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DEVELOPMENT OF AN ADAPTIVE FUZZY LOGIC LOAD FREQUENCY CONTROL MODEL

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Abstract

Fuzzy logic solves the problem of non linear systems and handles them with great efficiency and provides robustness to the system. However our aim lies in achieving the adaptive Fuzzy logic load frequency control model for gain scheduling Fuzzy provides a robust inference mechanism with no learning and adaptability and artificial neural network provides learning and adaptability. Artificial neural networks and fuzzy systems have been successfully applied to the LFC problem with rather promising results. The salient feature of these techniques is that they provide a model-free description of control systems and do not require model identification. It has been shown that the proposed adaptive fuzzy logic controller offers better performance than fixed gain controllers.

Keywords: – Fuzzy logic, robustness, artificial neural network, adaptability

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I. Introduction

Fuzzy logic is a powerful problem-solving methodology with a myriad of applications in embedded control and information processing. Fuzzy provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information. In a sense, fuzzy logic resembles human decision making with its ability to work from approximate data and find precise solutions. Unlike classical logic, which requires a deep understanding of a system, exact equations, and precise numeric values, Fuzzy logic incorporates an alternative way of thinking, which allows modeling complex systems using a higher level of abstraction originating from our knowledge and experience. Fuzzy Logic allows expressing this knowledge with subjective concepts such as very hot, bright red, and a long time, which are mapped into exact numeric ranges. The validity and effectiveness of designing the controller has been applied to more generating stations and the result s presented and discussed. [1] The validity of the proposed method has been demonstrated on a 25 nodes IEEE system comprising five generators. *Keywords:* Multiobjective optimization; Fuzzy set; Decision making; Membership function; Evolutionary optimization technique. [2] Simple numerical examples are used to show the practical procedures of problem formulation and solution. These examples are: generator maintenance scheduling, dynamic programming, and power system stabilizer. [3] The salient features of the proposed method are: (i) ability of solving multi-objective problem which guarantees that a global no inferior solution will be generated; and (ii) the possibility to obtain a reasonable no fuzzy solution under consideration of the ambiguity of parameters. [4] This paper presents a comprehensive set of references on fuzzy set theory applications in power systems. [5] Their performances are evaluated through a computer simulation study. The preliminary study shows that it is feasible to design a simple, satisfactory dynamic forecaster to predict very short-term power system load trends online. FL and NN can be good candidates for this application. [6] This paper presents the current status of fuzzy system applications to power systems and future considerations of fuzzy system applications. [7] Lastly when flexible constraints and uncertain processing times are to be jointly considered, the use of possibility decision theory leads to the computation of robust schedules. [8] The output is a ranked list of components, with the most critical ones at the top, which indicates the selection of the components to be inspected. [9] Test results from daily peak and total load forecasts for one year of data from a large scale power system indicate that the fuzzy rule bases can produce results similar in accuracy to more complicated statistical and back propagation neural network methods. [10]

II. FUZZY LOGIC APPLICATIONS

At present Fuzzy logic are used in many applications. Today it's being used in a simple washing machine that we use in our houses to automatic focusing system of an industry.

The few applications of fuzzy logic are:

- Washing Machine,
- Automatic Focusing System,
- Servo Motor Force Control,
- Dead Time Compensator (glass),
- Error Compensator (glass), Reactor Temperature Control,
- Two Stage Inverted Pendulum,
- Automated Manufacturing,
- Camera Auto focus,
- Servo Motor Force Control,
- Glass Melting Furnace Control,
- Air Conditioner Control,
- Reactor Control,
- CAR Automatic Transmissions,
- Disc Drive Spindle Servos,
- Fuzzy Automated Manufacturing,
- Two-Stage Inverted Pendulum, etc.

III. Fuzzy Operation

FL requires some numerical parameters in order to operate such as what is considered significant error and significant rate-of-change-of-error, but exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them. For example, a simple temperature control system could use a single temperature feedback sensor whose data is subtracted from the command signal to compute "error" and then time-differentiated to yield the error slope or rate-of-change-of-error, hereafter called "error-dot". Error might have units of degs F and a small error considered to be 2F while a large error is 5F. The "error-dot" might then have units of degs/min with a small error-dot being 5F/min and a large one being 15F/min. These values don't have to be symmetrical and can be "tweaked" once the system is operating in order to optimize performance. Generally, FL is so forgiving that the system will probably work the first time without any tweaking.

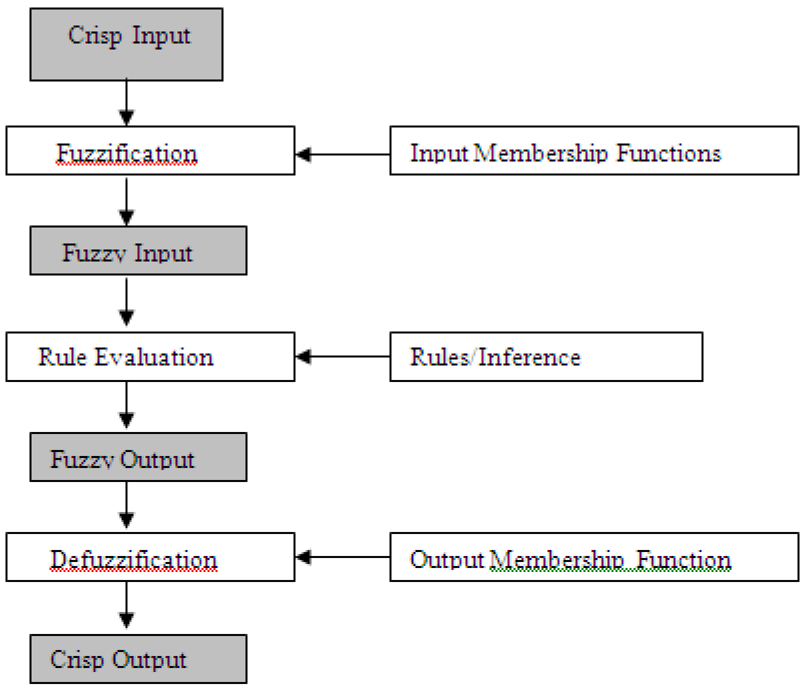

Figure 1: Fuzzy Operation

IV. NEURAL NETWORK

In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.

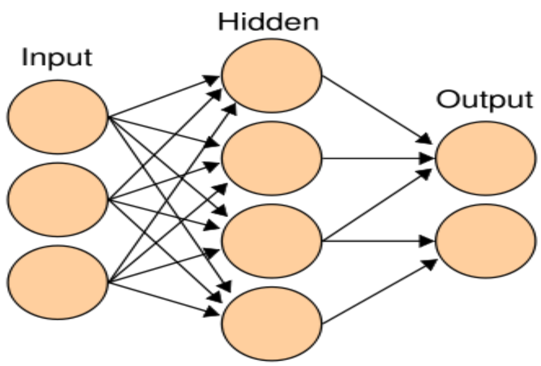

Figure 2: neural network

There is no precise agreed definition among researchers as to what a neural network is, but most would agree that it involves a network of simple processing elements (neurons) which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters. The original inspiration for the technique was from examination of the central nervous system and the neurons (and their axons, dendrites and synapses) which constitute one of its most significant information processing elements (see Neuroscience). In a neural network model, simple nodes (called variously "neurons", "neurodes", "PEs" ("processing elements") or "units") are connected together to form a network of nodes — hence the term "neural network." While a neural network does not have to be adaptive per se, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

V. Types of neural networks:

- Feed forward neural network
- Radial basis function (RBF) network
- Kohonen self-organizing network:
- Recurrent network:
- Simple recurrent network
- Associative Neural Network (ASNN):
- Neuro-fuzzy networks

VI. Case Study and Problem Formulation

S.No.	Operating condition1	Operating Condition2	Operating condition3	Gain
1	10	0.145	0.125	1.46
2	10	0.145	0.275	0.65
3	10	0.145	0.425	0.44
4	10	0.345	0.125	1.41
5	10	0.345	0.275	0.63
6	10	0.345	0.425	0.41
7	10	0.545	0.125	1.12
8	10	0.545	0.275	0.51
9	10	0.545	0.425	0.33
10	20	0.145	0.125	1.33
11	20	0.145	0.275	0.72
12	20	0.145	0.425	0.52
13	20	0.345	0.125	1.37
14	20	0.345	0.275	0.78
15	20	0.345	0.425	0.53
16	20	0.545	0.125	1.29
17	20	0.545	0.275	0.72
18	20	0.545	0.425	0.49
19	30	0.145	0.125	1.09
20	30	0.145	0.275	0.66
21	30	0.145	0.425	0.49
22	30	0.345	0.125	1.05
23	30	0.345	0.275	0.71
24	30	0.345	0.425	0.52
25	30	0.545	0.125	1.01
26	30	0.545	0.275	0.68
27	30	0.545	0.425	0.49

VII.Simulation And Testing

S.No.	Operating condition1	Operating Condition2	Operating condition3	Gain	Gain obtained by fuzzy logic model
1	10	0.145	0.125	1.46	0.875
2	10	0.145	0.275	0.65	0.875
3	10	0.145	0.425	0.44	0.875
4	10	0.345	0.125	1.41	0.873
5	10	0.345	0.275	0.63	0.9
6	10	0.345	0.425	0.41	0.9
7	10	0.545	0.125	1.12	0.879
8	10	0.545	0.275	0.51	0.9
9	10	0.545	0.425	0.33	0.9
10	20	0.145	0.125	1.33	1.37
11	20	0.145	0.275	0.72	0.9
12	20	0.145	0.425	0.52	0.9
13	20	0.345	0.125	1.37	0.9
14	20	0.345	0.275	0.78	0.9
15	20	0.345	0.425	0.53	0.9
16	20	0.545	0.125	1.29	0.9
17	20	0.545	0.275	0.72	0.9
18	20	0.545	0.425	0.49	0.9
19	30	0.145	0.125	1.09	1.37
20	30	0.145	0.275	0.66	0.9
21	30	0.145	0.425	0.49	0.9
22	30	0.345	0.125	1.05	0.9
23	30	0.345	0.275	0.71	0.9
24	30	0.345	0.425	0.52	0.9
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24	30	0.345	0.425	0.52	0.9
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26	30	0.545	0.275	0.68	0.9
27	30	0.545	0.425	0.49	0.9

VIII. RESULTS AND DISCUSSION

Total Gain =21.4

Average gain=21.4/27 =0.79

Total gain by fuzzy logic model=25.117

Average gain by fuzzy logic model=25.117/27 = 0.93

Total gain by Adaptive fuzzy logic model=23.492

Average gain by Adaptive fuzzy logic model=23.492/27 = 0.87

IX. CONCLUSION AND FUTURE SCOPE

Fuzzy provides a robust inference mechanism with no learning and adaptability and artificial neural network provides learning and adaptability. Artificial neural networks and fuzzy systems have been successfully applied to the LFC problem with rather promising results. The salient feature of these techniques is that they provide a model-free description of control systems and do not require model identification. In this thesis, an adaptive fuzzy gain scheduling scheme for conventional PI and optimal controllers has been simulated and tested for off-nominal operating conditions. From the simulation and the result obtained in this thesis it has been shown that the proposed adaptive fuzzy logic controller offers better performance than fixed gain controllers.

REFERENCES

1. A.B. Beevi and R. Iyer, " A New Approach For The Solution Of Economic Load Dispatch Using Fuzzy Logic Controller" Asian Power and Energy Systems - 2007 pp. 560-567

2 Y.S. Brar, Jaspreet S. Dhillon, D.P. Kothari "Multiobjective load dispatch by fuzzy logic based searching weightage pattern" Electric Power Systems Research (2002) pp. 149-160

3 Momoh, J.A. Ma, X.W. Tomsovic, K., "Overview and literature survey of fuzzy set theory in power systems" IEEE Transaction On Power Systems, Aug 1995 Volume: 10, Issue: 3 pp. 1676-1690

4 Vlaisavljevic, D.; Djukanovic, M.B.; Sobajic, D.J.; Babic, B.S., "Fuzzy linear programming based optimal power system rescheduling including preventive redispatch" IEEE Transactions on Power Systems, pp. 525-531, Volume: 14, Issue: 2, May 1999

5. Bansal, R.C., "Bibliography on the fuzzy set theory applications in power systems (1994-2001)" IEEE Transactions on Power Systems, Nov. 2003 Volume: 18, Issue: 4 pp. 1291- 1299

6. Liu, K. Subbarayan, S. Shoults, R.R. Manry, M.T. Kwan, C. Lewis, F.I. Naccarino, J. , " Comparison of very short-term load forecasting techniques" IEEE Transactions on Power Systems , May 1996 Volume: 11, Issue: 2 pp. 877-882

7. Hiyama, T. Tomsovic, K. , " Current status of fuzzy system applications in power systems" IEEE International Conference on Systems, Man, and Cybernetics, 1999 Volume: 6, pp. 527-532 vol.6

8. Didier Duboi, Helene Fargier and Philippe Fortemps, "Fuzzy scheduling: Modelling flexible constraints vs. coping with incomplete knowledge" European Journal of Operational Research Volume 147, Issue 2, 1 June 2003, pp.231-252

9. Amalia Sergakia , Kostas Kalaitzakis, " A fuzzy knowledge based method for maintenance planning in a power system" Journal on Reliability Engineering & System Safety Volume 77, Issue 1, July 2002, pp.19-30

10. D. K. Ranaweera, N. F. Hubele and G. G. Karady, "Fuzzy logic for short term load forecasting" International Journal of Electrical Power & Energy Systems Volume 18, Issue 4, May 1996, pp. 215-222

11. Ertugrul Cam and İlhan Kocaarslan "A fuzzy gain scheduling PI controller application for an interconnected electrical power system" Electric power system Research, Vol.10, Kırıkkale University, Faculty of Engineering, Yahsihan, Kırıkkale, Turkey