the best fuzzy PID controller having better stability and accuracy compare with the GA-Multistage FPID and other controller. The Result of this best fuzzy PID controller; that is, GA-TYPE2 is compare with the previous paper, we observe that proposed controller is excellent energy consumption and minimum settling time require

### **8.**FUTURE SCOPE

(1)Future work will be devoted to implementing this controller algorithm on material targets like FPGA circuits.



(2)Neuro-fuzzy PID controller can be designed by the implementation of neural network to fuzzy PID controller.

(3)In Future Propose controller will be use in application like Air traffic control, Control-gas pipeline, Signal Processing, Wired and Wireless Communication Networks and so on.

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