Fuzzy Logic in Power Engineering

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1. Artificial Intelligence in Power Engineering:
The goal of introduction of AI in equipment or software is to produce a machine or a system that simulate or emulate a human being's intelligence. AI consists of few sub-fields. Apart from those related to pattern recognition, natural language processing, it covers the fields of expert system, neural networks, fuzzy logic and genetic algorithms. The last four techniques, found an increasing number of applications in industry in general and in power engineering field in specific(1). In 1988, the first symposium on the application of expert system in power systems was held in Stockholm. In 1991, the International Forum on Applications of Neural Networks to Power Systems was held in Washington.

1.1 Expert Systems
In expert systems knowledge is represented in sets of "if-then-else" rules. The kwnoledge is to be collected from human experts by the knowledge engineers. Well defined problems may be solved by expert systems easily. It had its well known and successful application in medicine as well as troubleshooting. Training of power system operators can also be done through rule based expert system(2) In general expert systems are suitable for problems which are governed by a known set of rules, whether these rules are logical or consisting of mathematical formulae. However the applications which contains some vague information , expert systems when are used suffer difficulties(1).Expert systems find a verity of applications in power engineering. There where about a 100 papers published before 1993 about expert systems applications in power engineering in Japan alone(3).
Problems such as diagnosis (especially transformer/generator malfunctioning diagnosis), alarm processing, and other diagnosis, can be solved independently by expert system approach(11)

1.2 Artificial Neural Networks
There are similarities and differences between fuzzy logic and neural networks approaches. They both store knowledge and use it to make decisions on new inputs. They both can generalize, both produce correct responses despite minor variations in the input vector. They are however differ in techniques. ANN stores knowledge through training. This has a major advantage often the training set can be composed of actual observations of the physical world, rather than being formed of the human opinions used for fuzzy (or expert) systems, ie the ANN lets the data speak for itself. The training set must be however adequate to provide the ANN with enough information. ANN like expert system both cannot deal with fuzzy information except with fundamental modifications.(1)
There are basically four types of ANN in use : Single-Layer perception, multi-Layer Feed-forward Network, Hopfield Neural Networks and Self-Organizing Networks. Neural Networks are used in many power engineering applications. Among these applications is Short Term Load Forecasting. A lot of research has taken place in this area(4)

1.3 Genetic Algorithms:
Evolutionary computing is based on principles of genetics of natural selection. The features of genetic algorithms differ from other search techniques in optimizing the trade-off between exploring new points in the search and exploiting the information discovered thus far. Secondly GA have the property of implicit parallelism ie extensive search of hyperplanes of the given space without testing all the hyperplanes. Thirdly, GA are randomized algorithms , ie they use operators whose results are governed by probability. Finally GA operate on several solutions simultaneously, gathering information from current search points to direct subsequent search,
One of the applications reported for genetic algorithm is in the solution of short term optimization of hydro-thermal scheduling so that hourly schedule of power generation is obtained(5)

1.4 Fuzzy Systems:
Fuzzy systems are like expert systems in relaying upon certain rules.These rules here allows fuzzy input. Natural way of behavior of human being are almost fuzzy in all its aspects. Fuzzy systems can solve problems which are difficult for expert systems. It allows the possibility of representation of imprecise human knowledge. Fuzzy systems are based on fuzzy logic which will be discussed in details later on in this paper.

1.5 Hybrid System:

There are several possibilities of combinations of the above methods; eg fuzzy logic with neural networks, fuzzy logic with expert systems, genetic algorithms with fuzzy logic and so on. Such systems are developing slowly and find their applications in some problems(1).
There has been many reported application of such method in engineering applications (6). Transit systems scheduling witnessed also applications of expert systems with some fuzzy control(7)
In some cases a combination of expert system, neural networks and fuzzy logic is used . Optimization of VAR control may use neural networks enhanced by fuzzy sets to model the uncertainty of reactive load. Expert systems are used also in heuristic based method, in order to reach a feasible solution(17)

1.6 Integration of AI in Power Systems
AI and in particular expert systems may be integrated in energy management system environment(8) Suitable interface between AI and the energy management systems are to be introduced. Such interface is to be ready for plugging the AI in the energy management systems whenever felt necessary. The integration of AI with energy management system reduces the cost of installing , maintaining an existing application and reduces cost of new applications. The key issue to the success of such integration is the common power system model. Research in this area is still undergoing.

2. What is Fuzzy Logic?:
Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth , i.e. truth values between "completely true" and "completely false". It was introduced by Dr. Lotfi Zadeh of UC/Berkeley in the 1960's as a means to model the uncertainty of natural language(9)

2.1 Fuzzy Subsets:
Just as there is a strong relationship between boolean logic and the concept of a subset, there is a similar strong relationship between fuzzy logic and fuzzy subset theory. In practice, the terms "membership function" and "fuzzy subset" get used interchangeably.
Let's talk about people and "tallness". In this case the set S (the universe of discourse) is the set of people. Let's define a fuzzy subset TALL, which will answer the question "To what degree is person x tall?" Zadeh describes TALL as a LINGUISTIC VARIABLE, which represents our cognitive category of "tallness". To each person in the universe of discourse, we have to assign a degree of membership in the fuzzy subset TALL. The easiest way to do this is with a membership function based on the person's height.

The term DEGREES OF MEMBERSHIP is introduced so that its value ranges between 0 and 1. Suppose this term is to describe a person is "Tall" if he or she is 175cm. and not "Tall" or "Short" if he is 150cm. then the Degree of membership is 1 for the person of 175cm or more , 0.8 for 170cm, 06 for 165cm, 0.4 for 160cm, 0.2 for 155cm and 0.0 for 150cm or less. This is on the basis that the degree of membership function is linear.

2.2 Fuzzy Predicates:
Variables or terms which do not hold very exact meaning and may be understood differently by different, g is referred to as a possibility measure. people. Such predicates are like: expensive, safe, old, rare dangerous, educated, tall, heavy, light, smooth, rough, beautiful, etc(10)

2.3 Fuzzy Quantifiers:
Quantitative terms which when added to measurable quantities may be considered fuzzy predicates e.g. many, few, almost all, usually, almost nobody, almost everybody etc.

2.4 Fuzzy Truth Values:
Grades of truth or falsehood can be put in a set of level e.g. extremely true, quite true, very true, almost true, more or less true, mostly true, mostly false, more or less false, almost false, very false, quite false, extremely false.. etc.

2.5 Fuzzy Modifiers:
They are the terms related to likelihood of the happening of event e.g. likely, extremely unlikely, almost impossible etc.
The above terms used in fuzzy truth values and fuzzy modifiers like very, extremely, more or less etc. are called hedgers.

2.6 Fuzzy relational operators:
In comparing two qualities in a fuzzy way, terms like approximately equal, slightly greater than, much greater than, much less than etc.

2.7 Basic Fuzzy Sets Relations:
2.7.1 Definitions:
Let X be the universe of objects with elements x, where A is called a fuzzy sub-set of X (generally called a fuzzy set).
In a classical set A, the membership of x can be considered as a characteristic function mA from X to {0,1} such that:

$$uA(x) = \begin{cases} 1 & \text{if } x \quad A \\ 0 & \text{if } x \quad A \end{cases}$$

For a fuzzy set A of the universe X, the grade of membership of x in A is defined as:

uA(x)   [0,1]

where uA(x) is called the membership function.
The value of u A(x) can be anywhere from 0 to 1. As u A(x) is nearer to 1.0, then x belongs to A more.
Fuzzy set elements are ordered pairs giving the value of a set element and the grade of membership i.e.:

A = { (x, m A(x)) | x   X }

Fuzzy sets are called equal if uA(x) = uB(x) for every element x   X and is denoted as:

A = B

Fuzzy sets A and B are not equal (u A(x)   u B(x) for at least one x   X) and is written as:

A = B

2.7.2 Basic Fuzzy Operations

The complement of a fuzzy set m A(x) is given by:

uA(x) = 1 - uA(x)

In order for any function to be considered as a fuzzy complement, it must satisfy at least the following two requirements:

1) c(0) = 1 and c(1) = 0 i.e. c behaves as the ordinary complement of crisp sets.
2) For all a,b   [0,1] if a < b then c(a)   c(b) . i.e. c is monotonic nonincreasing.
The Following are additional desirable requirements:
3) c is a continuous function.
4) c is involutive i.e. c(c(a)) = a for all a   [0,1].

An example of general fuzzy complements that satisfy only axiomatic skeleton:

c(a) = 1 for a   t
c(a) = 0 for a > t

where a   [0,1] and t   [0,1] : t is called the threshold of c.
While the following fuzzy complement is continuous but not involutive:

c(a) = 1/2 (1 + cos   a)

As an example for involutive fuzzy complement:

cw(a) = (1 - a)

where w   (0,   )
When w = 1 the above function becomes:

c(a) = 1 - a

Fuzzy union of two sets A & B is given in general by the function:

u: [0,1] X [0,1]   [0,1]

For each element x in the universal set:

uA   B (x) = u(mA (x) , uB (x))

Any function of this form to be qualified as a fuzzy union; it must satisfy at least the following axioms:
1) u(0,0) = 0 ; u(0,1) = u(1,0) = u(1,1) = 1. i.e. u behaves as the classical union with crisp sets.
2) u(a,b) = u(b,a). i.e. u is commutative.
3) If a < a′ and b < b′ then u(a,b) < u(a′,b′). i.e. u is monotonic.
4) u(u(a,b),c) = u(a,u(b,c)). i.e. u is associative.
An example of fuzzy union is Yager class which is defined by the function:

uw(a,b) = min (1,(a + b)

when w = 2

u2(a,b) = min (1,sqrt(a + b))

In other words:

uA   B(x) = max (uA(x), uB(x))

Fuzzy Intersection of two fuzzy sets A & B is given by the function:

i : [0,1] X [0,1]   [0,1]

The function returns the membership grade of the element in the set A   B , thus:

mA_ B (x) = i (mA(x), mB(x))

Such function should satisfy axioms similar to those given above for union as follows:
1) i (1,1) ; i (0,1) = i (1,0) = i (0,0) = 0. i.e. I behaves as the classical intersection with crisp sets.
2) i (a,b) = i (b,a). i.e. i is communicative.
3) If a < a′ and b < b′ then i (a,b) < i (a′,b′). i.e. i is monotonic.
4) i (i (a,b),c) = i (a,v (b,c)). i.e. i is associative.
In other words:

uA   B (x) = min (uA(x), uB(x))

A useful fuzzy binary operation is defined as:

R = { (x,y, uR(x,y)) | x   X,y   Y}

For a fuzzy relation R, there is the following fuzzy computation:

ur(y) = sup (min (uR(x), uR(x,y)))
y   Y

2.7.3 An Example

Assume that the variable x,y and z all take on values in the interval(0,10), and that the following membership functions and rule are defined:
low(t) 1-(t/10)
high(t)=t/10
rule1: if x is low and y is low then z is high
rule 2: if x is low and y is high then z is low
rule 3; if x is high and y is low then z is low
Let the membership table shows the results

Table (1)

x	y	low-x	high-x	low-y	high-y	a1	a2	a3
0.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0
0.0	3.2	1.0	0.0	0.68	0.32	0.68	0.32	0.0
0.0	6.1	1.0	0.0	0.39	0.61	0.39	0.61	0.0
0.0	10	1.0	0.0	0.0	1.0	0.0	1.0	0.0
.2	0.0	0.68	0.32	1.0	0.0	0.68	0.0	0.32
6.1	0.0	0.39	0.61	1.0	0.0	0.39	0.0	0.61
10	0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0
3.2	3.1	0.62	0.32	0.69	0.31	0.68	0.31	0.32
3.2	3.3	0.62	032	0.67	0.33	0.67	0.33	0.32
10	10	0.0	1.0	0.0	1.0	0.0	0.0	0.0

2.8 Steps for Application of Fuzzy Set Theory:
Whe set theory is used to solve real problems, the following are generally followed:
(1) Describe the original problem in a mathematical form.
(2) Define the thresholds for variables; ie the greatest degree of satisfaction as well as the unacceptable value. These will be assigned the 1 and 0 degree of membership respectively.
(3) Based on the threshold values from step (2) above select the type of membership function (linear, piece-wise linear, trapezoidal, parabolic and so on). The membership fuvction reflects the change in degree of satisfaction with changes in variable evaluated by experts.
(4) Fuzzy operation should be selected so that the results obtained are like those given by the human expert. (11)
(5) The problem has to be defuzzified if necessary to obtain crisp values and be translated into meaningfull values.

3. Fuzzy Logic in Power System Operation and Planning:
There is an increasing number of publications on the application of fuzzy logic in the field of power engineering. This shows the potential of this field in getting better performance of power systems with this logic. There are problems in power systems that contain conflicting objectives. In power systems operation, economy and security, maximum load supply and minimum generating cost are conflicting objectives. The combination of these objectives by weighing coefficients is the traditional approach to solve this problem. Fuzzy theory offers better compromise and obtain solutions which cannot be found by weighing methods. The benfits of fuzzy set theory over traditional methods are as follows:
(1) It provides alternatives for the many attributes of objective selected.
(2) It resolves conflicting objectives by designing weights appropriate to a selected objective.
(3) It provides capability for handling ambiguity expressed in diagnostic process which involves symptoms and causes.
(4) It develops process control as fuzzy relation between information about the condition of the process to be controlled.
(5) It develps intelligent robots that employ sensors for path or position determination.
(6) It improves human reliability models in cases where many people perform multiple tasks. (11)
The areas where fuzzy logic can be used in power systems cover all the aspects of the power system:

3.1 Fuzzy logic in Planning and long/mid term scheduling related areas.
Fuzzy logic has been used in planning. long/mid term scheduling and in reliability calculations(11)
Fuzzy linear programming may be used to allow the decision makers to solve the problem of uncertainty of input informatio within the fuel scheduling optimization. Decision- maker may learn to recognize the relative importance of factors in specific domain of optimal fuel scheduling problem. Such approach may be useful also to deal with multi-objective problems. The fuzziness in such problem may be due to impossibility to predict exact values or to lack of firm position regarding some other values. The possibility that the decision-maker may reassess the parameters if the constraints are about their limits and the cost function is going to give a substantial change(22).

3.2 Fuzzy logic in Operation areas.
Fuzzy logic is used in contingency analysis, VAR/Voltage control, stability evaluation, load forecasting, load management, decision-making support, multi-objective coordination, monitoring & control, unit commitment and state estimation(11).
Dynamic voltage security including both voltage collapse and unacceptable voltage profile may be evaluated using knowledge based fuzzy approaches. Rules such as “ If the voltage value at some bus is VL at the JAD state, the possibility of dynamic voltage insecurity of the system subsequent to the JAD state is VH” where VL is the “very low” state, VH is the “very high” state and the JAD is the “just after disturbance” state. The terms very high and very low are fuzzy terms which can only be modeled using fuzzy logic. By applying approximate fuzzy reasoning and a series of fuzzy calculus, the complex dynamic voltage-instability behavior is finally mapped into a fuzzy severity index(13)
When optimum power flow is formulated , fuzzy modeling is introduced in static security constraints due to uncertainity in bus loads. Uncertainty in MW load generations are translated into possibility distribution functions. The fuzzy optimum power flow problem is composed into sub-problems corresponding to the possibility distributions of loads. The effects of phase shifters are modified as equivalent real power injections at corresponding system buses , which reserves the Y-bus symmetry and maintains minimum memory requirements. Fuzzy sets are utilized to exercise a tighter control on least cost real power generation with minimum emission dispatch solution. The final solution is thus a compromise among cost, static security and emission considerations(16)

(4)In distribution systems, transformers and feeder's load balancing reduces the risk of overloads due to load changes. Balancing of load based on fuzzy set decision theory is possible. The determination of the proper set of switching operations to balance the load often is difficult due to seemingly contradicting requiremnts. Fuzzy logic reasoning based on experienced operator's preferences could result in a good load balancing.(20)

There are usually two types of constraints: Physical limits and operating limits. It is not acceptable to violate physical limits or constraints. An operating limit , however is oftem imposed to enhance system security but does not represent a physical bound. This kind of "soft limits" can be temporarly violated " a little bit" if necessary, but not "too much" These constraints are therefor "fuzzy" in nature and crisp treatment of them may lead to over conservative solutions. Hence problems related to scheduling may be first converted into a crisp and seperable optimization problem and then can generate a near optimal schedule and provide an effective trade-off between minimizing cost and satisfying constraints(23)

Service restoration of primary distribution system when performed it is usually depends on conflicting goals. Hence the problem is a multi-criteria decison making problem. The most preferable decison may be reached via fuzzy evaluation of these multi-criteria Such decion may result into a more practical soluton(24.

3.3 Fuzzy logic in Control areas.

Fuzzy logic has been used in control area by using fuzzy logic stabilizer, converter/drives and in other types of control(11).

In order to design a robust controller for the auxiliary control loop of static VAR system, both fuzzy logic and variable structure system concepts are used. The design of a simple fuzzy controller using the least number of rules for stabilisation of a synchronous generator connected to a large power system gives a a superior results compared to conventional control in better damping during transient disturbances(18)

In order to enhance voltage security of an electric power system, fuzzy set theory for voltage reactive control of poer system is use by translating voltage bus voltage and s\controlling variables into fuzzy set notations to formulate the relation between voltage violation level and controllong ability of controlling devices. Max- Min method is employed on the fuzzy sets in accordance with requirement of real-time control. By fuzzification the bus voltage violation level and controlling ability of controlling devices to essentially reflect the operator's intuition in operation , the aim of enhancing the control effects is achieved. This is to simmulate the usual action of the operator if he is not satisfied with the grading of the fuzzy model , he can adjust the parameters used in the definition of the membership functions, so that his desire will be closely matched(19).

Conventional Optimal Power Flow solutions utilize standard techniques. These techniques limit the practical value and scope of optimal power flow applications. Different considerations have to make a trade-off between minimum objective function, satisfying constraints and desirable moving control variables. In real-life system, it has been found that a slight violation of of the normal operation limits may result in significant cost saving. Fuzzy logic can reach the trade-off in a better way using eg. Min-Max techniques(21).

Demand side management programs are strategies designed to alter the shape of the load curve. In order to succeefully implement such a strategy, cusotmer acceptance of the program is vital. It sis thus desirable to design a model for direct load control which may accomodate customer preferences. Fuzzy logic may be used to optimize both customer satisfaction and utility unit commitment savings based on a fuzzy load model for the direct load control of appliances(25).

3.4 Fuzzy logic in Diagnosis areas.

Fuzzy logic has been used in diagnosis are in transformer, network and machine diagnosis. Neural network with fuzzy logic can help a lot in diagnosis area(11).

Diagnosis of power systems faults is an involved process since it contains a lot of uncertainities. To handle these uncertainities and rank various fault hypotheses a fuzzy signal model based on fuzzy information theory may be developed. Such a model makes a measure of the degree of correctness of recieved and nonrecieved input data. The fuzzy symbols has to be classified through a knowledge base which include network mode, predefined subnetworks, relaying scheme, and fuzzy diagnosis rules. Invironmental factors such as type, substation voltage level, age of protective devices as well as thei quantities, related communication, channel reliability etc may all be included(12)

4. Load Foercsting;

Long term load forecasting which is needed at design stages usually present different senarios. The decision of following one of such senarios includes a trade-off between conflicting requirements. Fuzzy logic can fuse the available information for spatial load forecasting. Such methods can provide planners with different alternatives to aggregate their information for spatial forecasting(25).

As for short term load forecasting extensive research is going on using neural network alone or with fuzzy logic or using fuzzy logic alone.

The use of fuzzy logic takes two shapes: either for a good approximation of load curve shape or to improve the shape reached by neural network.
As for the first method, an optimal structure is constructed of simplified fuzzy inference that minimizes model errors and number of membership functionss to grasp nonlinear behavior of power system short term loads. The model is identified by simultaneous annealing and the steepest descent method(28,29,33).
In neural method forecasting , the mode is trained using a past data. When suitable parameters are obtained, then the system may be used for the future load forecasting. However it has been found that a good improvement may be obtained if the use of fuzzy logic accompanies the neural network. Fuzzy logic can be introduced in neural network in the form of fuzzy rules. It is initially creates a rule base from existing historical load data. The parameters of the rule bas are then tuned through a training proces, so that the output adequetely matches the available historical load data. Once trained the system can forecast future load. The accuracy of such system is comparable to that of the neural networks but the training is much faster than neural networks(27)
The other form of the introduction of fuzzylogic in the neural network forecasting is through the temperature rules. Two steps are to be performed. The first is the normal training of the neural netowrk to obtain the provisional forecast. In the second step, the fuzzy expert system modifies the provisional foecasted load considering the possibility of load variation due to change in temperature and load behavior of holiday(30,32).

4.1 An Example

The following figure shows how a nonlinear function may be approximated into piecewise linear portion and then each of which is to be replaced by membership functions which may then be codes into fuzzy logic with the parameters of the membership function varied in order to reach the optimum solution required.

5. Fuzzy Logic in Power Electronics and Motion Control:

5.1 Fuzzy Logic in Power Electronics

The perspective of extensive use of AI tools, such as expert system, fuzzy logic , neural networks and genetic algorithms, are expected to usher a new ara in power electronics and motion control in the comming decades.In spite of AI progress, their applications in power electronics is just at it beginning(34)
Logic controllers have witnessed quite a number of applications of fuzzy logic. A rule based fuzzy logic controller to control output power of a pulse width modulated (PWM) inverter used in stand alone wind energy conversion scheme has been used(35). The self excited induction generator used has the inherited problem of fluctuations in the magnitude and frequency of its terminal voltage with changes in wind velocity and load. To overcome this drawback the variable magnitude, variable frequency voltage at the generator terminals is rectified and the power is transferred to the load through a PWM inverter. In order to extract maximum power from the wind energy system and transfer it to the load, a fuzzy logic controller has to be provided to regulate the modulation index of the PWM inverter based on the input signals. By fuzzifying these signals and the use of rules based on these fuzzified signals, the fuzzy control is performed giving the fuzzy output required after defuzzification. This will provide an optimum utilization of the wind energy(35).

5.2 Fuzzy Logic in Controllers

A self learning fuzzy logic control may be obtained by using a consistent set of rules to a predetermined criterion and by evaluation of its transient performance over a veriety of tests. An appliction of such a self learning fuzzy logic control to a laboratory liquid level process. Even with limited knowledge of the process , the self learning procedure is able to yield a satisfactory performance withdegree of robustness and with high repeatability(45).
Direct torque control of induction machines uses the stator resistance of the machine for estimation of the stator flux. Variation of stator resistance due to changes in temperature ofr frequency make such operation difficult at low speeds. A method for estimation of chnges in staor resistance during the operation of the machine may be performed. Proportional-Integrated (PI) control and fuzzy logic control scheme are incorporated in such system. The estimators observe the machine staor current vector to detect the changes in stator resistance(36). A Quazi-fuzzy estimation of stator resistance of inuction motor has been also implemented, where resistance value is derived from the staot winding temperature esimation(43)
Speed control of shunt DC motors using fuzzy logic is reported in many applictions(37,39). Speed control of inuction motors and reluctance motors are reported also(40,42). Other control approaches to force control, position control are also available(38,39).

5.3 An Example:

Consider as an example: 120V motorwith armature resistance of 0.25 ohm, a field resistance of 60.0 ohms and a rated speed of 1800rpm. Since increasing load results in an increased line current, load variations on the motor are simulated by varying the line current. A a result, armature current , counter emf and motor speed result as shown in the following Table:

I-L(A)_I-f(A)_I-a(A)_Ec(V)_n(rpm)__84.0_2.00_82.0_099.50_1628__73.5_2.00_71.5_102.13_1671__63.0_2.00_61.0_104.75_1714__52.5_2.00_50.50_107.38_1757__42.0_2.00_40.00_110.0_1800__31.5_2.00_29.50_112.63_1843__21.0_2.00_19.00_115.25_1886__10.5_2.00_8,5_117.88_1964__

In order to maintain a fairly constant speed of the motor as load changes, a fuzzy controller is to be designed. The input variables to the fuzzy controller are the speed and the field current while the field current is also an output variable. Fuzzy rules for this problem shall be:

IF Speed... AND Field current (at that speed) is ... THEN Field current (required to effect speed control) is ...

A simple algorithm can be used to calculate motor speed for various loading levels, line voltages, and field resistances. Based on that fuzzy associations may be defined as in the following Table:

_Fuzzy Variable 1:Speed___Fuzzy Association_Description_RPM Range__LS_Low speed_1500-1700__US_Under speed_1685-1785__NS_Normal speed_1775-1825__OS_Over speed_1815-1915__RA_Run-Away_1900-2100___Fuzzy Variable 2: Field Current___Fuzzy Association_Description_Numerical Rang(A)__S_Small_1.60__BNO_Below Normal_1.55-1.95__NO_Normal_1.90-2.10__ANO_Above Normal_2.05-2.45__L_Large_1.40______

Using the notation of the above table, the fuzzy sets required for the controller is shown in Figure( ) .

_ EMBED Word.Picture.6 ___

_Using the notations of Table I and Table II above the fuzzy sets required for the controller is shown in Figure( ). The fuzzy system is represented by fuzzy associative Table III where the output is the field current required to restore the motor speeed to the normal range using a feedback loop which feeds the actual speed back to the fuzzy controller.

____speed______LS_US_NS_OS_RA__Field_S__ANO_S_ANO_L__Current_BNO_NO_BNO_BNO_ANO_ANO___NO_ANO_ANO_NO_ANO_ANO___ANO_NO_NO_ANO_NO_NO___L_BNO_BNO_L_BNO_BNO__

6. Discussion and Conclusion:

The use of artificial intelligence in power engineering is showing and increasing depth. In specific fuzzy logic had witnessed in the last decade veriety of applications in power system strategic planning, control, operation, diagnosis and load forecasting. It had been used in power electronics and motion control. in the future it is expected that the trend will show further progress of fuzzy applications in power ingineering with more depth even more than the previous progress.

7. References:

1. Young-Hua Song and Allan T. Johns, Application of fuzzy logic in power systems, Part1 (Oct. 1997) and Part 2 (Aug. 1998), Power Enginering Journal.
2. M.Z. Khedher , Expert System for Power System Operator
3. Saifur Rahman, Artificial Intelligence in Electric Power Systems, IEEE Trans on Power Systems Vol 8, No. 3, Aug 1993, p 1211-1218
4. Raj Aggarwal and Yonghua Song , Artificial neural networks in power systems, Part 2 (Feb 1998) and Part 3 (Dec 1998)
5. S.O.Orero and M.R. Irving, A Genetic Algorithm Modelling Framework and Solution Technique for Short Term Optimal Hydrothermal Scheduling, IEEE Trans on Power Systems, Vol 13, No. 2, May 1998, pp 501-516
6. Rechel Pearce and Peter Cowley, Use of Fuzzy Logic to Describe Constraints Derived from Engineering Judgment in Genetic Algorithms IEEE Trans on Industrial Electronics, Vol 43, No. 5 Oct. 1996, pp 535-540
7. C.S. Chang and B.S. Thia, Online rescheduling of mass rapid transit systems: fuzzy expert system approach, IEE Proc. Electric Power Applications, Vol 143, No. 4, July 1996, pp 307-316
8. J.Bann , et al , Integration of Artificial Intelligence Applications in EMS: Issues and Solutions, IEEE Trans on Power System, Vol 11, No, 1 Feb 1996, pp 475-482
9. Mark Kantrowitz, Erik Horstkotte, and Cliff Joslyn
http://www.cs.cmu.edu/Web/Groups/AI/html/faqs/ai/fuzzy/part1/faq.html
http://www.cs.cmu.edu/Web/Groups/AI/html/faqs/ai/fuzzy/part1/faq.html
10 Mohammed Zeki Khedher and Ahmed M.Z. Khedher, Fuzzification General Program, Proceedings of Second Computer Conference of Phyladelphia University , Amman, July 1997
11. J.A. Momoh and K. Tomsovic , Overview and Litrature Survey of Fuzzy Set Theory in Power Systems, IEEE Trans on Power Systems, Vol 10, No. 3, Aug. 1995, pp 1676-1690
12. H. Monsef, A.M. Ranjbar and S. Jadid, Fuzzy rule-based expert system for power system fault diagnosis, IEE Proc. Transm, Distrib. Vol 144, No.2 March 1997, pp 186-192
13. S.K.Tso, T.X. Zhu, Q.Y.Zeng and K.L.Lo, Fuzzy reasoning for knowledge-based assessment of dynamic voltage security, IEE Proc. Gener. Transm. Distrb., Vol 143, No.2 March 1996, pp 157,162
14. Chih-Wen Lio, Chen-Sung Chang and Mu-Chun Su, Neuro-Fuzzy Networks for Voltage Security

Monitoring Based on Synchronized Phasor Measurements, IEEE Trans. on Power Systems, Vol 13, No. 2 May 1998, pp326-332
15. S.E. Papadakis, J.B.Theochatis, S.J. Kiartzis and A.G. Bakirtziz, A novel approach to short-term load forecasting using fuzzy neural network, Trans. on Power Systems, Vol 13, No. 2 May 1998, pp480-492
16. K.H. Abdul-Raaaahman and S.M. Shahidehpour, Static Security in Power System Operation with Fuzzy Real Load Conditions, IEEE Trans on Power Systems, Vol 10, No. 1 Feb 1995, pp77-87
17. K.H. Abdul-Raaaahman , S.M. Shahidehpour and M. Danesdoost, AI Approach to Optimal VAR Control with Fuzzy Reactive Loads, IEEE Trans on Poer Systems, Vol 10, No. 1 Feb 1995, pp88-97
18. P.K. Dash, S. Mishra and A.C. Liew, Fuzzy logic based VAR stabiliser for power system, IEE Proc. Gener. Transm. Distrb., Vol 142, No.6 Nov 1995, pp 618-624
19. Ching-Tzong Su and Chien-Tung Lin, A New Fuzzy Control Approach to Voltage Profile Enhancement for Power Systems, IEEE Trans on Power Systems, Vol 11, No. 3 Aug 1996, pp1654-1659
20 B. Naga Raj and K.S. Parkasa Rao, A New Fuzzy Reasoning Approach for Load Balancing in Distribution System, IEEE Trans on Power Systems, Vol 10, No. 3 , Aug 1995, pp14261432
21. W.H. Edwin Liu and Xiaohong Guan, Fuzzy Constraint Enforcement and Control Action Curtailment in an Optimal Power Flow, IEEE Trans on Power Systems, Vol 11, No. 2 May 1996, pp639-645
22. Miodrag Djukanovic, et al, Fuzzy Linear Programming Based Optimal Fuel Sceduling Incorporating Blending/Transloading Facilities,

IEEE Trans on Power Systems, Vol 11, No. 2 , May 1996, pp1017-1023
23. Xiahong Guan, Peter B. Luh and Balakumar Prasanan, Power System Scheduling with Fuzzy Reserve Requirement, IEEE Trans on Power Systems, Vol 11, No. 2 , May 1996, pp864-869
24. Seung Lee, Seong-Il Lim and Bok-Shin Ahn, Service Restoration of Primary Distribution Systems Based on Fuzzy Evaluation of Multi-Criteria, IEEE Trans on Power Systems, Vol 13, No. 3, Aug 1998, pp1156-1163
25. K. Battacharyya and M.L. Crow, A Fuzzy Logic Based Approach to Direct Load Control, IEEE Trans on Power Systems, Vol 11, No. 2, May 1996, pp708-714
26. Mo-yuen Chow and Hahn Tram, Appliction of Fuzzy Logic Technology for Spatial Load Forecasting, IEEE Trans on Power Systems, Vol. 12, No. 3, Aug. 1997, pp 1360-1366
27.A.G. Bakirtzis, J.B Theocharis, S.J. Klartzis and K.J. Satsios, Short Term Load Forecasting Using Fuzzy Neural Network, IEEE Trans on Power Systems, Vol. 10, No. 3, Aug. 1995, pp 15518-1524
f28. Hiroyuki Mori and Hidenori Kobayach, Optimal Fuzzy Inference for Short Term Load forecasting, IEEE Trans on Power Systems, Vol. 11, No. 1, Feb. 1996, pp 390-396
29. K. Lu, et al, Comparision of Very Short Term Load Forecasting Techniques, IEEE Trans on Power Systems, Vol. 11, No. 2, May. 1996, pp 877-882
30. Kwan-Ho Kim, Jong-Keun Park, Kab-Ju Hwang and Sung-Hak Kim, Implementation of Hybrid Short Term Load Forecasting System Usin Artificial Neural Networks and Fuzzy Expert Systems, IEEE Trans on Power Systems, Vol. 10, No. 3, Aug. 1995, pp 1534-1539
31. I. Drezga and S. Rahman, Input Variable Selection for ANN-Based Short Term Load Forecasting, IEEE Trans on Power Systems, Vol. 13, No. 4, Nov. 1998, pp 1238-1244
32. M. Daneshdoost, M. Lotfalian, G. Gumroonggit and J.P Ngoy, Neuaral Network with Fuzzy Set Based Classification for Short Term Load Forecasting, Vol. 13, No. 4, Nov. 1998, pp 1386-1391
33. Hong-Tzer Yang and Chao-Ming Huang, A New Short Term Load Forecasting Approach Using Self Organizing Fuzz ARMAX Models, Vol. 13, No. 1, Feb. 1998, pp 217-225
34. B.K. Bose , Expert system, fuzzy logic, and neural network application in power electronics and motion control, Proc. of the IEEE, Vol 82, Issue 8, Aug 1994, pp 1303-1323.
35. Rodin M. Hilloowala and Adel M. Sharaf, A Rule-Based Fuzzy Logic Controller for a PWM Inverter in a Stand Alone Wind Energy Conversion Scheme, IEEE Trans on Inductry Applications, Vol 32, No. 1, Jan/Feb 1996, pp 57-65
36. Sayeed Mir, Malik E. Elbuluk and Donald Zinger, PI and Fuzzy Estimator for Tuning the Stator Resistance in Direct Torque Control of Induction Machines, IEEE Tran on Power Electronics, Vol 13, No 2, March 1998, pp 279-287
37. Seydraloul Saneifard, Nadipuram R. Parsad, Howard A. Smolleck and Jiryes J. Wakileh, Fuzzy-Logic-Based Speed Control of Shunt DC Motor, IEEE Tran of Education, Vol 41, No 2, May 1998, pp 159-164
38. Masaali Shibata, Toshiyuki Murakami and Kouhei Ohnishi, A Unified Approach to Position and Force Control by Fuzzy Logic, IEEE Trans on Inducstrial Electronics, Vol 43, No 1, Feb 1996, pp81-87
39. Pierre Guillemin, Fuzzy Logic Applied to Motor Control, IEEE Trans on Inducstry Applications, Vol 32, No 1, Jan/Feb 1996, pp51-56
40. Mao-Fu, Michio Nakano and Guan-Chyun Hsieh, Application of Fuzzy Logic in the Phase-Locked Loop Speed Control of Induction Motor Drive, IEEE Trans on Industrial Electronics, Vol 43, No 6, Dec 1996, pp630-639
41. Jason T. Teeter, Mo-yuen Chow and James J. Brickley, A Novel Fuzzy Friction Compesation Approach to Improve the Performance of a DC Motor Control System, IEEE Trans on Inducstrial Electronics, Vol 43, No 1, Feb 1996, pp113-120
42. Silverio Bolognani and Mauro Zigliotto, Fuzzy Logic Control of a Switched Reluctance Motor Drive, IEEE Trans on Inducstry Applications , Vol 32, No 5, Sept/Oct 1996, pp1063-1068
43. Bimal K. Bose and Nitin R. Patel, Quasi-Fuzzy Estimation of Stator Resistance of Induction Motor, IEEE Trans on Power Electronics, Vol 13, No 3, May 1998, pp401-409
44. Hartmut Surmann, Genetic Optimization of a Fuzzy System for Charging Batteries, IEEE Trans on Inducstrial Electronics, Vol 43, No 5, Oct 1996, pp541-548
45. S.H. Ghwanmeh, K.O Jones and D. Williams, Robustness Study of an On-Line Application of a Digital Self-Learning Fuzzy Logic Controller, Proc of the IASTED International Conference on Computer Systems and Applications, March 30-April 2, 1998, Irbid, Jordan, pp 78-82
46. John Durkin, Expert Systems Design and Development, Mcmilan Publishing Co., 1994, pp 363