FUZZY LOAD MODELING AND LOAD FLOW STUDY USING RADIAL BASIS FUNCTION (RBF)

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ABSTRACT

In this paper load flow study is carried out by modeling the load using the concepts of Fuzzy Set Theory (FST).The input load patterns are generated by adopting Trapezoidal Membership Function(TMF) for both real and reactive power demands. The NRLF is used to obtain the voltage magnitudes and phase angle of the buses for different loads obtained by the TMF. The RBF neural network is trained to learn the features of the load to estimate the bus bar voltage and angles. The ANN is used to instantly recall the output for an untrained set of inputs without going through the conventional iteration procedure. The RBF's are easy to train and the training time required is observed to be less. The load flow study of that forecasted data is carried out on an IEEE -14 bus test system. The Recall response of RBFN for untrained set of load is close agreement with the standard Newton-Raphson Load Flow (NRLF) algorithm.

Keywords: *Fuzzy set theory, Artificial Neural Network (ANN), load flow study*

1. INTRODUCTION:

It is well known that the purpose of load flow analysis of a power system is to obtain a snap shot solution of a power system for various operating powers on the bus bars[1]. Usually the data required for the solution of load flow algorithm are the specified power injections at buses, magnitude of voltage settings of generators, real power generations, and transformer tap settings and line data. Out of that data, the power injections at the bus bars vary randomly and they form the crisp inputs to the load flow solution. And in many instances they are highly unrealistic. In that juncture, the FST is thought and implemented to be a model to address the uncertainty of occurrence of the load [3]. A trapezoidal membership function is defined for real and reactive power loads. The ANN have been considered to be popular in power system studies due to the fact that a well trained ANN's can instantly recall the output for an untrained set of inputs without going through the laborious iteration procedure .The training data for an ANN can be obtained either from actual experimentation or by well-proved standard algorithms.

In this work the input load patterns are generated by adopting TMF for both real and reactive power demands. The NRLF is used to obtain the voltage magnitudes and phase angle of the buses for different loads obtained by the TMF. The load flow solution thus obtained is used to train the Radial Basis Function (RBF) in MATLAB 7.0 neural networks tool box. The RBF's are easy to train and the training time required is reasonably less [4] . The performance of the RBFN is compared with a standard AC Load flow algorithm for an IEEE-14 bus power system network.

2. FUZZY MODELING :

It is a fact that uncertainty is present in each and every real life problem. Sometimes this uncertainty is neglected to simplify the analysis procedures. It is reported that, through fuzzy sets ,it is possible to model the imprecise knowledge and perception of human beings into meaningful probability distributions in a natural way [5]. The requirement is that, each uncertain variable must be assigned a degree of membership that represents the degree of participation of the parameter under study. The uncertain variables are modeled as intervals in the real axis and the corresponding imaginary axis shows their degree of participation. A fuzzy set $\bar{A}$ in the universe of discourse 'U' can be defined as a set of ordered pairs, where each subset includes some element 'x' and its membership function μ_A. This membership function denoted by μ_A indicates the degree that 'x' belongs to A. This relationship is expressed in a mathematical form in equation

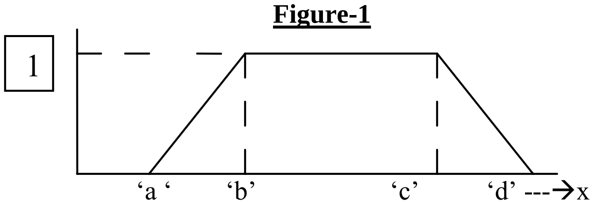
$\bar{A} = \{(x, \mu_A (x))| x \in U\}$ →1

In fuzzy set theory there exist several forms of distribution functions, (eg, triangular, trapezoidal, ramp, exponential etc.) to suit to the need and requirement of the problem. In this paper, the uncertainties in the input parameters are modeled with the help of trapezoidal membership functions. A trapezoidal fuzzy membership function as indicated in **figure 1** is usually expressed by the characteristic points a, b, c, d such that the fuzzy number under study can assumed any value between a and d, but values within the range b and c are most likely to place. All the values within the range b and c have membership value ($\mu_x = 1$) that indicates complete membership for event. However, the values within ranges (a-b) and (c-d) have membership values ($0 \leq \mu_x \leq 1$), which indicates partial membership values.

Any value outside the range of a and d has membership value ($\mu_x = 0$) indicating non membership for parameter. Thus the uncertainty of the parameter 'x' is conveniently characterized by a trapezoidal fuzzy distribution with suitable left right slopes. A specific relationship for the element 'x' and its degree of membership 'μ_x 'for the trapezoidal membership function is presented in equation.

Trapezoid (x, a, b, c, d)
= max (min (x-a/b-a, 1, d-x/d-c), 0) →2

Figure-1



3. RADIAL BASIS FUNCTION NEURAL NETWORKS (RBFN)

4.

Of late RBFN has become increasingly popular because of its structural simplicity and training efficiency[5][6] . The RBFN consists of two fully connected layers namely, "hidden" and "output" layers or neuron as shown in **figure (2).** The input nodes are directly connected to the hidden layers neurons.

The output of the j^{th} "hidden" neuron can be written as

$$H_j = \frac{\Phi (||x - c_j||)}{J} \quad \rightarrow 3$$

Where h_j is the output of j^{th} neuron, Φ is the non-linear radial basis function, x is the input vector, c_j is the neuron's center and J is the center speed parameters.

The non-linearity of the RBFN is due to its transfer function Φ. The most commonly used type of RBF function is Gaussian.

$$H_j = e^{(|| x C_j || 2)} \quad \rightarrow 4$$

The neurons of the output layer have a linear transfer function. It is simply the weighted summation of outputs of all "hidden" neurons connected to that "output" neuron.

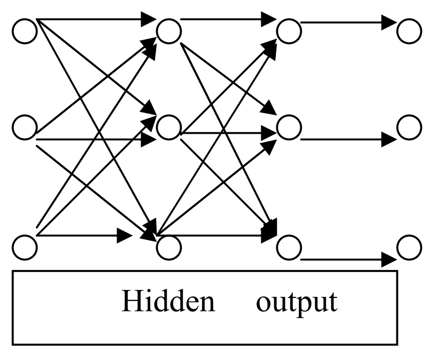
For the k^{th} neuron the output y_k is

$$Y_k = \quad W_{KJ}.h_J$$

Where W_{kj} is the syseptic weight connecting hidden neuron 'j' to the output neuron k and m is the number of hidden layer neurons.

$[P_1 \ldots\ldots P_n]$ input vectors of size [px1];
$[T_m]$ output vectors of size [mx1];
[w] weight matrix of size [mxn]

Figure-2



4. FORMULATION OF RBFN: - A RBFN neural network is created as per the given algorithms given in neural network tool box[6] making use of "newrbe" function. Typically the function has 4 arguments namely input, targets, goal, and spread factor. The syntax used in the MATLAB program for the above said function is

[net, perf]= newrbe (inputs, targets, goal, spread factor)

The "newrbe" function returns neural network properties and performance during the training.

5. FUZZY LOAD FLOW MODEL ALGORITHM:

It is clear from equ.2, that for any value of "x" on real axis the P_L and Q_L can assume any value depending on its degree of membership.

The steps that are followed to obtain the real and reactive fuzzy loads are as follows

Step 1: Read from the table 1 the values a, b, c, d, coordinates.

Step 2: Input (x) vector randomly in the range of 0 to 1

Step 3: Use the equ. (2) and compute P_L (x), Q_L (x)

Step 4: Repeat the Steps 2 and 3 for any other value of (x).

Step 5: Store the P_L and Q_L for varying membership values.

Newton-Raphson power flow algorithm is used to obtain the power flow solution for various load and generator settings for an IEEE – 14[2] bus test system which has 14 buses and 20 lines. Bus1is treated as slack and the buses 2 to 5 are treated as voltage control (PV) buses. Remaining buses 6 to 14 are treated as load (PQ) buses

For each state of P_L and Q_L , the following steps of NR power flow algorithm is followed to obtain the solution.

1. Read line data, bus data P_L (x), Q_L (x) and real power generators at bus (2).
2. Form [Y]bus matrix
3. Compute scheduled bus powers
4. Assume state variables voltage and bus angles (v, δ).
5. Compute calculated bus power Pcal, Qcal using at i^{th} bus.

$$Pcal(i) = \sum |V_i|\,|V_j|\,(Y_{ij})\,\mathrm{Cos}((\theta_{ij}) - (\delta_i) + (\delta_j))$$
$$Qcal(i) = \sum |V_i|\,|V_j|\,(Y_{ij})\,\mathrm{Sin}((\theta_{ij}) - (\delta_i) + (\delta_j))$$

for 'i' = 1 to n and "i" ≠ slack bus and "j" =1 to n

6. Compute bus real and reactive power mismatches ΔP, ΔQ. If mismatches are within the tolerance, the iteration processes is stopped and print the result. Otherwise go to step (7).
7. Compute voltage and bus angle increments.

$$\begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix}^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$$

Where $J_1 = (\partial P/\partial\delta)$, $J_2 = (\partial P/\partial V)$, $J_3 = (\partial Q/\partial\delta)$, $J_4 = (\partial Q/\partial V)$

8. Update the state variables go to step 6.

6. RESULTS AND ANALYSIS:

Many load patterns are generated using the FST and NR algorithm is applied to the selected load patterns.

Out of different load patterns generated, some of the load patterns are randomly selected and the "newrbe" function is applied with the bus real and reactive power injections as "inputs" and the voltage magnitudes and bus angles as the "targets". Also different spread factors have been chosen in the range of 0.1 to 0.9 with an error goal of 0.001.

It is observed that for the spread factor of 0.8, the performance of the neural network is reasonably goal for error goal specified.

The performance of RBFN is shown in figure-3.

The trained neural network has been tested for untrained test data .Few test samples are shown in the Table2. The function mapping of RBFN is also shown in the form of graphs in the figure-4 . It is observed from the graph that the RBFN has successfully the mapped the power injection. Also it is observed from voltage and angle graphs that power flow solution of the entire power system network closely follows.

Table-1

Bus No	Real Power modeling co-ordinates			
	a	**b**	**c**	**d**
2	0.15	0.20	0.25	0.30
3	0.85	0.90	0.95	1.00
4	0.05	0.10	0.15	0.20
5	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00
7	0.40	0.45	0.50	0.55
8	0.01	0.06	0.10	0.15
9	0.20	0.25	0.30	0.35
10	0.02	0.07	0.11	0.16
11	0.01	0.02	0.04	0.05
12	0.03	0.05	0.08	0.10
13	0.05	0.10	0.15	0.20
14	0.08	0.13	0.17	0.22

Bus No	Reactive Power modeling co-ordinates			
	a	b	c	d
2	0.05	0.10	0.15	0.20
3	0.10	0.15	0.90	1.00
4	0.02	0.05	0.09	0.12
5	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00
7	0.01	0.03	0.05	0.07
8	0.00	0.01	0.02	0.03
9	0.10	0.15	0.20	0.25
10	0.03	0.05	0.07	0.09
11	0.00	0.01	0.02	0.03
12	0.00	0.01	0.02	0.03
13	0.04	0.05	0.06	0.07
14	0.03	0.04	0.06	0.07

Table-2

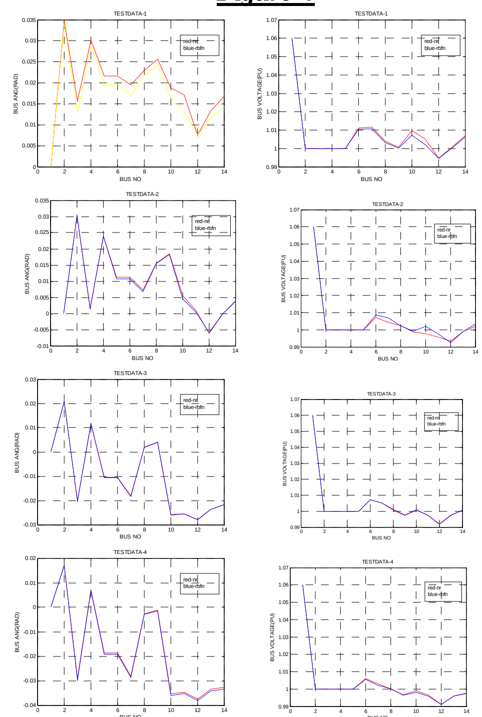
Power	Data 1	Data 2	Data 3	Data 4
PS(2)	0.3855	0.3566	0.2698	0.2264
QS(2)	-0.0079	-0.0238	-0.0714	-0.0953
PS(3)	0.0000	0.0000	0.0000	0.0000
QS(3)	0.0000	0.0000	0.000	0.0000
PS(4)	0.0000	0.0000	0.000	0.0000
QS(4)	0.0000	0.0000	0.000	0.0000
PS(7)	0 .0000	0.0000	0.0000	-0.0236
QS(7)	-0.0042	-0.0125	-0.0374	-0.0498
PS(8)	-0.0127	-0.0380	-0.0760	-0.0760
QS(8)	0.0000	0.0000	-0.0128	-0.0160
PS(9)	0.0000	0.0000	0.0000	0.0000
QS(9)	0.0000	0.0000	0.0000	0.0000
PS(10)	0.0000	-0.180	-0.0900	-0.0900
QS(10)	0.0000	-0.058	0.0000	0.0000
PS(11)	0.0000	-0.0350	-0.0321	-0.0304
QS(11)	0.0000	-0.0180	-0.0165	-0.0156
PS(12)	-0.0610	-0.0610	-0.0610	-0.0610
QS(12)	-0.0027	-0.0080	-0.0160	-0.0160
PS(13)	0 .0000	0.0000	-0.0120	-0.0210
QS(13)	-0.0011	-0.0032	-0.0095	-0.0127
PS(14)	0.0000	0.0000	-0.0091	-0.0182
QS(14)	0.0000	0.0000	-0.0031	-0.0061

In table-2

Ps: Scheduled real power injection in pu at node n and

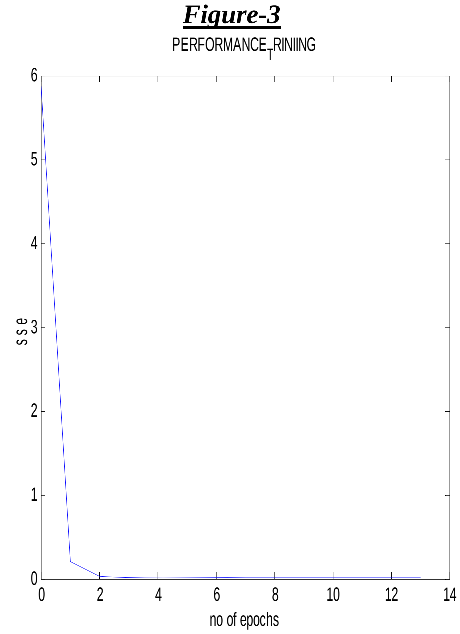
Qs: Scheduled reactive power injection in pu at node n

Figure-4



7. TRAINING PERFORMANCE OF RBFN

Figure-3



8. CONCLUSIONS:

The uncertainty of the load on power system bus bars is successfully modeled by assuming Trapezoidal Member Function (TMF). The load is bound to have variable magnitude and power factors. The NR power flow method is reliable in obtaining the high voltage and low voltage solutions of transmission network. In this an RBF network has been trained to verify the mapping capability of the load features extracted from FST. It is verified that mapping capability of the RBFN network is in close agreement with standard NR power flow algorithm. It is observed from the results presented that RBFN has successfully followed the non-linearity of Bus power injections to obtain the load flow solution. The results presented in this paper confirm that the effectiveness of FST in modeling the uncertainty (load) and the ability of RBFN neural network for power flow solutions.

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