Advances in Computer Science and Information Technology (ACSIT)
Print ISSN: 2393-9907; Online ISSN: 2393-9915; Volume 2, Number 3; January-March, 2015 pp. 230-232

http://www.krishisanskriti.org/acsit.html

Combination of Genetic Algorithm with Fuzzy Systems

Gaurav[1] and Nidhika Yadav[2]

[1]CSE &IT Dept. ITM University Gurgaon, India
[2]CSE &IT Dept. ITM University Gurgaon, India
E-mail: [1]gauravgarg2209@gmail.com, [2]nidhikayadav@itmindia.edu

Abstract— *Fuzzy systems show their ability to solve various kinds of problems in different application areas. Presently, there is great interest to fuzzy systems with learning and adaptation capabilities. Fuzzy inference system uses some rule-based systems which are more to handle complex and poorly-defined process, especially those which needs some skilled human operator. Fuzzy controllers either use expert's knowledge for learning and optimization of rules. But alternatively this can be handle through genetic algorithms. Main objective of this paper is to explore the advantages and current issues of using two of the most successful approaches i.e. hybridize fuzzy systems with learning and adaptation technique. This paper highlights real life applications of Genetic algorithm with different fuzzy methods.*

Keywords: *Soft Computing, Fuzzy infernce engine, Fuzzy logic controller, Genetic algorithm, evolutionary techniques, applications, Fuzzy Cognitive Maps, Fuzzy controller.*

1. INTRODUCTION

Soft computing techniques are very strong and efficient, as solutions provided through these techniques are more practical and less costly as compared to hard computing techniques. Fuzzy Logic (FL) and Genetic Algorithm (GA) are the most widely used techniques. Technique's based on fuzzy logic can handle vagueness, uncertainty and human generated knowledge representation is possible; but self-learning and rules generalization cannot be handle through fuzzy logic, so fuzzy logic need some methods for learning. Fuzzy system learning can be possible in two ways either with the help of neural networks where expert provides knowledge in the form of weights or through evolutionary computation also known as genetic learning as shown in Fig.1. Right combination of Genetic Algorithms with Fuzzy Logic offers benefits of both the techniques [1,2].

Fuzzy systems have been successfully applied to problems in many domains like classification, modeling, and control. Generally, the key for success of fuzzy system was its ability to incorporate human expert knowledge. So by using genetic algorithm with fuzzy provides it's a way of learning. Genetic fuzzy system (GFS) is a very a fast evolving hybrid methodology for solving different kind of problems in many fields. There are a number of models of genetic fuzzy systems that are used in many industrial processes [2,3].

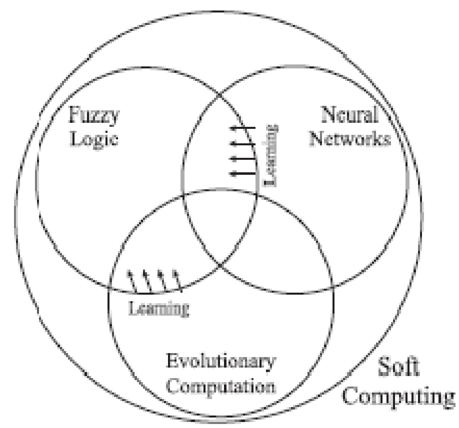

Fig. 1: Learning of fuzzy system

A GFS is a fuzzy system improved by a learning process based on the genetic algorithm. GAs are optimum search algorithms, which is based on natural heredities, that provide robust search capabilities in complex spaces, and thereby offer a valid approach to problems requiring efficient and effective search processes [4].

GFS are used for fuzzy knowledge extraction. The paper also includes some of the main points required for implementation details of genetic fuzzy systems. A GFS is hybrid methodology for the difficult Decision Making processes [2].

O. Cordon and et.al. Shows that the most widely used GFSs are genetic fuzzy rule based systems (GFRBSs) in their literature review [3]. Fig. 2 shows how genetic process learns or tunes different parts of a fuzzy rule-based system (FRBS). Two basic elements of a GFS are genetic design and fuzzy processing also referred in fig. 2. Learning (rule generation) and adaptation (parameter optimization) can also be easily distinguishable in GFRBSs [4].

The rest of the paper is organized as follows. Section II presents the literature review of GA and then basic modes of GFRBSs. Section III present various applications of GFS. Finally, section IV concludes the basic trends and future scope of the GFRBS's[4].

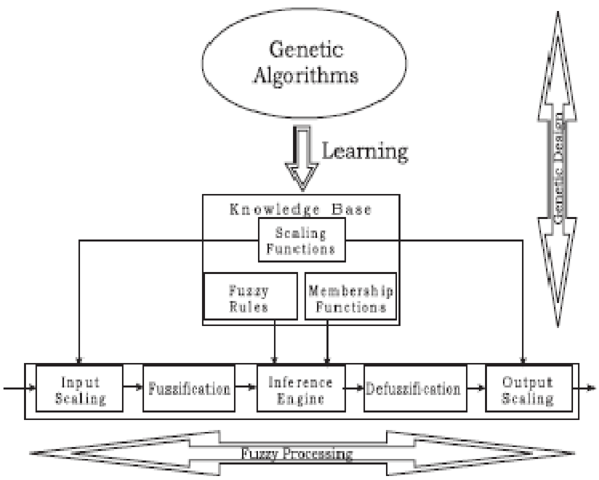

Fig. 2: Genetic fuzzy rule based system

2. LITERATURE REVIEW

Genetic algorithm

GAs are search algorithms which are inspired by natural genetics to found the optimal value in a search space. Any GA starts with a population of randomly generated solutions (chromosomes) and moves towards better solutions.it evolves over a time through a process of competition and controlled variation[6,7].

```
begin (1)
t = 0;
inicialize P(t);
evaluate P(t);
While (Not terminationc-condition) do
begin (2)
t=t+1
select P(t) from P(t - 1);
recombine P( t );
evaluate P(t);
end (2)
end (1)
```

Fig. 3: Procedure genetic algorithm

Though many variants of basic GA are possible depending on the application domain, the very fundamental principle comprises of three basic operations: evolution of individual fitness, formation of gene pool through selection mechanism, recombination through cross over and mutation operators; is shown below [6,7].

As shown in Fig. 3 algorithm, we maintain a population of solutions for a given problem; this population undergoes evolution in a form of natural selection. In each generation, relatively good solutions reproduce to give offspring that replace the relatively bad solutions, which die. An evaluation or fitness function plays the role of the environment in distinguishing between good and bad solutions. Although there are many possible variants of the basic GA, the fundamental underlying mechanism operates on a population of individuals, and consists of three operations:

1. Evaluation of individual fitness,
2. Formation of a gene pool, and
3. Recombination and mutation.

Fig. 3 shows the structure of a simple GA. The recombination is produced using the crossover operator, which combines the features of two parent structures to form two similar offspring; this is applied under a random position cross with a probability of performance (the crossover probability) Pc. The mutation operator arbitrarily alters one or more components of a selected structure so as to increase the structural variability of the population. Each position of each solution vector in the population undergoes a random change according to a probability defined by the mutation rate [6]

This simple mechanism of GA make it very robust and potentially useful tool to search for a good parameter configuration for the set of fuzzy control rules in the input/output spaces, which justify its use for tuning FLCs.

3. MODELS OF GENETIC FUZZY RULE-BASED SYSTEMS#

There are many papers, which have been devoted to the generation of the knowledge base of an FRBS using GAs automatically. The basic thing to employ an genetic based learning process is to automate the design of the knowledge base, which can be handle as an optimisation or search problem.

According to learning rules and rule based system, there are three main approaches that have been mainly used in the literature: Pittsburgh, Michigan and iterative rule learning [4,8]. Pittsburgh and Michigan approaches are the mostly used methods for rule learning developed in the area of GAs. In Pittsburgh approach, entire rule set is characterised by a set of chromosome, which maintains a population of candidate rule sets and by using selection and mutation operators to produce new generations of rule sets. Where as in Michigan approach follows different approach where the members of the population are individual rules and a rule set is represented by the entire population. In the iterative one, chromosomes code individual rules, and a new rule is adapted and added to the rule set, in an iterative fashion, in every run of the GA.[4,9]

The first step in designing a GFRBS is to decide which parts of the KB are subject to optimisation by the GA. The KB of an FRBS does not constitute a homogeneous structure but is rather the union [4,9].

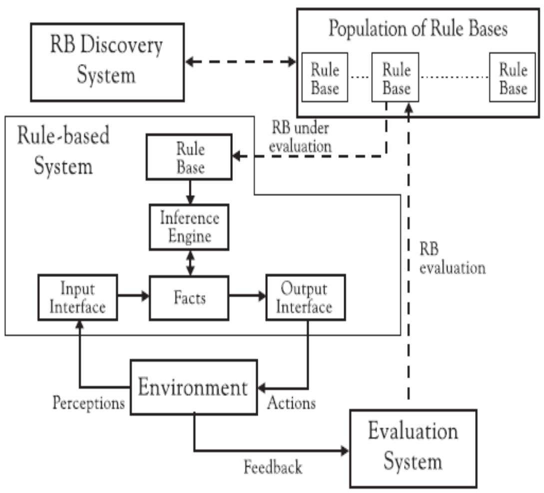

Fig. 4: Pittsburgh approach of learning

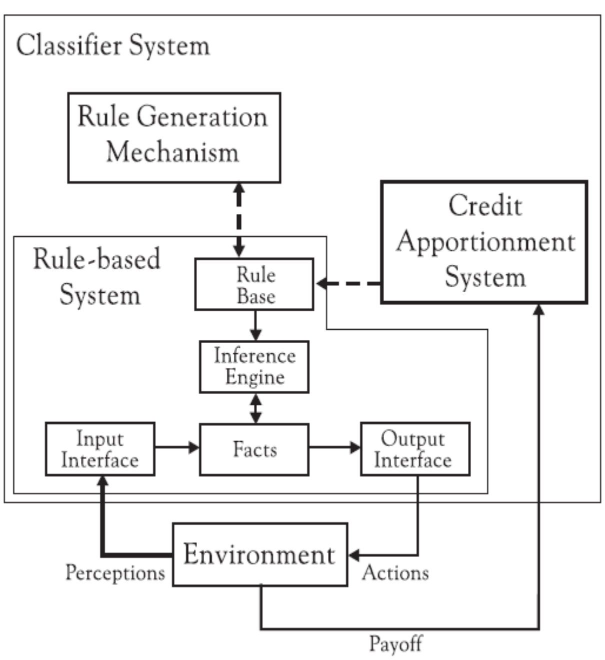

Fig. 5: Michigan approach of learning

4. TUNING AND LEARNING OF FRBS

Genetic tuning

Tuning of the scaling functions and fuzzy membership functions is an important task in FRBS design. It means adjusting few components of the knowledge base without completely redefining it. This genetic tuning process changes the symbolic representations of fuzzy rule and the meaning of the involved membership functions.

In tuning processes, there is a predefined RB and one objective of finding a set of optimal parameters for the membership and the scaling functions of fuzzy system. But in case of learning a new rule base is generated with the help of data set as shown in Fig. 6.

Scaling functions applied to the input and output variables of FRBSs in which the fuzzy membership functions are defined. Usually, by using scaling functions parameters are parameterized within a lower and upper bound [10,11].

These parameters are changed in such a way that the scaled values better matches in the underlying variable range. Tuning process is performed in two stages. In the first one, a learning method is used to get a rule base from an early database. Then the tuning method improves the previously obtained rule base and the initial database as shown in fig. 6 [10,11].

Genetic learning of knowledge bases(DB and RB)

Genetic algorithm was used to automatically learn the knowledge base (KB) by finding a suitable data base (DB) to derive the rule base (RB). The genetic process used in this research learns the number of linguistic terms per variable and the membership function parameters that describe their semantics; while a rule base generation method discovers the number of rules and their composition [12,13].

The production of the knowledge base (KB) of a fuzzy rule based system (FRBS) shows some problems because the KB depends on the concrete application, which makes the accuracy of the FRBS directly dependent on its composition.

Till now, many approaches have been developed to automatically learn the KB from numerical information but most of them have focused on the rule base (RB) learning, using a predefined data base(DB)as shown in fig.7[13].

There are mainly two problems that arise when generating the KB of a FRBS[14]:

1) The DB learning contains the specification of the universes of discourse and the number of labels for every variable with the fuzzy membership functions related to each label.

2) The RB derivation, for finding the number of rules and of the specific composition of each one of them.

Genetic learning of the KB deals with heterogeneous search spaces (Fig. 4.c), it consists of different genetic representations like variable length chromosomes, multi-chromosome genomes and chromosomes encoding single rules instead of a whole KB.

There are various proposals to learn KBs which include systems obtaining approximate Mamdani-type FRBSs with scatter partitions, linguistic Mamdani-type FRBSs[4,14].

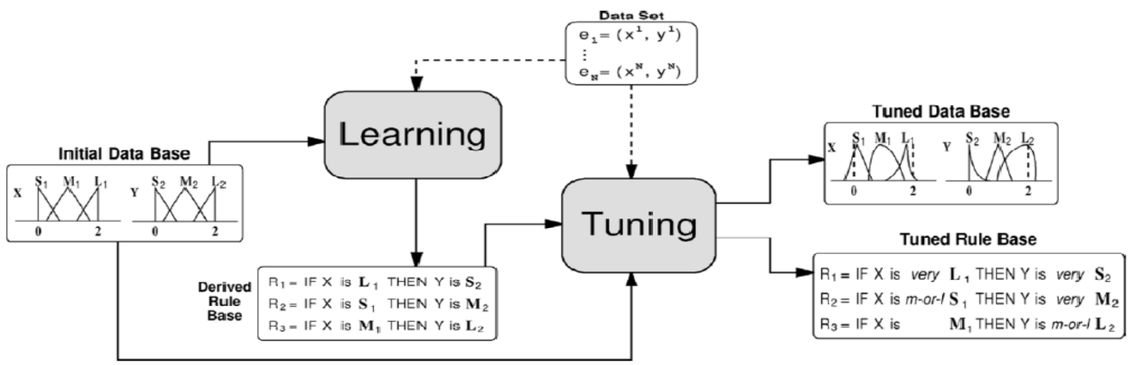

Fig. 6: Genetic tuning and learning of Knowledge base(Rule base+Database)

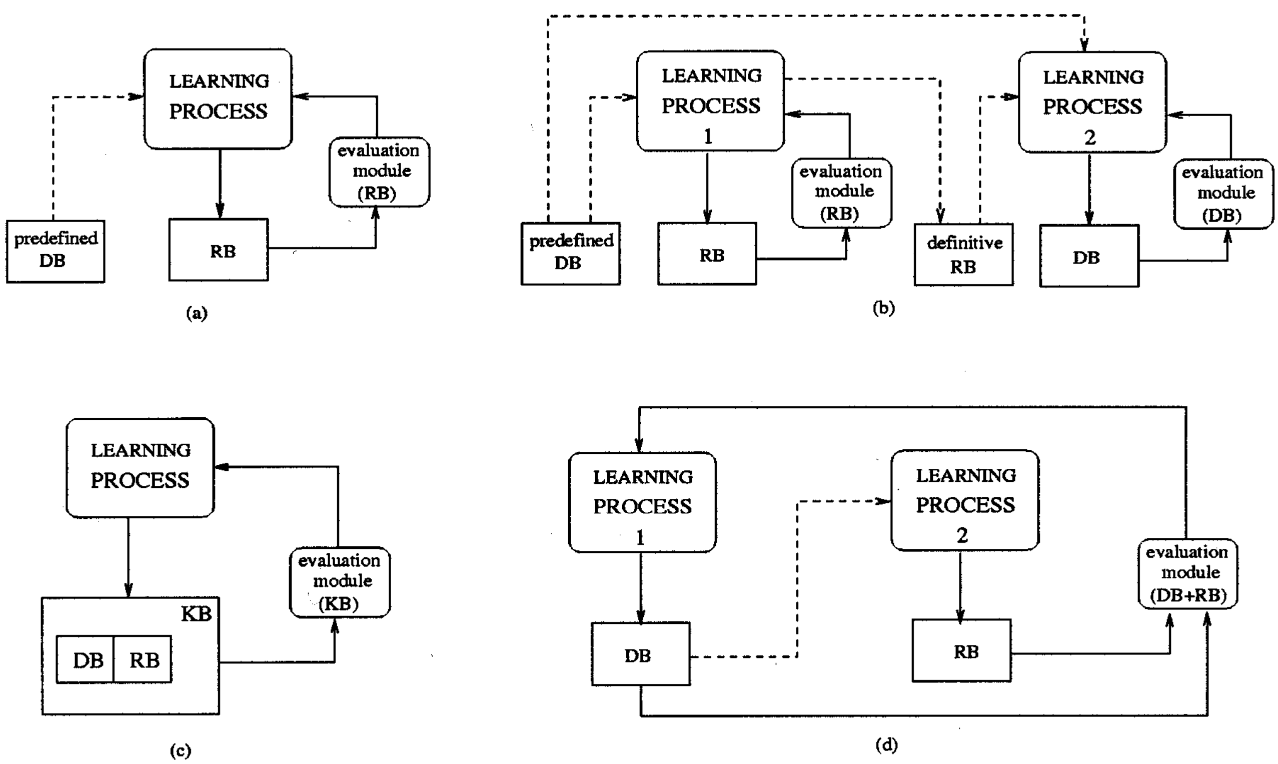

Fig. 4: Graphical representation of the different KB learning approaches

5. APPLICATIONS OF GENETIC FUZZY SYSTEMS

Soft Computing provides many techniques to focus on design, analysis and modeling problems in the case of ambiguous and vague information. Many soft computing techniques like Genetic algorithms fuzzy logic, probabilistic computing and neural networks are considered as balancing techniques rather than competing methodologies.

There are a number of applications of Genetic fuzzy systems used in real-world problems, like travelling salesman problem, complex industrial process, Medical Diagnosis transportation, trajectory control, modeling, and decision making.[15,16,17,18,19]

Mahapatra & et. al. shows in their paper that Multi-objective travelling salesman problem has gained much attention in the past but the problems with multiple objectives travelling salesman problem are not fully investigated. The authors have used two objectives time and travel cost to solve the problem in a fuzzy environment. Solid TSP allows a traveler to use a different conveyance facility. An approach is proposed using possibility/necessity measure of fuzzy cost and time to deal with the problem in a fuzzy environment. Numerical studies show that the algorithm is well suited for the proposed problems [15].

Pitalúa & et. al refer in their article, a simple genetic algorithm is used, with the purpose of obtaining the rule base of a fuzzy controller to solve an optimization problem that minimizes an objective function. Direct current servo system is experimented under load angular position. The objective function used here is the criterion IAE (Integrated Absolute Error). The obtained results have shown that the optimization method to obtain de fuzzy rule base is acceptable with a simple genetic algorithm [16].

Chrysostomos D. Stylios and Voula C. Georgopoulos show a new way of making decision for the Complex processes with the help of this hybrid modeling methodology. The authors proposed an algorithm which leads to more dependable Advanced Medical Decision Support Systems that are suitable to handle such circumstances where the decisions are not clearly well-defined. The methodology proposed is practically used to model and analyses a diagnosis problem from the speech pathology area for the diagnosis of language deficiencies [17].

P. Subbaraj & et. al. considers expert's knowledge. Optimization of the Knowledge Base components is important and crucial to the performance of the controller and has been achieved through trial and error process. This approach is applicable for FLCs having low number of input variables. However more formal methods of Knowledge Base optimization are required for large number of inputs. Genetic Algorithms (GAs) provide such method to optimize the FLC parameters. An intelligent multi input multi output (MIMO) control for the cement milling circuit is presented. GA is used to optimize FLC varying nonlinearity in the plant. MATLAB is used to test the proposed algorithm and to develop a cement mill simulation model. Parameters of the simulation model were set on the basis of actual cement mill characteristics. A comparison is conducted to compare the performances of the proposed control technique with various other control techniques [18].

Mona Subrananiam & et. al.have described a study on tuning of parameters in weighted-rule fuzzy system using genetic algorithm for trajectory control of PUMA560. Fuzzy system can be tuned in various like parameters of membership functions, tuning the scaling factors, rule weights and changing the type of the membership function itself. The various parameters rules, rule-weights and the membership functions are tuned using Genetic Algorithm. Individual parameters tuning are available but the comparative analysis of these three tuning methods are not available. Hence the Performances of these three parameter tuning is evaluated and the best method of tuning the rule base is decided [19].

6. CONCLUSION

This paper throws light on the major useful applications in the current scenario and all possible directions of the Genetic algorithm with fuzzy logic system where fuzzy handle uncertainty and vagueness and GA provide a self-learning tool for the fuzzy system. And it's also gives a brief overview of the classical models and applications of GA and fuzzy system.

As author discussed fuzzy can handle some uncertain problems but Knowledge base i.e. rule base and database that needs some human intervention can handle through GA. Human intervention makes many process error prone. But in some real life applications error makes problem or application more complicated.

Here authors refer many papers where a number of applications are handled through this technique. This also shows how a process can achieve optimum values with a vague database and rule base. By the whole discussion authors can say that this hybrid technique can go beyond simple combinations.

REFERENCES

[1] Chi, Z., Yan, H., & Pham, T. (1996). Fuzzy algorithms: with applications to image processing and pattern recognition (Vol. 10). World Scientific.

[2] Mankad, K., Sajja, P. S., & Akerkar, R. (2011). Evolving rules using genetic fuzzy Approach-An educational case study. International Journal on Soft Computing, 2(1), 35-46.

[3] ordón, O., Herrera, F., Gomide, F., Hoffmann, F., & Magdalena, L. (2001, July). Ten years of genetic fuzzy systems: current framework and new trends. In IFSA World Congress and 20th NAFIPS International Conference, 2001. Joint 9th (Vol. 3, pp. 1241-1246). IEEE.

[4] Goldberg, D. E., & Holland, J. H. (1988). Genetic algorithms and machine learning. Machine learning, 3(2), 95-99.

[5] O. Cord&on, F. Herrera, F. Ho+mann, L. Magdalena, Genetic Fuzzy Systems—Evolutionary Tuning and Learning of Fuzzy Knowledge Bases, World Scienti5c, Singapore, 2001

[6] Herrera, F., Lozano, M., & Verdegay, J. L. (1995). Tuning fuzzy logic controllers by genetic algorithms. International Journal of Approximate Reasoning, 12(3), 299-315.

[7] Holland, J. H. (1975). Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence. U Michigan Press.

[8] S.F. Smith, A learning system based on genetic adaptive algorithms, Doctoral Dissertation, Department of Computer Science, University of Pittsburgh, 1980.

[9] Cordon, O., del Jesús, M. J., & Herrera, F. (1998). Genetic learning of fuzzy rule-based classification systems cooperating with fuzzy reasoning methods.International Journal of Intelligent Systems, 13(10-11), 1025-1053.

[10] Magdalena, L., & Monasterio-Huelin, F. (1997). A fuzzy logic controller with learning through the evolution of its knowledge base. International Journal of Approximate Reasoning, 16(3), 335-358.

[11] Ng, K. C., & Li, Y. (1994, June). Design of sophisticated fuzzy logic controllers using genetic algorithms. In Fuzzy Systems, 1994. IEEE World Congress on Computational Intelligence., Proceedings of the Third IEEE Conference on (pp. 1708-1712). IEEE.

[12] Alpaydin, G., Dundar, G., & Balkir, S. (2002). Evolution-based design of neural fuzzy networks using self-adapting genetic parameters. Fuzzy Systems, IEEE Transactions on, 10(2), 211-221.

[13] Bonissone, P. P., Chen, Y. T., Goebel, K., & Khedkar, P. S. (1999). Hybrid soft computing systems: industrial and commercial applications. Proceedings of the IEEE, 87(9), 1641-1667.

[14] Castro, J. L., Mantas, C. J., & Benítez, J. M. (2002). Interpretation of artificial neural networks by means of fuzzy rules. Neural Networks, IEEE Transactions on, 13(1), 101-116.

[15] Changdar, C., Mahapatra, G. S., & Kumar Pal, R. (2014). An efficient genetic algorithm for multi-objective solid travelling salesman problem under fuzziness.Swarm and Evolutionary Computation, 15, 27-37.

[16] Lagunas-Jimenez, R., & Pitalua-Diaz, N. (2007, September). Tuning fuzzy control rules via genetic algorithms. In Electronics, Robotics, and Automotive Mechanics Conference, Cuernavaca, Morelos, México, september (CERMA).

[17] Stylios, C. D., & Georgopoulos, V. C. (2008, June). Genetic algorithm enhanced Fuzzy Cognitive Maps for medical diagnosis. In Fuzzy Systems, 2008. FUZZ-IEEE 2008.(IEEE World Congress on Computational Intelligence). IEEE International Conference on (pp. 2123-2128). IEEE.

[18] Subbaraj, P., & Anand, P. S. G. (2010). GA Optimized Knowledge Base of FLC for Complex Industrial Process. JDCTA, 4(1), 123-136.

[19] Aa, M. S., Ab, M. A. N. J. U., & MJ, N. (2011). A STUDY ON PARAMETER TUNING OF WEIGHTED FUZZY RULEBASE USING GENETIC ALGORITHM FOR TRAJECTORY CONTROL OF PUMA560.