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An ANFIS Approach for Overload Alleviation in Electric Power System

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A power system configuration undergoes frequent changes due to contingencies and/or disturbances. If the power system survives after the disturbance, it will be operating in a new steady state in which one or more transmission lines may be overloaded. A corrective control action must be taken to eliminate such overloads. The most practiced technique for overload alleviation is generator rescheduling and/or load shedding. This paper proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS) based generation reschedule to alleviate transmission line overloads. The system parameters such as overload factor (OF), generation shift sensitivity factor (GSSF) and sensitivity of vulnerability index of generation system (SVIGS) are given to the ANFIS as inputs. The output (ANFISOUT) from the ANFIS gives the quantity of real power to be rescheduled. The effectiveness of the proposed approach has been tested for modified IEEE 30 bus system, 39 bus New England system and modified IEEE 57 bus system in MATLAB environment and their results are compared with fuzzy logic based approach.

Keywords: Adaptive Neuro-Fuzzy; Fuzzy Logic; Generator Rescheduling; Severity Index; Overload Alleviation.

1. Introduction

An electric power system is a complex system, whose operating condition may not remain at a constant value. This necessitates the power system operator be alert to keep the system performance in normal condition. The various contingencies like, large load variations, outage of components (transmission lines, transformers, generators, etc.) are more common. Any of these, may cause overloads and system parameters to exceed the limits thus resulting in an insecure system. For secure operation of power system, the network loading has to be maintained within specified limits. Hence, the operator has to maintain the security level by proper analysis and reschedule the system accordingly.

The possible corrective control actions are shifting generation to redistribute power flows, switching the transmission network, change of effective phase displacement between the input voltage and the output voltage of a transmission line and load shedding [1]. The use of phase shifting transformers, line switching and load shedding leads to additional reserves and interruption of power supply. The real power generation rescheduling is the most widely used control for network overload alleviation. This is due to no need of additional reserves and ease of control.

In [2], the authors' proposed a non linear programming method to eliminate the branch overloads in power systems. The idea of adaptive local optimization was introduced to reschedule the generation. The generators with large sensitivities with respect to eliminating the overloads were included by the use of adaptive local optimization. In [3], the authors' proposed a genetic-algorithm (GA) based OPF algorithm to identify the optimal values of generator active-power output and the angle of the phase-shifting transformer. The phase shifters location was selected based on sensitivity analysis. The line overloads were relieved through rescheduling of generator outputs and adjustment of the phase angle of a phase-shifting transformer. In [4], the authors' proposed alleviation of

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network overload by real power generation rescheduling. The desired proportion of generations for the desired overload relieving was obtained based on relative electrical distance (RED) concept. In [5], the authors' proposed an intelligence technique based on cascade neural network (CNN) to predict and alleviate the overloaded transmission lines through generation rescheduling. In [6], the authors' proposed an optimal sizing and placement of TCSC for congestion management in a power system. Minimization of severity index was taken as objective function. The optimal location of TCSC was done by sensitivity analysis and sizing of TCSC by using genetic algorithm. In [7], the authors' proposed an optimal location of interline power flow controller (IPFC) in a power system network using artificial bee colony algorithm (ABC). Minimization of line loss, economic dispatch of generators, improve power flow and reduction in the overall system cost which includes the cost of active power generation and the installation cost of IPFC were also considered for obtaining the optimal location.

In [8], the authors' proposed a new zonal/cluster-based overload management approach. The zones were formed based on lines real and reactive power flow sensitivity indexes. The generators in the most sensitive zones were identified for rescheduling their real power output for overload management. In [9], the authors' proposed a cost-efficient overload management method for smooth and non-smooth cost functions using multi-objective particle swarm optimization (MOPSO) method. The overloads in a transmission network were alleviated by generation rescheduling and/or load shedding of participating generators and loads. In [10], the authors' proposed to remove the overloaded lines by generation rescheduling. The optimal rescheduling of active powers of generators was selected based on the generator sensitivity to the congested line. The fuzzy adaptive bacterial foraging algorithm (FABF) was used to optimize the congestion cost. In [11], the authors' proposed an important issue of transmission system congestion management in a pool electricity market environment with the consideration of voltage stability as loadability limit. The optimal generators rescheduling had been obtained for three bid block structure to ensure static security and voltage stability limits. The congestion cost of each hour of day had been calculated without and with FACTS controllers and compared to the case without FACTS controllers. The comparison was made on total congestion cost of day, real power loss, reactive power loss and loadability factor. Among the considered FACTS devices, UPFC performed well to improve the loadability margin with minimum congestion cost when compared to STATCOM and SSSC. In [12], the authors' proposed graphical user interface (GUI) based on a genetic algorithm to determine the optimal location and sizing parameters of multi type FACTS devices for maximization of power system loadability in a transmission network. In [13], the authors' proposed a static security enhancement through optimal utilization of thyristor-controlled series capacitors (TCSC). The branches ranking in the system was based on determination of single contingency sensitivity (SCS) index which helped to decide the best locations for the TCSCs. The objective of the optimization problem was to eliminate or minimize line overloads as well as the unwanted loop flows under single contingencies. In [14], the authors' proposed a fuzzy logic based approach to alleviate the network overloads by generation rescheduling. The generation shift sensitivity factor (GSSF) was used to recommend the changes in generation. In [15], the authors' proposed alleviation of line overloads by real power generation rescheduling using fuzzy logic. The vulnerability index (VI) and its sensitivity were combined with the GSSF method to enhance the safety margins.

This paper proposes a new method for calculating amount of generation rescheduling based on adaptive neuro-fuzzy inference system.

The organization of the paper is as follows: Section 2 presents ANFIS architecture. Section 3 presents modeling of ANFIS. In section 4 the algorithm of proposed approach in solving the network overload alleviation is presented. The simulation results for different contingency cases in modified IEEE 30 bus system, 39 bus New England system and modified IEEE 57 bus system are presented in section 5. Finally, conclusions are given in Section 6.

2. ANFIS Architecture

The design objective of the fuzzy controller is to learn and achieve good performance in the presence of disturbances and uncertainties. The design of membership functions is done by ANFIS batch learning technique, which amounts to tune a fuzzy inference system with back propagation algorithm based on a collection of input-output data pairs.

Generally, ANFIS is a multilayer feed forward network in which each node performs a particular function (node function) on incoming signals. For simplicity, consider two inputs ' x ' and 'y ' and one output ' z '. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno type [16].

Rule 1: IF x is A1 and y is B1 THEN $f1 = P1x + Q1y + R1$

Rule 2: IF x is A2 and y is B2 THEN $f2 = P2x + Q2y + R2$ (1)

The ANFIS architecture shown in figure 1 is a five layer feed forward network as follows [17].

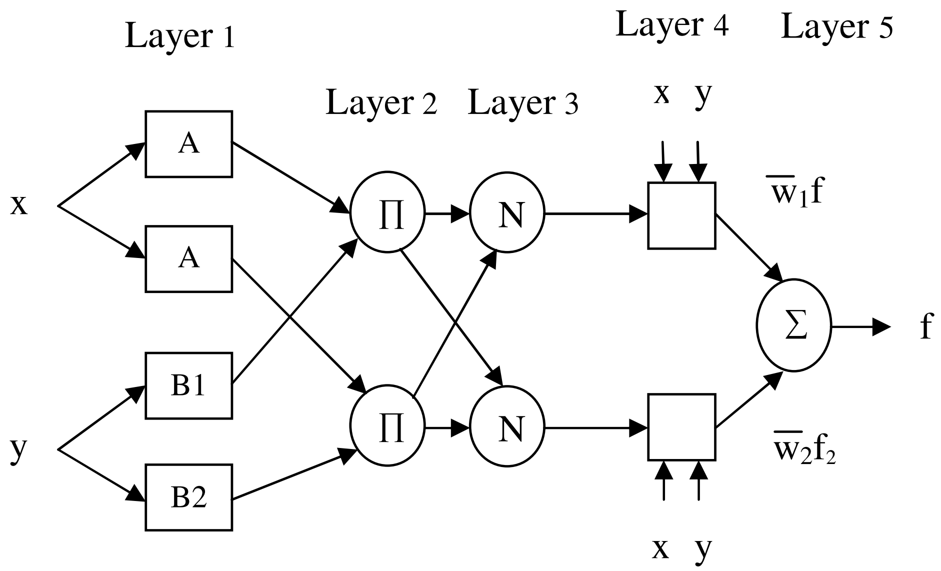

Fig.1 ANFIS Architecture

Layer 1: Every node in this layer is a square node with a node function (the membership value of the premise part)

$$O_i^1 = \mu A_i(x) \tag{2}$$

where, x is the input to the node i, and A_i is the linguistic label associated with this node function.

Layer 2: Every node in this layer is a circle node labeled Π which multiplies the incoming signals. Each node output represents the firing strength of a rule.

$$O_i^2 = \mu A_i(x)\mu B_i(x), \text{ where, } i = 1:2 \tag{3}$$

Layer 3: Every node in this layer is a circle node labeled N (normalization). The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all firing strengths.

$$O_i^3 = \overline{W_i} = \frac{W_i}{W_1 + W_2}, \text{ where, } i = 1:2 \tag{4}$$

Layer 4: Every node in this layer is a square node with a node function.

$$O_i^4 = \overline{W_i} f_i = \overline{W_i}(P_i x + Q_i y + R_i), \text{ where, } i = 1:2 \tag{5}$$

Layer 5: The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals

$$O_i^5 = \text{System Output, where, } i = 1:2 \tag{6}$$

Equation (6) represents the overall output of the ANFIS, which is functionally equivalent to the fuzzy system in (1).

3. Modeling of ANFIS

The ANFIS model is developed in MATLAB environment and FIS editor window of ANFIS is shown in figure 2.

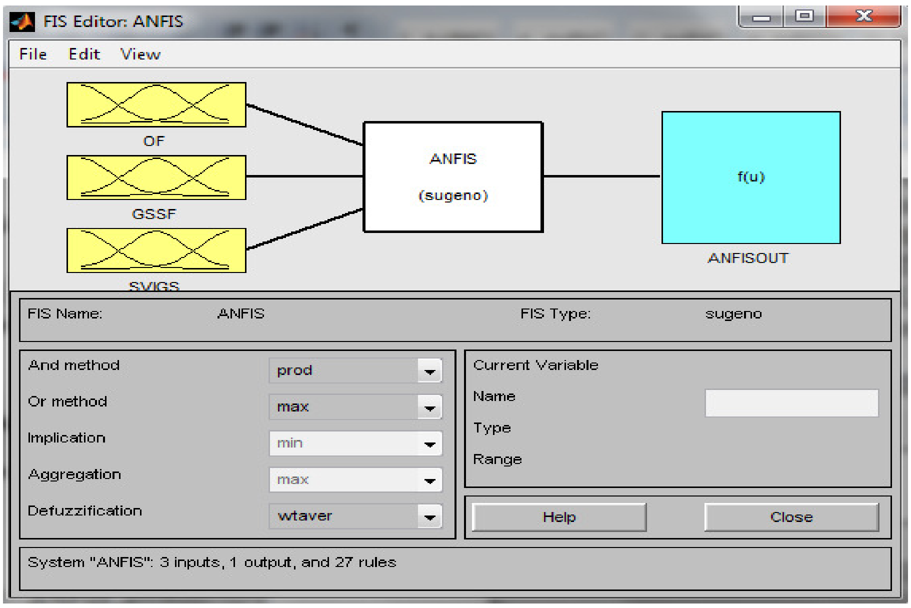

Fig.2 FIS Editor Window of ANFIS

The inputs of ANFIS are OF, GSSF and SVIGS. The output (ANFISOUT) obtained from ANFIS gives the quantity of real power to be rescheduled.

3.1. Test Systems, training and testing data

Three test systems are considered for simulation studies viz. Modified IEEE 30 bus system, 39 bus New England system and modified IEEE 57 bus system. In modified IEEE 30 bus system, 1100 input and output pairs are generated for various contingencies under base case and increased loading using fuzzy logic based approach. Out of these input and output pairs, 870 input and output pairs are selected arbitrarily for training and remaining data are used for testing. In 39 bus New England system, 1400 input and output pairs are generated for various contingencies under base case and increased loading using fuzzy logic based approach. Out of these input and output pairs, 1116 input and output pairs are selected arbitrarily for training and remaining data are used for testing. In modified IEEE 57 bus system, 1900 input and output pairs are generated for various contingencies under base case and increased loading using fuzzy logic based approach. Out of these input and output pairs, 1517 input and output pairs are selected arbitrarily for training and remaining data are used for testing. Figures 3, 4 and 5 illustrate the membership function of input variables.

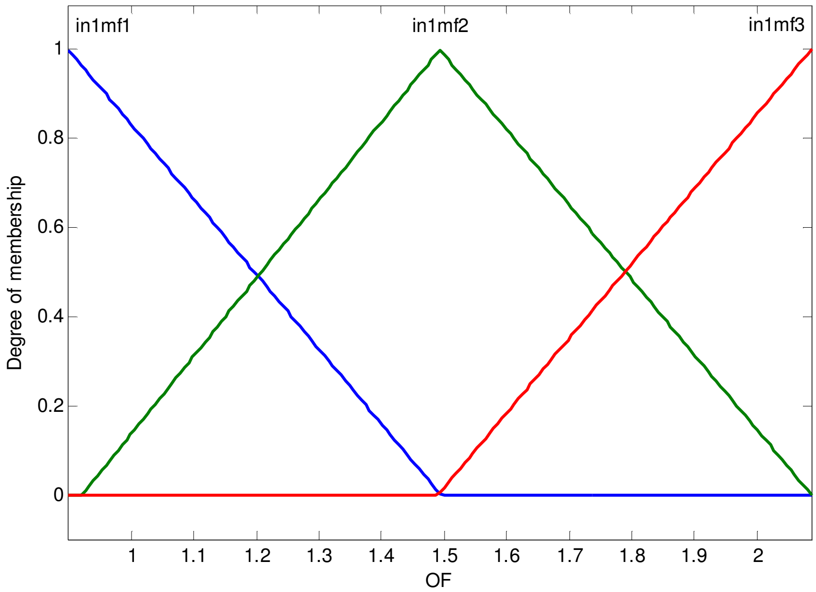

Fig.3 Membership Function of Input Variable-OF

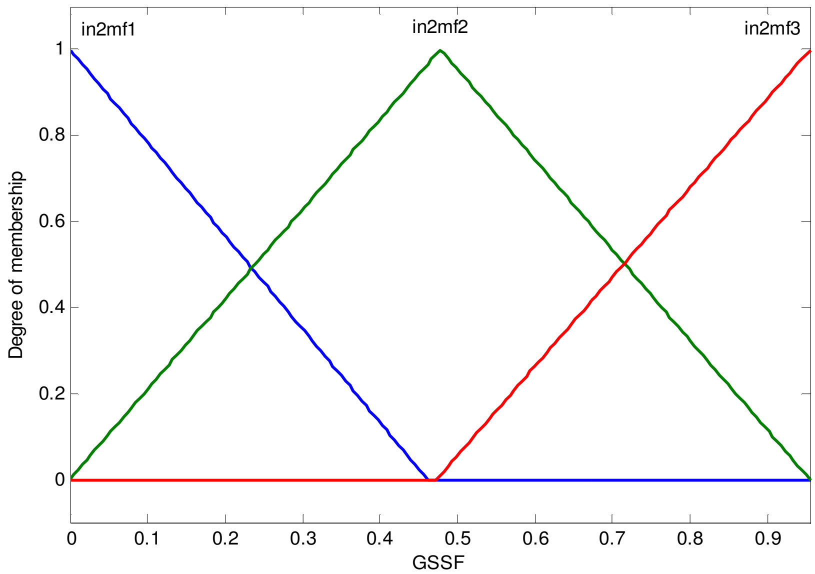

Fig.4 Membership Function of Input Variable-GSSF

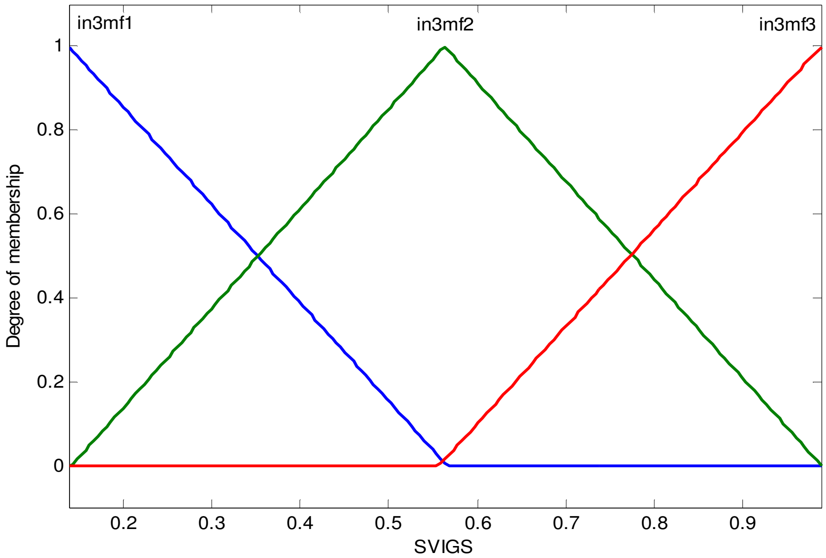

Fig.5 Membership Function of Input Variable-SVIGS

3.2. Inputs of Adaptive Neuro Fuzzy Inference System

The first input of the adaptive neuro fuzzy inference system (ANFIS) is the overload factor [18] as follows:

$$OF_l = \frac{S_l}{S_l^{\max}} \tag{7}$$

where, S_l Flow in line l in MVA, $S_l^{\max}$ Rating of the line l in MVA.

The second input is the GSSF [18] which gives the change in line flow for a given change in generation at a generator bus. First, a base case load flow is performed and the line flows (S_l^o) are computed. Then, every generator is disturbed by a small amount (ΔP_{gi}) one at a time and the line flows are recalculated (S_l^{new}). The ratio of the change in line flow to the change in generation gives the GSSF of lines for that particular generator as follows:

$$GSSF_l = \frac{(S_l^{new} - S_l^o)}{\Delta P_{gi}} \tag{8}$$

This process is repeated for all generators yielding a matrix (GSSF matrix) of dimension $(tl \times g)$.

where, tl is the number of transmission lines and g is the number of generators in the system.

The last input is the sensitivity of vulnerability index of generation system, SVIGS [18] as follows:

$$SVIGS_i = \frac{P_{gi}}{P^2{}_{gi,\max}.SVIGS_{\max}} with, \tag{9}$$

$$SVIGS_{\max} = \frac{1}{\min(P_{g\max,1}, P_{g\max,2}, \cdots\cdots\cdots, P_{g\max,i})}$$

3.3. Outputs of Adaptive Neuro Fuzzy Inference System

The output obtained from ANFIS has to be converted into the change in generation required for each generator. The amount of generation to be increased or decreased is calculated by the following relations [18].

$$\Delta P_i^{inc} = \min(\Delta P^{\max, i}, W_{li} \frac{(OF_l - 0.9) S_l^{\max}}{GSSF_i} ANFISOUT) \tag{10}$$

$$\Delta P_i^{dec} = \min(\Delta P^{\min, i}, W_{li} \frac{(OF_l - 0.9) S_l^{\max}}{GSSF_i} ANFISOUT) \tag{11}$$

where, W_{li} = the weighting factor = $OF_l \ X \ GSSF_i \ X \ SVIGS_i$

$$\Delta P^{\max,i} = P_{gi,\max} - P_{g,i} \quad \& \quad \Delta P^{\min,i} = P_{gi} - P_{gi,\min} \tag{12}$$

The proposed ANFIS has 78 nodes, 108 linear parameters, 27 nonlinear parameters and 27 fuzzy rules.

3.4. Contingency Ranking

The line overloading in a power system is created by N-1 contingency and/or increasing in demand. In order to select the most critical line a severity index (SI) is used.
The severity index expresses the stress on the power system in the post contingency period [19].

$$SI_l = \sum_{l \in Lo}^{n} \left(\frac{s_l}{s_l^{\max}} \right)^{2m} \tag{13}$$

where, S_l = flow in line l (MVA); $s_l^{\max}$ = rating of the line l (MVA); L_o = set of overloaded lines; and m=integer exponent =1(Assumed).
The line flows in (13) are obtained from Newton–Raphson load-flow calculations. While using the above severity index for security assessment, only the overloaded lines are considered to avoid masking effects. The SI values are calculated for all possible N-1 contingency in a system. The maximum value of SI corresponds to a contingency is the most critical line.

4. Algorithm of the Proposed ANFIS Approach

The step by step procedure of proposed ANFIS algorithm is given below.
Step 1: Compute the GSSF values for the given test system using equation (8) and form the matrix.
Step 2: Create N-1 contingency, run NR power flow and compute SI using equation (13).
Step 3: Rank the lines based on SI.
Step 4: Create the line outage in most severe line.
Step 5: Run NR power flow and compute OF.
Step 6: Check overloaded lines, if overloaded, then identifies the most overloaded line from them, otherwise stop the process.
Step 7: Take the GSSF values corresponding to the most overloaded line.
Step 8: Separate GSSF values into two lists.
(a) GSSF<0, the generation should be increased (GI).

(b) GSSF>0, the generation should be decreased (GD).
Step 9: Calculate SVIGS values using equation (9) and form the matrix.
Step 10: Determine ANFISOUT using OF, GSSF and SVIGS.
Step 11: Calculate the amount of generation increase and decrease using equations (10) and (11) using ANFISOUT.
Step 12: Update the generation values and go to step 5.
Step 13: The same procedure is repeated for different contingency cases.
The above procedure is illustrated in figure 6.

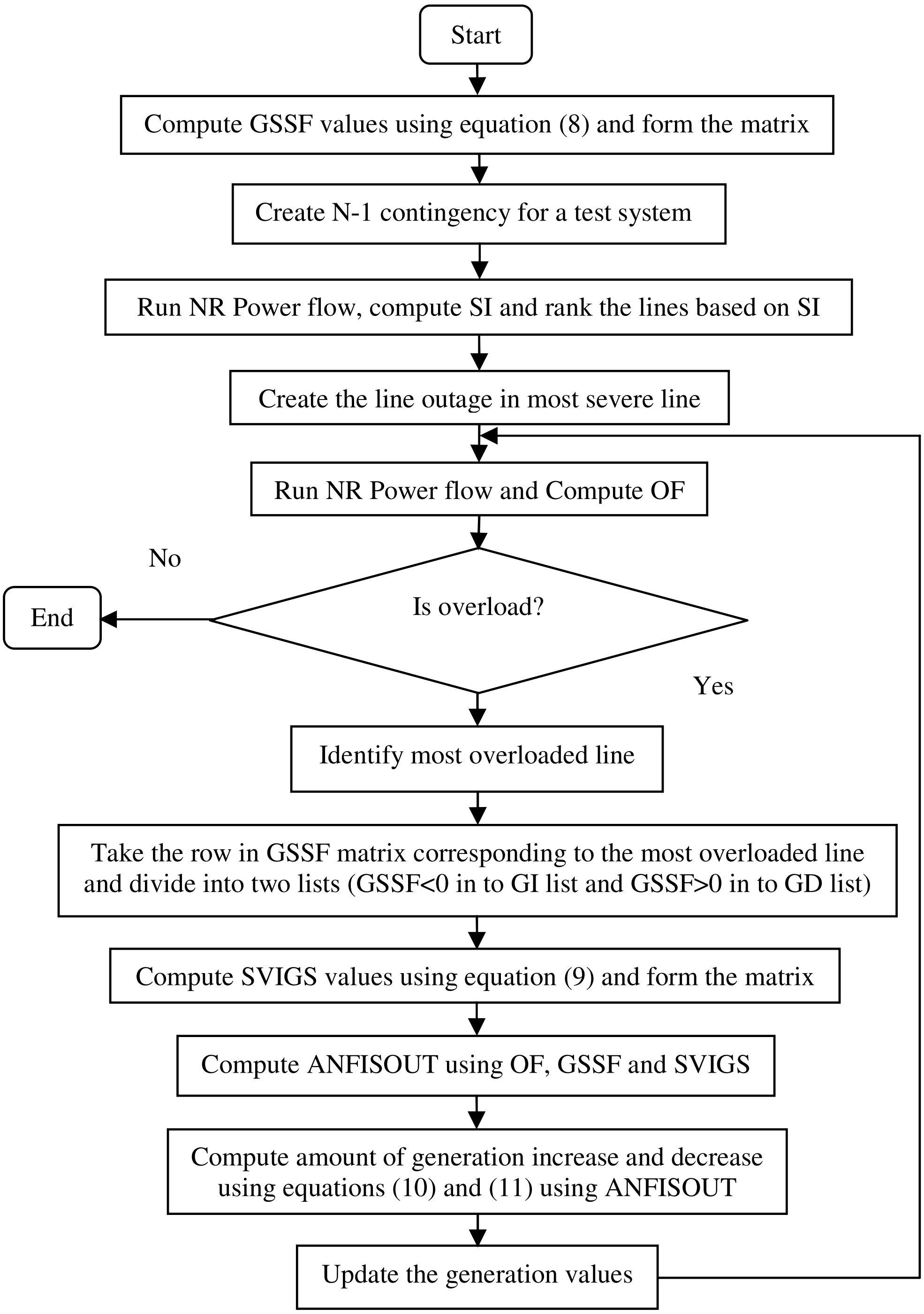

Fig.6 Flow chart of the proposed ANFIS Approach

5. Simulation Results

An adaptive neuro fuzzy based generation redispatch approach is implemented under MATLAB environment. The power flow is obtained using MATPOWER [20]. The transmission line limits for IEEE 30 bus is taken from [21], 39 bus New England system is from [22] and IEEE 57 bus system is from [23].

5.1. Overload Alleviation in modified IEEE 30 Bus System

5.1.1. Case A: Line 4-6 outage

In standard IEEE 30 bus system, the active power generation values of generator bus numbers 5, 8, 11 & 13 are modified as 1, 4, 2 & 3 MW respectively instead 0. The proposed adaptive neuro fuzzy based generation redispatch approach is applied to alleviate transmission line overloads in modified IEEE 30 bus system. Contingency ranking is carried out under base load conditions to identify the harmful contingencies. It is found that line outage 4-6 is one of the severe contingencies. As a consequence of line 4-6 outage, lines 1-2 & 2-6 get overloaded. The overloaded line details after contingency (AC) is shown in table 1. The ANFIS sample output of 1st iteration is shown in table 2. The generation dispatch suggested by both Fuzzy and ANFIS based approaches for overload alleviation is shown in table 3. The changes in generation suggested by both Fuzzy and ANFIS based approaches are shown in figure 7. The overloaded line details after rescheduling is shown in table 4.

Table 1: Overloaded line details after contingency

Outage line	Overloaded lines	Power Flow (MVA)	Line flow limit (MVA)	OF	Power Loss (MW)
4-6	1-2	191.7801	130	1.4752	19.36
	2-6	93.8844	65	1.4444	

Table 2: ANFIS output for 1st Iteration

Generator Bus Number	OF	GSSF	SVIGS	FISOUT	ANFISOUT
2	1.4752	0.9029	0.2041	1.5000	1.4612
5	1.4752	0.8762	0.0100	1.5000	1.4962
8	1.4752	0.7490	0.0400	1.5000	1.5155
11	1.4752	0.7378	0.0200	1.5000	1.4742
13	1.4752	0.6997	0.0300	1.5000	1.4862

Table 3: Generation dispatch suggested by Fuzzy and ANFIS

Generator Bus Number	AC	Fuzzy	ANFIS	Changes in Generation (MW)	
	Generated Real Power (MW)			Fuzzy	ANFIS
1	252.77	155.59	155.92	-97.18	-96.85
2	40.00	50.21	50.56	+10.21	+10.56
5	1	7.11	7.19	+6.11	+6.19
8	4	35.68	36.63	+31.68	+32.63
11	2	17.84	17.30	+15.84	+15.30
13	3	26.76	25.59	+23.76	+22.59

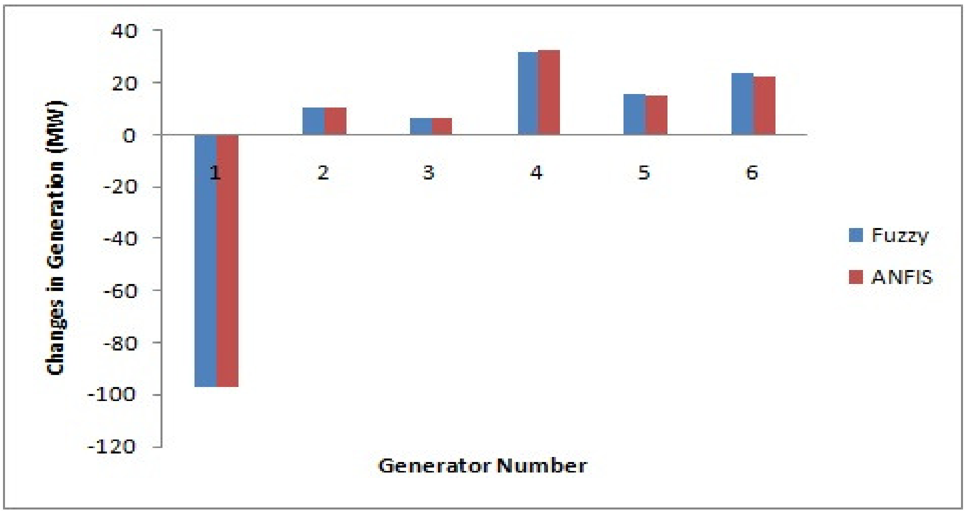

Fig.7 Changes in generation

Table 4: Overloaded line details after rescheduling

Approach	Overloaded lines	Power Flow (MVA)	OF	Power Loss (MW)	SI	Generation Cost ($/h)	No. of iteration
Fuzzy	1-2 2-6	117.0063 58.5032	0.9000 0.9000	9.79	0	830.49	31
ANFIS	1-2 2-6	117.0056 58.5028	0.9000 0.9000	9.78	0	829.40	30

In the considered outage case, both fuzzy and ANFIS approaches relieved all the overloaded lines by 31 (15.5 Seconds) and 30 (15 Seconds) iterations respectively. Among the two overloaded lines, the OF of most overloaded line 1-2 is 1.4752 and that after rescheduling is reduced to 0.9000 and 0.9000 using fuzzy and ANFIS approaches respectively. Similarly, the power loss is reduced from 19.36 MW to 9.79 and 9.78 and also the severity index is reduced to zero from 4.26. From table 4, it is clear that ANFIS approach to generation rescheduling is well proving its ability to remove the overloaded lines with minimum number of iterations, minimum transmission loss and minimum rescheduling cost of 829.40 $/h, when compared to fuzzy logic based approach.

5.2. Overload Alleviation in 39 Bus New England System

5.2.1. Case B: Line 6-11 outage

In this case, contingency ranking is carried out under base-load conditions to identify the harmful contingencies. It is found that line outage 6-11 is one of the severe contingencies. As a consequence of line 6-11outage, lines 4-14, 10-13 and 13-14 get overloaded. The Adaptive neuro fuzzy based generation redispatch approach is applied to alleviate the line overloads. The overloaded line details after contingency is shown in table 5. The ANFIS sample output of 1st iteration is shown in table 6. The generation dispatch suggested by both Fuzzy and ANFIS based approaches for overload alleviation is shown in table 7. The changes in generation suggested by both Fuzzy and ANFIS based approaches are shown in figure 8. The overloaded line details after rescheduling is shown in table 8.

Table 5: Overloaded line details after contingency

Outage line	Overloaded lines	Power Flow (MVA)	Line flow limit (MVA)	OF	Power Loss (MW)	SI
6-11	4-14	528.8190	500	1.0576	48.33	3.34
	10-13	621.1195	600	1.0352		
	13-14	640.1029	600	1.0668		

Table 6 : ANFIS sample output for 1st Iteration

Generator Bus Number	OF	GSSF	SVIGS	FISOUT	ANFISOUT
30	1.0668	0.2881	0.7143	0.5319	0.5105
32	1.0668	0.2392	0.4044	0.9398	0.9464
33	1.0668	0.3734	0.4128	1.0587	1.0277
34	1.0668	0.3742	0.4810	1.0128	0.9848
35	1.0668	0.3764	0.4044	1.0644	1.0356
36	1.0668	0.3747	0.4500	1.0337	1.0029
37	1.0668	0.2873	0.4614	0.9903	0.9404
38	1.0668	0.3103	0.3359	1.1106	1.0542
39	1.0668	0.1626	0.2893	0.9222	0.9759

Table 7: Generation dispatch suggested by Fuzzy and ANFIS

Generator Bus Number	AC	Fuzzy	ANFIS	Changes in Generation (MW)	
	Generated Real Power (MW)			Fuzzy	ANFIS
30	250.00	350.00	341.65	+100	+91.65
31	682.56	1167.52	1094.40	+484.96	+411.84
32	650.00	424.73	464.91	-225.27	-185.09
33	632.00	510.65	529.01	-121.35	-102.99
34	508.00	410.69	363.46	-97.31	-144.54
35	650.00	525.70	545.35	-124.30	-104.65
36	560.00	448.98	465.66	-111.02	-94.34
37	540.00	623.05	624.10	+83.05	+84.10
38	830.00	740.95	775.32	-89.05	-54.68
39	1000.00	1088.10	1088.00	+88.10	+88.00

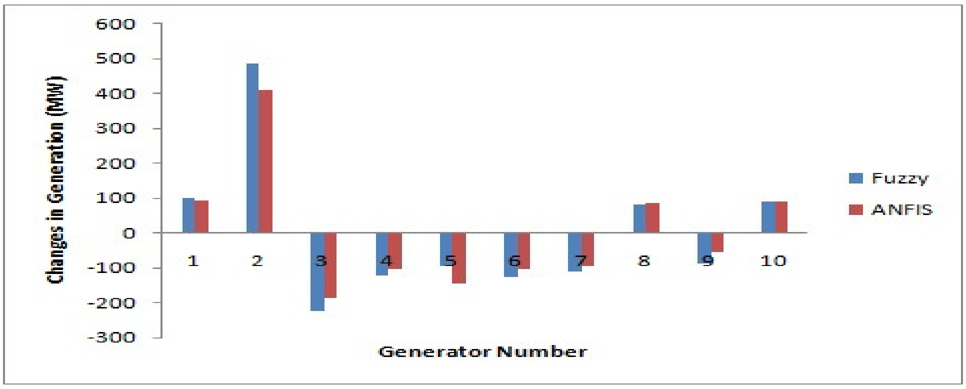

Fig.8 Changes in generation

Table 8: Overloaded line details after rescheduling

Approach	Overloaded lines	Power Flow (MVA)	OF	Power Loss (MW)	SI	Generation Cost ($/h)	No. of iteration
Fuzzy	4-14	191.6	0.3831	36.19	0	48834	32
	10-13	409.5	0.6825				
	13-14	417	0.6951				
ANFIS	4-14	223.8	0.4475	36.67	0	48201	30
	10-13	446.6	0.7443				
	13-14	456.6	0.7609				

In the considered outage case, both fuzzy logic and ANFIS approaches relieved all the overloaded lines by 32 (17.6 Seconds) and 30 (16.5 Seconds) iterations respectively. Among the the overloaded lines, the OF of most overloaded line 13-14 is 1.0668 and that after rescheduling is reduced to 0.6951 and 0.7609 using fuzzy and ANFIS approaches respectively. Similarly, the power loss is reduced from 48.33 MW to 36.19 and 36.67 and also the severity index is reduced to zero from 3.34. From table 8, it is clear that ANFIS approach to generation rescheduling is well proving its ability to remove the overloaded lines with minimum number of iterations and minimum rescheduling cost of 48201 $/h, when compared to fuzzy logic based approach.

5. 3. Overload Alleviation in modified IEEE 57 Bus System

5.3.1. Case C: Transformer outage

In standard IEEE 57 bus system, the active power generation values of generator bus numbers 2, 6 & 9 are modified as 1, 1 & 1 MW respectively instead 0. The proposed adaptive neuro fuzzy based generation redispatch approach is applied to alleviate transmission line overloads in modified IEEE 57 bus system. In this case, an outage is created on transformer connected between the buses 15 and 45 along with increase in real and reactive power of system load by 20%. As a consequence of outage, line 13-15 gets overloaded. The overloaded line details after contingency is shown in table 9. The ANFIS sample output of 1st iteration is shown in table 10.

Table 9: Overloaded line details after contingency

Outage line	Overloaded lines	Power Flow (MVA)	Line flow limit (MVA)	OF	Power Loss (MW)	SI
15-45	13-15	101.8779	100	1.0188	64.02	1.07

Table 10 : ANFIS sample output for 1st Iteration

Generator Bus Number	OF	GSSF	SVIGS	FISOUT	ANFISOUT
2	1.0188	0.0074	0.0100	0.5000	0.6127
3	1.0188	0.0338	0.2041	0.5000	0.7386
6	1.0188	0.0907	0.0100	0.5000	0.6129
8	1.0188	0.1648	0.1488	0.8240	0.6889
9	1.0188	0.2146	0.0100	1.0000	1.0095
12	1.0188	0.2138	0.1844	1.0000	0.8452

The generation dispatch suggested by both Fuzzy and ANFIS based approaches for overload management is shown in table 11. The changes in generation suggested by both Fuzzy and ANFIS based approaches are shown in figure 9. The overloaded line details after rescheduling is shown in table 12.

Table 11: Generation dispatch suggested by Fuzzy and ANFIS

Generator Bus Number	AC	Fuzzy	ANFIS	Changes in Generation (MW)	
	Generated Real Power (MW)			Fuzzy	ANFIS
1	761.98	710.08	709.96	-51.90	-52.02
2	1	0.47	0.58	-0.53	-0.42
3	40	27.43	27.61	-12.57	-12.39
6	1	3.73	3.69	+2.73	+2.69
8	450	471.98	471.04	+21.98	+21.04
9	1	4.35	4.98	+3.35	+3.98
12	310	338.94	339.10	+28.94	+29.10

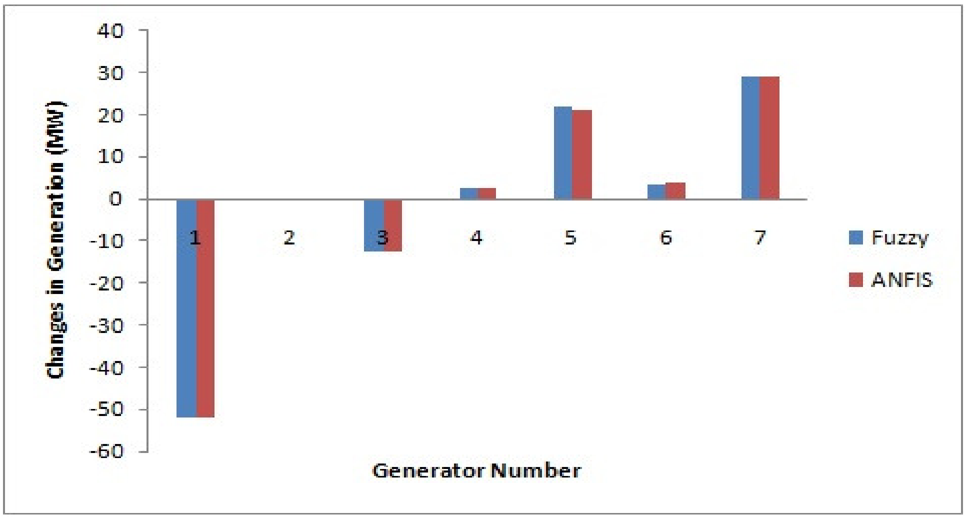

Fig.9 Changes in generation

Table 12: Overloaded line details after rescheduling

Approach	Overloaded lines	Power Flow (MVA)	OF	Power Loss (MW)	SI	Generation Cost ($/h)	No. of iteration
Fuzzy	13-15	90.0049	0.9000	56.02	0	79272	115
ANFIS	13-15	90.0045	0.9000	56.00	0	79259	109

In the considered outage case, both fuzzy and ANFIS approaches relieved the overloaded line 13-15 by 115 (65.68 Seconds) iterations and 109 (62.25 Seconds) iterations respectively. The power loss is reduced from 64.02 MW to 56.02 and 56.00 and also the severity index is reduced to zero from 1.073. From table 12, it is clear that ANFIS approach to generation rescheduling is well proving its ability to remove the overloaded line with minimum number of iterations, minimum transmission loss and minimum rescheduling cost of 79259 $/h when compared to fuzzy logic based approach.

6. Conclusion

An Adaptive neuro fuzzy based generation redispatch approach has been proposed and developed for alleviating network overloads. N-1 contingency analysis is carried out to identify the most severe lines and those lines are selected for outage. Line overloads due to unexpected line outage with and without 20% increase in load cases are considered. The line overloads are relieved through rescheduling of generators with minimum shifts in real power generation from initial values, minimum severity index as well as overload factors. Numerical results on three test systems namely modified IEEE 30 bus, 39 bus New England and modified IEEE 57 bus systems are presented with illustration and their results are compared with fuzzy logic based approach. The proposed approach has been tested for all possible line contingencies in all the three systems. However, only three cases have been presented namely Case A for modified IEEE 30 bus system, Case B for 39 bus New England system and Case C for modified IEEE 57 bus system. In all the three cases, the proposed ANFIS approach is well proving its ability to remove the overloaded lines with a minimum number of iterations and minimum rescheduling cost when compared to fuzzy logic based approach. Also in many cases, ANFIS approach takes less number of iterations. Thus, the developed ANFIS based overload alleviation model is simple and robust.

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