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OPTICAL CAPACITOR PLACEMENT USING NEURO-FUZZY SYSTEM FOR POWER QUALITY IMPROVEMENT

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ABSTRACT

In any power system capacitor placement is a main concern in order to attain voltage stability. Neuro-fuzzy is an efficient approach for capacitor placement at optimum locations and size of conductors with the objective of improving voltage profile and reduction of losses. In this paper capacitor placement is done by the neuro-fuzzy technique. The optimal capacitor placement (OCP) problems contain the integer variables because the each capacitor bank is integer value. For optimization discrete nature of capacitors and different load levels are taken into considerations. Various sets of equality and inequality constraints are considered for non differentiable and non linear mixed integer optimization. The loss minimization in distribution systems has assumed greater significance recently since the trend towards distribution automation will require the most efficient operating scenario for economic viability variations.

Keywords—***Electric Power System, Generation, Losses, Ann, Fuzzy, Power-Quality***

I INTRODUCTION

The goal of power engineers is to provide an uninterrupted supply of high quality power to customers in a secure and economic environment. The quality supply means constant voltage and constant frequency power supply under normal operating conditions.

Optimization technique is defined as the process of finding the conditions that give the minimum or maximum value of a function, where the function represents the effort required or the desired benefit. The optimization technique is important for reducing the losses and cost of the system. Optimization is done by the capacitor placement for providing voltage stability. Capacitor placement problem is the main concern in the power system planning. So it is required for finding the optimum location where the capacitor is to be placed. This paper presents a development using fuzzy optimization process. -- Capacitor placement plays an important role in distribution system planning and operation. Optimal capacitor placement can result in system loss reduction, power factor correction, voltage profile improvement, and feeder capacity release.

This paper starts with theoretical aspects of the fuzzy optimization process and then, an example using power system energy saving is presented. Neuro-Fuzzy (NF) computing is a popular framework for solving complex problems. Fusion of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) have attracted the growing interest of researchers in various scientific and engineering areas due to the growing need of adaptive intelligent systems to solve the real world problem.

II PROBLEM FORMULATION

The NEURO-FUZZY technique is totally different from the conventional techniques. It has got the unique feature for mapping the relationship among the input-output features differently through its weighted links and the thresholds. An NEURO-FUZZY requires very little time to learn with the help of the given training input-output values. A well trained NEURO-FUZZY provides the desired results, within permissible range of accuracy, practically within no time.An elaborate study is performed on a sample 14-bus power-system. The figure and the data for 14-bus system is given below. The load flow analysis was carried out for the sample 14-bus power-system [14] using Newton Raphson method on MATLABsoftware. Several solutions were obtained for training the NEURO-FUZZY models with appropriate information. Results were also obtained for the test sets so as to compare the NEURO-FUZZY results with that of the conventional methods and to check the accuracy of the suggested NEURO-FUZZY model. A multi layer feed forward network with one hidden layer comprising of eight nodes was found to be the most optimally suitable NEURO-FUZZY structure for the Analysis.

III ARTIFICIAL NEURAL NETWORK(ANN)

In recent years, artificial neural network computing hasbecomean important branch of the artificial intelligence [10]. The ANNis the functional imitation of a human brain which simulates thehuman intuition. In this study, ANN is applied to the short term unit commitment [11], [12].

3.1 Structure of ANN

According to biological studies, the human brain is made upof billions of neurons. Each neuron performs like a computerwith verylimited capabilities. When these neurons areconnected together,the most intelligent system - a human brain is formed. Similarly,ANN represents a new class of computing systems formed by hundredsand thousands of simulated neurons, connected to each otherin much the same way as the brain neurons are interconnected.Each neuron has multi-inputs from other neurons with assignedweights which represent the strength of the input connections. Theoutput of a neuron is determined by a signal which is proportional to the sum of all the inputs as shown in Fig. 1.

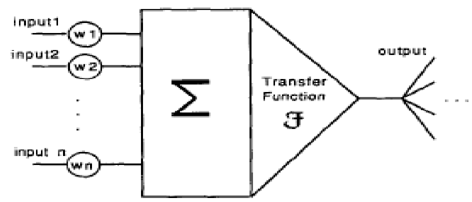

Fig.1. Structure of An Artificial Neuron

A three layer model is used for this application [13]. The inputlayer of the ANN is configured to adapt to a load demand profile,which consists of M neurons, with M being the total hours in theschedule span. For the daily scheduling, there are 24 neurons in theinput layer to represent the forecasted load demand for the next 24hours. Input neurons are normalized by the maximum swing in MWat each hour as:

$$\bar{L}_j = \frac{L_j - L_{\min,i}}{L_{\max,i} - L_{\min,i}} \quad (1)$$

Where,

J – index for hour,

L – given load demand,

$\bar{L}$ – Normalized value of L,

$L_{max,j}$ – upper bound of L at hour j,

$L_{min,j}$ – lower bound of L at hour j

The neurons in the output layer form the output schedule, which is a N X M matrix, and N corresponds to the number of unitsto be scheduled. A commitment schedule contains on/off states ofeach unit in every hour within the scheduling time span. The statevariable can only take 1 or 0 values, so the output layer matrix displayswhite blocks for off or 0, and dark blocks for on or 1, as shownin Fig. 2 [14]. In this display, a portion of the schedule for five unitsovera four hour period ispresented. When the training is completed,ANN will produce the corresponding schedule pattern for any inputload profile that is similar to Fig. 2 at the output layer. However, iftheinput loads profile is not exactly the same as any of the profilesused in the training, some of the output neurons will takevaluesbetween 0 and 1. In the graphical display, such neurons are representedby gray blocks. The brightness indicates the probability thatthe ANN assumes a 0 state, therefore, darker display means thatthe state is closer to 1. In other words, ANN cannot determine theexact on/off state of the unit at this hour, but it can guess the valuebased on its previous knowledge. Such a graphical matrix with variousbrightness is referred to as a template.

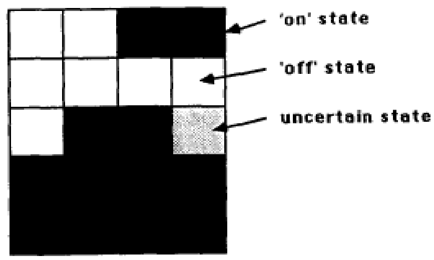

Fig.2. Example of ANN output display

The fuzzy controller is developed based on the optimal control theory. This is capable of obtaining a near optimal fuzzy controller that is characterized by its systematic nature in design. Two fuzzy logic controllers are used in this work. One controller for Area 1,2 and 3, which consists of three thermal plants, and the other controller are designed for Hydro controller [15]. The design steps required for developing the fuzzy controller is as follows:

3.2 Choice of Process State and Control Output

A first step is to choose the correct input signals to the FLC. For this controller the choice of process state variables representing the contents of the rule-antecedent (If-part of a rule) is selected as generator speed deviation (ω) and change in speed deviation (ώ) signal. The control output signals (process input) variable represents the contents of the rule-consequent (then-part of the rule) and denoted by (u).

3.3 Normalization

Normalization performs a scale transformation and it also called input normalization. It maps the physical values of the current process state variables into a normalized universe of discourse. It also maps the normalized value of control output variables into its physical domain (output de-normalization). For this controller, normalization is obtained by dividing each crisp input on the upper boundary value for the associated universe.

3.4 Fuzzification

Fuzzification is the process of making crisp quantity to fuzzy. In many of the quantities that considered being crisp and deterministic are actually not deterministic at all. Fuzzification is related to the vagueness and imprecision in a natural language. It is a subjective valuation, which transforms a measurement into a valuation of a subjective value. Fuzzification plays an important role in dealing with uncertain information, which might be objective or subjective in nature.

3.5 Determination of membership function

The ranges of input and output variables are assigned with linguistic variables. These variables transform the numerical values of the input of the fuzzy controller to fuzzy quantities. These linguistic variables specify the quality of the control. As the number of the linguistic variables increases, the computational time and required memory space are increased. Among all membership functions, triangular membership function and gauss membership function gives good results and easy to implement. So the triangular membership function and gauss membership function are used for simulating the model. The generator speed deviation (ω),change in speed deviation (ώ) and control output are classified into Negative maximum (ω-vemax); Negative medium (ω-vemed); Zero (ω-zero); Positive medium (ω+vemed); Positive maximum (ω+vemax).

3.6 Knowledge Base

The knowledge base of an FLC is comprised of two components, a database and fuzzy control base. The concepts associated with a database are used to characterize fuzzy control rules and a fuzzy data manipulation in an FLC. It should be noted that the correct choice of the membership function of a term set plays an essential rule in the success of an application. A lookup table based on discrete universes defines the output of a controller for all possible combinations of the input signals. A fuzzy system is characterized by a set of linguistic statements. It is in the form of "IF-THEN" rules; these rules are easily implemented by fuzzy conditional statements. In fuzzy logic the collection of fuzzy control rules that are expressed as fuzzy conditional statements forms the rule or the rule set of an FLC.

3.7 Defuzzification

This process is used to convert a fuzzy value back to the actual crisp output value for the final decision-making. The simplest method of defuzzificztion is centroid method. The crisp control output (u) is obtained by

$$u = \frac{\sum_{i=1}^{N} f_i \mu_i}{\sum_{i=1}^{N} \mu_i}$$

3.8 Basic Fuzzy Algorithm

In a fuzzy logic controller, the control action is determined from the evaluation of a set of simple linguistic rules. The development of rule requires a thorough understanding of the process to be controlled,but does not require mathematical model of the system.The internal structure of the fuzzy controlleris shown in fig. 3, Here the error 'e' andchange error 'ce' are used as numericalvariable into linguistic variables ,the following five fuzzy levels or sets are chosen .NB (negative big), NS (negative small), ZE (zero), PS (positive small) and PB (positive big).

The fuzzy controller is characterized as follows;

1. Five fuzzy sets for each input and output.
2. Triangular membership functions for simplicity.
3. Fuzzification using continuous universe of discourse.

4. Implication using mamdani's 'min' operator.
5. Defuzzification using the 'height' method.

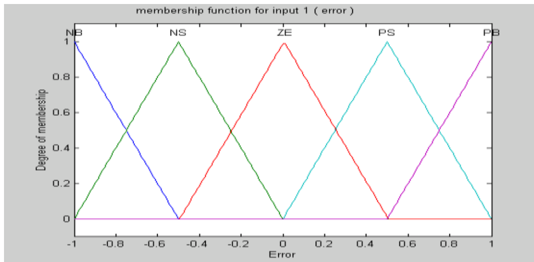

Fig.3. Different Member functions representing different rules

IV NEURO FUZZY LOGIC

Neuro-fuzzy is an intelligent product that combinestwo new forefront technologies [1]-[6], namely,fuzzy logic and neural networks. By properlycombining these technologies, neuro-fuzzy attemptsto solve the problems associated with both fuzzylogic and neural nets. Neuro-fuzzy learns systembehavior by using system input-output data and sodoes not use any mathematical modeling. Afterlearning the system's behavior, neuro-fuzzy automatically generates Fuzzy Rules and membership functions and thus solves the keyproblem of fuzzy logic and reduces the designcycle very significantly. Neuro-fuzzy then verifiesthe solution (generated rules and membershipfunctions). It also optimizes the number of rulesand membership functions. The fuzzy logicsolution developed by neuro-fuzzy solves theimplementation problem associated with neuralnets.Unlike conventional fuzzy logic, neuro-fuzzy usesnew defuzzification, rule inferencing andAntecedent processing algorithms, this provides more reliable and accurate solutions. These newalgorithms are developed based on neural netstructure. Finally, neuro-fuzzy converts theoptimized solution (rules and membershipfunctions) into National's embedded controller'sassembly code. The fuzzy solution fromneuro-fuzzy may also be obtained in standard C code. Fig.3 shows the neuro-fuzzy in block diagramform.

It has 4 major blocks, namely,

1. Neural Netlearning
2. Fuzzy Rules and Membership function generator
3. Fuzzy Rule Verifier & Optimizer and
4. Automatic Code converter.

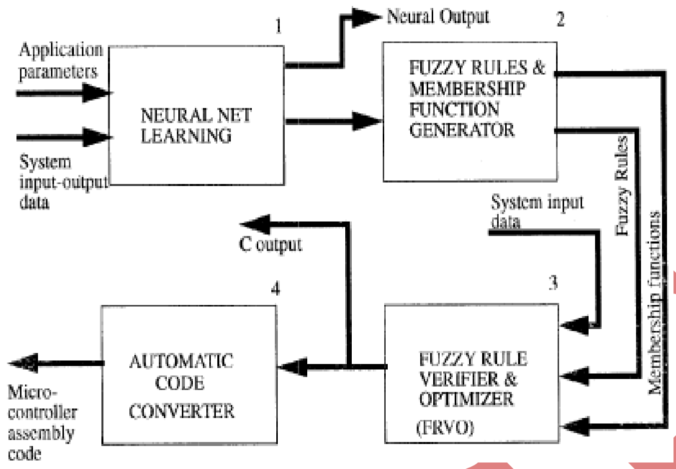

Fig.4. Nero-Fuzzy Combining Neural Networks with Fuzzy Logic

4.1 Neuro-Fuzzy Model for 14 Bus System

The effect of change in real and reactive loads at load buses is investigated on the corresponding total real and reactive power losses in the 14-bus system. The input nodes carried the information about the real and reactive loads at all the buses and their variation for training the Network, while the output node represented the corresponding total line-loss in the system. The results obtained from conventional Newton Raphson method usingIDEAPAS software were used for preparing the training data.

V SIMULATION RESULT

The Real and Reactive power losses in IEEE 14 Bus system shown in calculated using N-R Mehod and capacitor is placed using Neuro-Fuzyyand the results are compared with Partical Swarm Optimization Technique. The program is written in MATLAB. The results show the optimality of the Nero-Fuzzy Method which gives the accurate results Active and Reactive Power losses in 14 Bus system is improved.

The type of the Buses used for the simulation work is as:

1 – Slack Bus

2 – PV Bus

3 – PQ Bus

Table 1show the optimal location of the capacitor placement which is calculated with the help of Neuro Fuzzy System. The comparison of Active and Reactive power improvement by Neuro-Fuzzy with the PSO after compensation has been shown in Table 2. The results show that the Neuro-Fuzzy method is more accurate to calculate the Active and Reactive power losses in the transmission network and also faster compared to Newton Raphson Method.

Table 1 Optimal location of the capacitors

Bus No.	Q_{cnew} (kVAr)
6	0.000000
3	0.000000
11	235.023060
4	214.554041
12	14.018860
14	72.757498
7	0.000000
13	0.000000
8	0.000000
5	134.119311

Table 2 – Active/Reactive Power Losses

Bus No.	Nodal Voltage (p.u.) Without Compensation	Nodal Voltage (p.u.) With Compensation (Neuro-Fuzzy)	Nodal Voltage (p.u.) With Compensation (PSO)
1	1.000000	1.000000	1.000000
2	0.986852	0.990255	0.993641
3	0.979599	0.983161	0.985534
4	0.964937	0.970903	0.967543
5	0.948357	0.958467	0.960267
6	0.933898	0.948207	0.942274
7	0.912757	0.931637	0.921637
8	0.897775	0.920313	0.910043
9	0.882804	0.908916	0.904916
10	0.873136	0.901352	0.900012
11	0.864140	0.894027	0.885439
12	0.855149	0.886686	0.874462
13	0.847202	0.880176	0.875468
14	0.841651	0.875447	0.870021

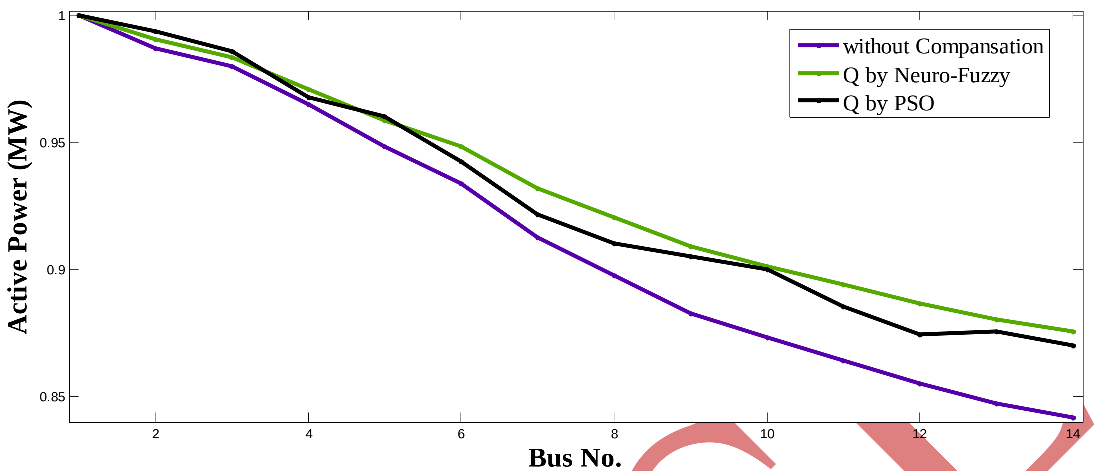

Fig. 5 Comparison Nodal Voltage with and Without compensation and PSO

Table 2 shows the comparison of nodal voltages without compensation to neuro - fuzzy system. The results of neuro- fuzzy system are also compared with existing PSO method of compensation. Figure 5 showing the graphical representation of the same.

VI CONCLUSION

In this paper the study was carried out to explore the applicability of Neuro-Fuzzy System for the direct assessment of losses for 14-bus power-system. There is a slight percentage deviation in the active and reactive power losses. Thus it is concluded that the Neuro-Fuzzy model could give accurate results within nearly no time for any size of power-system. Hence it can be a tool for monitoring the power quality.

REFERENCES

[1]. I.J. Nagrath, and D.P. Kothari, "*Power System Engg.",* Tata McGraw Hill Publication Co. Ltd, 1994.

[2]. J.Arrillaga, and C.P. Arnold, "Computer Modeling of Electric Power Systems", John Wiley & Sons, 1983.

[3]. L.P. Singh, "*Advance Power System Analysis and Dynamics",* 3rd Edition, Eiley Eastern Ltd, 1992.

[4]. J.K. Mandal, and A.K. Sinha, "Application of Artificial Neural Networkfor short Term Load forecasting in Electric Power System" IE(I) Journal EL, Vol. 77, May 1996, pp. 40-43.

[5]. J. Pal et al., "*A Fast Algorithm for Determining the Bus Voltage profileof Power System For Real Time Application"*, IE(I) Journal EL, Vol. 79, May 1998 pp. 1-6.

[6]. J.Kohlbeck, K.Ashenayi, and O.Marcus, "*Application of BackPropagation Neural Network to Load force casting"*, 27th Annual fronties of Power Conference, Stillwater, Oklahoma, USA, 1994, pp. 1-8.

[7]. J. M. Shane, "*An Introduction to Neural Nets*", Journal of Hewlett Packard, February 1992, pp. 62-65.

[8]. K.Y. Lee, Y.T.Cha, and J.H. Park, "*Short Term Load forecasting using An Artificial Neural Network*", IEEE Trans. on Power Systems, Vol-7, No.1, February 1992, pp.124-132.

[9]. B.Dwivedi, "*Status assessment of Power lines using ANN*",a thesis for the degree of Ph.D., R.S.U.2000.

[10] S.Gupta, A.S. Zadgaonkar, "*Application of Artificial Neural Network for Assessment ofReactive Power for Power Quality Improvement"*, National conference on Trends in Electrical Engg. atTegBahadurKhalsa Institute of Engg.and Tech, Chhapinwali(Malout), Punjab, May 28-29, 2004.

[11] S.Gupta, A.S. Zadgaonkar, "*Voltage profile using ANN for Improving Power Quality*", 13th National Power System Conference (NPSC-2004) at IIT Madras Dec27-30.

[12] Y. H.Pao, "*Adaptive Pattern Recognition and Neural Networks*", Addison-Wesley, Reading, MA, 1989.

[13] Z.Ouyang,S. M.Shahidehpour, and S. M.Divakaruni, "*A Generation Scheduling Decision Supported by Neural Networks,*" Proceedings of EPRl Conference on Decision Support Methods for the Electric Power Industry, Cambridge, Massachusetts, May 1990.

[14] C. Wang, Z.Ouyang, S. M.Shahidehpour, N. Deeb, "*Neural Networks in Generation Unit Commitment*," Proceedings of the 52nd Annual Meeting of the American Power Conference, Chicago, Illinois, April 1990.

[15] L. Zadeh et al., "*Fuzzy Theory and Applications''*, Collection of Zadeh's good papers,1986

[16] D.Nauck, F. Klawonn,and R. Kruse, "*Foundations of Neuro-Fuzzy Systems*", John Wiley and Sons, 1997, ISBN: 0471971510.

[17] B. Kosko, "*Neural nets & Fuzzy Systems*", Prentice Hall, 1992

[18] J. S. R. Jang, C. TSun, and EMizutani, "*Neuro-Fuzzy and Soft Computing".* Prentice Hall, 1997. ISBN:0132610663.

[19] E. Khan et al, "*Neufuz: Neural Network Based Fuzzy Logic Design Algorithms*", Proceeding of the FUZZ-IEEE93, Vol. 1, Mar 1993, pp. 647

[20] S. Rahman, "*Neural-Fuzzy in Consumer Appliance Application*", Proceeding of the Fuzzy Logic 93 organized by Computer Design", SanFrancisco, July 1993.