Application of Neural Networks to Secure Scenario Based OPF of Power Systems Considering Transient Stability Criterion

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Abstract: In this paper, a scenario based optimal power flow (OPF) is presented considering economic (operation cost minimization) and security objective functions. Security objective functions include both reliability and system transient stability improvement. Energy not supplied (ENS) cost is considered as the criterion for system reliability and critical clearing time (CCT) is considered as the criterion for power system dynamic stability. In order to reduce the computational burden of the proposed method, off-line training of neural network is used to determine CCT based on the system operating point. For this purpose, CCT parameter is calculated in Dig silent Software environment for various operating points of system and a data set is obtained to train neural network. In the proposed method, it is tried to improve dynamic stability of system, as well as decreasing the operation cost in post contingency state through optimal load shedding and generation rescheduling. Genetic algorithm (GA) is used as the optimization tool. The proposed framework is tested on IEEE 39-bus test system and results show efficiency of the proposed method.

Index Terms; Transient stability, Critical clearing time, Dig silent, Neural network, Genetic algorithm

1. Introduction

The dynamic aspect of power system has a direct relation with power system operation in a way that by increasing interactions between regions, power system stability seems more significant. In other words, balance between generating units for supporting predicted load, considering its economic aspect, makes some limitations for the power system. These behaviors highlight the importance of power system dynamic for stabilizing system. Consequently, power system operator should regard dynamic stability of system as well as its economic aspect [1-2]. In contingency condition such as generator outage or an outage in network, the first and the most important concern is maintaining the transient stability of the system. For this purpose, generation rescheduling and then load shedding are carried out. Rescheduling of load distribution and generation are among corrective measures in post contingency state.

A lot of researches have been done in the area of stochastic OPF and unit commitment. [3] presents an OPF in contingency conditions considering security constraints. In [4], the voltage stability is studied in post contingency state considering the generator and line outage. Besides, a new method of marginal calculation for determining voltage stability is proposed in [4]. In [5] load redistribution is used for voltage stability in contingency condition, so that the point which suffers from severe voltage fall can access more reactive power. [6] calculates maximum power that can be added to lines power flow considering CCT as a constraint. In this reference CCT is obtained by energy function method. [7] considers calculating CCT using neural network from dynamic point of view. [8] presents a stochastic framework which may influence system operation from dynamic stability point of view. Besides stability indices are categorized and investigated using neural networks in this reference. Load redistribution is used in [9] to increase the transient stability in market framework. In [10] a day ahead market clearing is

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presented considering dynamic security constraint. [11] proposes a load shedding method with the purpose of social welfare maximization.

In this paper, it is tried to help making decision in the contingency condition, so that the decision is made based on reality and present situation of network. As a result, a criterion of network needs to be available to inform the situation of the network in contingency condition. In this paper, critical clearing time is used as an index of network dynamic security. After load shedding and generation rescheduling, the system stability is analyzed. Generation and load dispatches are changed until desired transient stability is obtained, while reducing operation cost. In other words, an authentic and rational criterion is obtained to assess network status. For this purpose CCT is used as a criterion of system status assessment. In the proposed structure, transient stability is increased in the contingency condition through optimal power flow. The neural network which has been trained offline is employed to calculate CCT based on operating point of the system. For maintaining the system stability in contingency condition, genetic algorithm (GA) is used to determine optimal load shedding and generation rescheduling to minimize the operation cost and ENS cost.

2. Problem formulation

In this study generator outage is considered as the uncertainty source. In contingency condition, corrective measures need to be applied to maintain the system security. Optimal load shedding and generation rescheduling are the corrective measures in the proposed framework. CCT is used as an index of system transient stability.

A. Objective Functions

Operation Cost: Operation cost (OC) of units is considered as the first objective function, as:

$$F_1 = \min\left[OC = \sum_{i=1}^{n} \alpha_i P_i^2 + \beta_i P_i + \gamma_i \right] \tag{1}$$

where α_i, β_i and γ_i are coefficients of generation cost, $p_i$is generating power of i^{th} unit and n is the number of generating units.

Energy Not Supplied (ENS):

$$F_2 = \min\ [ENS = \sum_{j=1}^{n_S} h.P_j^{shedding}] \tag{2}$$

where $p_i^{shedding}$ is the load shed in j^{th}bus, n_s is the number of buses including load and h is the number of operation hours.

Critical clearing time(CCT):

$$F_3 = \max[CCT] \tag{3}$$

B. Problem Constraints

Power balance:

Units generating power should always be equal to sum of the power consumed by loads and network active losses, as eq. (4).

$$\sum_{i=1}^{N_g} P_{gi} = \sum_{j=1}^{N_l} P_{dj} + P_{Loss} \tag{4}$$

where P_{gi} is the generating power of i^{th} unit, Ng is the number of units, P_{dj} is consumed power of d^{th} load, N_l is the number of loads and P_{loss} is the network active losses.

Power flow constraints:

$P_k = (V, \delta) = \sum_{i=1}^{Nb} V_k . V_i . Y_{ki} . cos(\delta_k - \delta_i - \theta_{ki})$ (5)

$Q_k = (V, \delta) = \sum_{i=1}^{Nb} V_k . V_i . Y_{ki} . \cos(\delta_k - \delta_i - \theta_{ki})$ (6)

V_k and $\delta_k$are the magnitude and angle of the voltage of K^{th} bus. Y_{ki} and θ_{ki} are the magnitude and angle of ki element of admittance Matrix.

Security Constraints:

$-S_l^{\max} \le S_l \le S_l^{\max}$ (7)

S_l isthe apparent power flow of line l and S_l^{max} is the maximum capacity of line l.

$V_k^{\min} \le V_k \le V_k^{\max}$ (8)

V_k^{max} and V_k^{min} are the maximum and minimum voltages of K^{th} bus, respectively.

Operation constraints of units:

$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}$ (9)

$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}$ (10)

P_{gi}^{max} and P_{gi}^{min} are respectively maximum and minimum active power of i^{th} unit and Q_{gi}^{max} and Q_{gi}^{min} are respectively maximum and minimum reactive power of i^{th} unit.

System Reliability:
To enhance the system reliability, the maximum load shedding at each bus is restricted % 50 of total active load of that bus, as:

$P_j^{shed,\max} \le 0.5 P_{dj}$ (11)

3. Critical clearing Time (CCT)

The third objective (F_3) is to increase the power system dynamic security by improving its transient stability under contingency conditions. To this end, differential equations are solved to procure rotor angles and angular velocities of the generators at each time [8]. Under contingency conditions, the generators synchronism may be lost by increasing the values of relative rotor angles. Here, time-domain simulations are carried out to evaluate the CCT for each contingency, which is one of the most important indices of the system transient stability assessment. As for transiently stable operation, CCT should be greater than the actual operating time of circuit breakers, maximizing the CCT as the objective of the power system operation problem considerably enhances the power system transient stability. It is assumed that three-phase-to-ground faults occur at buses with generators, and are cleared by tripping the lines. Furthermore, the same conditions are considered for both the fault-cleared and pre-fault situations of the system [8], [12]. Using CCT index a reliable assessment of system status can be fulfilled. For this purpose, CCT index is calculated for various operating point of the system in the environment of Dig silent software. Then the obtained data set is used to train the neural network. Now, using the trained neural network CCT index can be quickly computed according to the operating point of the system.

A. Providing Data set for the neural network

In this paper a multi layered feed forward network (MLFFN) which is a common type of neural network is used to determine the CCT according to the power system operating point. Due to the effect of this event on the performance of surrounding generators and consequently the effect of these generators behavior on the system stability, voltage, rotor angle and the generating power of these generators have been used as input data of the neural network. CCT is the output data of the neural network. As aforementioned data set required for training the MLFFN, are provided by simulation in the environment of Dig silent software. For this purpose, it is assumed that an outage occurs in the network and it is cleared after a certain period of time (Relay Performance Time). This outage has its own CCT index denoting the opportunity to clear the outage. In fact, CCT defines the importance of an outage, so that the smaller CCT index of an outage means the more important outage and there is less opportunity to clear it. Consequently, it is more probable to make system instable. Therefore, to maintain network stability after clearing the outage, outage clearing time (Relays Performance time) is required to be shorter than CCT.

The generator power-phase curve is shown in Figure 1. The steps of calculating CCT index using simulation in the environment of Dig silent software are as follows:

- First, two regions of A_1 and A_2 are equalized as eq. (12) and the critical clearing angle (δ_{CCT}) is obtained.
- CCT is calculated as in eq. (13).

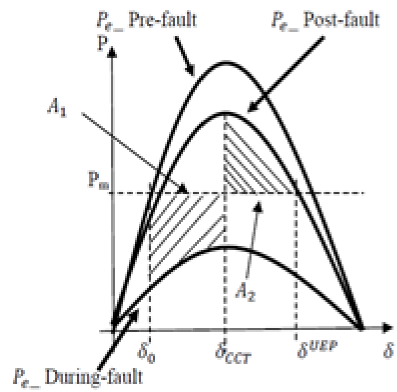

Figure 1.Generator Power-Phase curve

$$A_1 = A_2 \rightarrow \int_{\delta_0}^{\delta_{CCT}} (P_m - P_e^{D.F})\, d\delta = \int_{\delta_{CCT}}^{\delta^{UEP}} (P_e^{P.F} - P_m)\, d\delta \tag{12}$$

$$CCT = \sqrt{\frac{(\delta_{CCT} - \delta_0)}{\omega_0 \times P_{acc}^{av}} \times 4H}$$
$$P_{acc}^{av} = \frac{P_{acc}(\delta_{CCT}) + P_{acc}(\delta_0)}{2} \tag{13}$$
$$\begin{cases} P_{acc}(\delta_{CCT}) = P_m - P_e^{D.F}(\delta_{CCT}) \\ P_{acc}(\delta_0) = P_m - P_e^{D.F}(\delta_0) \end{cases}$$

By changing loads and generating power of generators, various operating points of system are created in a way that power balance constraint is satisfied in each operating point. In each operating point, faults are considered on the generators and the data set is obtained for these faults [6-7].

B. Neutral network

To decrease the computational burden of the proposed method, a MLFFN is used to calculate the value of CCT based on the operating point of the power system. As a matter of fact, MLFFN is employed to determine the value of CCT for each solution of GA population based on the related power system operating point. As described in Section 3.1, a data set including 1600 data pairs is obtained using the simulations. 70 %, 15 % and 15 % of the obtained data pairs are respectively considered for Training, testing and validation of the proposed MLFFN. The generators power output and rotor angles and voltage magnitude of the buses are taken as the inputs to the MLFFN. The number of inputs depends upon the topology of the network under consideration. MLFFN includes two hidden layers and nodes with nonlinear activation function [7]. Figure 2 shows the structure of the proposed neural network. As can be seen from Figure 2, each node in a layer is joined to other nodes in adjacent inputs with weighted coefficients.

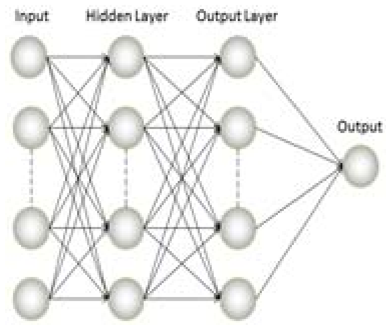

Figure 2.The structure of the proposed neural network

For neural network such inputs must be selected so that as a parameter of network possess sufficient information about network status for determining CCT [8, 12]. The used active function in hidden layers is tangent hyperbolic and in output layer the linear function is used as the active function. "Leven berg-Marquardt" back propagation algorithm [8] is employed to train the network due to its good convergence characteristic. For the optimal selection of the number of neurons in the hidden layers, it is assumed that the number of neurons is varied from 12 to 50 in the first hidden layer and from 2 to 11 in the second hidden layer. Changing the number of neurons in hidden layer, the square amount of error which is a feature of neural network correct function, can be changed. The final structure of MLFFN includes the number of neurons with minimum mean square error [8].

C. Fuzzy-weighting approach[13]

In this paper, weighting method based on fuzzy approach is used to transform the multi objective problem to a single objective one. In the proposed method, a fuzzy function is used to transfer the objectives to a fuzzy domain. For this purpose, Eq. (14) is used to normalize the objective functions which should be minimized and Eq. (15) is used to normalize the objective functions which should be maximized. Eq. (16) shows total fitness value of the proposed problem which should be maximized.

$$\mu_i^{Minimize} = \begin{cases} 1 & F_i \le Min(F_i) \\ \dfrac{Max(F_i) - F_i}{Max(F_i) - Min(F_i)} & Min(F_i) < F_i < Max(F_i) \\ 0 & F_i \ge Max(F_i) \end{cases} \tag{14}$$

$$\mu_i^{Maximize} = \begin{cases} 0 & F_i \le Min(F_i) \\ \dfrac{F_i - Min(F_i)}{Max(F_i) - Min(F_i)} & Min(F_i) < F_i < Max(F_i) \\ 1 & F_i \ge Max(F_i) \end{cases} \tag{15}$$

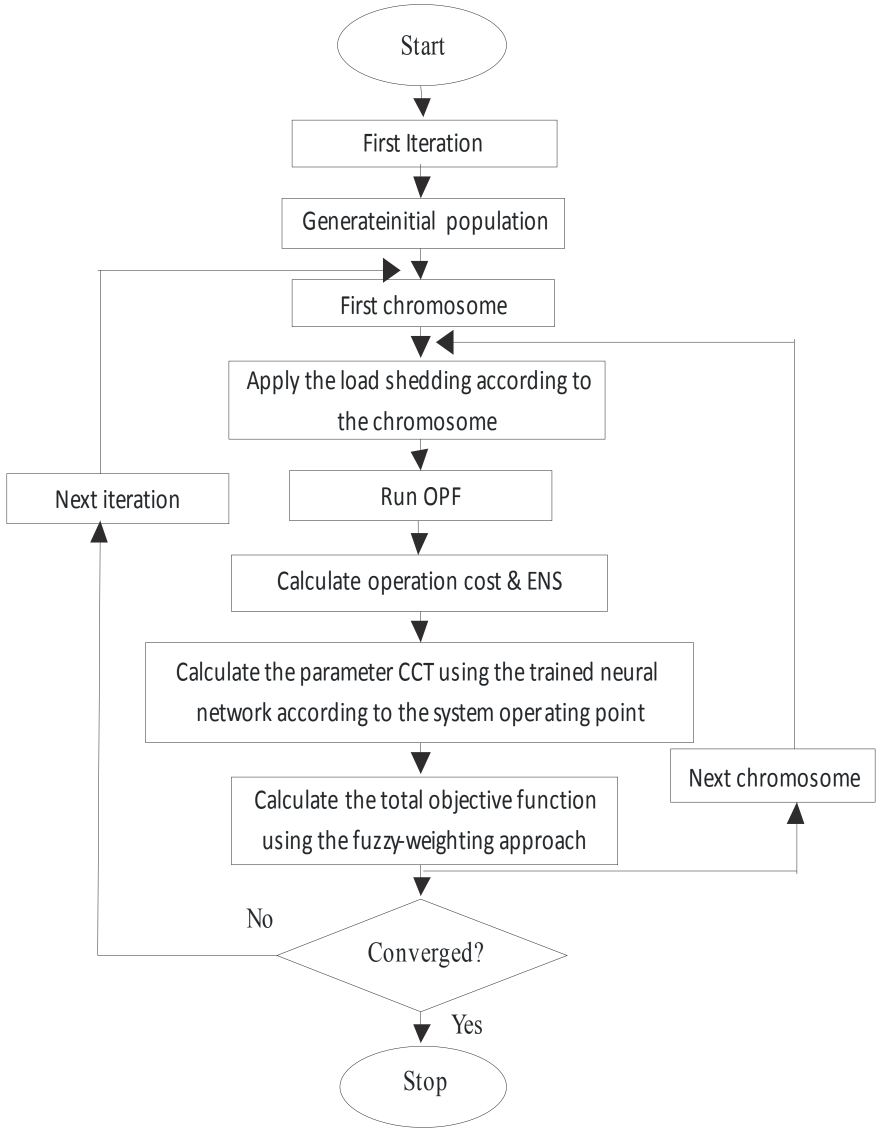

Figure 4. The flow diagram of the proposed scenario based OFF using GA

$$Max\ \ F = k_1\mu_{Oc} + k_2\mu_{ENS} + k_3\mu_{CCT} \tag{16}$$

k_1, k_2 and k_3 are weighting coefficients with the condition $k_{1+}k_{2+}k_3=1$. These coefficients can be set by the system operator according to the specific preference. Actually these coefficients determine the importance of the objective functions for the system operator.

4. Scenario based OPF using Genetic Algorithm (G.A)

In this paper, a binary GA is employed to optimize the scenario based OPF problem. The proposed structure of the GA chromosomes is shown in Figure 3. See [14] for more details about GA. Figure 4 illustrates the flow diagram of the proposed scenario based OPF using GA.

LS_1	LS_2	LS_3	…	LS_{37}	LS_{38}	LS_{39}

Figure 3. GA chromosome structure

5. Numerical Results

The proposed method is studied on IEEE 39-bus test system which includes 10 generators, 39 buses and 46 transmission lines [15]. Figure 5 shows the single diagram of the IEEE 39 bus test system. The total available generation capacity and the total system load of the system are 7367 MW and 6254.23 MW, respectively. In this paper, outage of the unit located on 38th bus has been considered as a scenario. This outage has also been simulated in the simulation environment of Dig silent software. This simulation has been carried out in different operating points. Due to the effect of this event on the performance of surrounding generators and consequently the effect of these generators behavior on the system stability, voltage, rotor angle and the generating power of these generators have been used as input data of the neural network. CCT is the output data of the neural network. A data set including 1600 data pairs are obtained using the simulations. 70 %, 15 % and 15 % of the obtained data pairs are respectively considered for Training, testing and validation. Regression which is an important criterion in assessment of neural network performance clearly shows the difference between

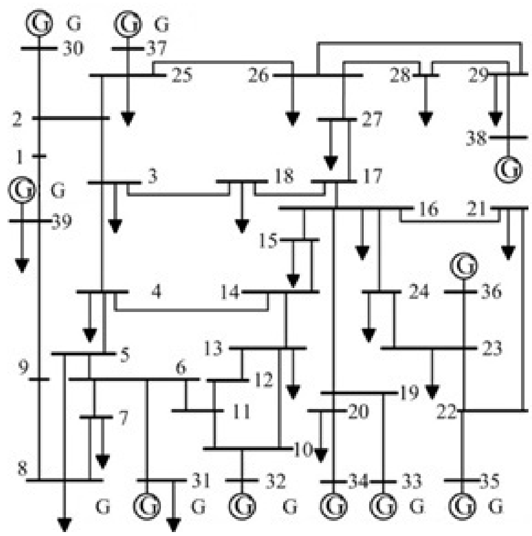

Figure 5. IEEE 39-bus test system

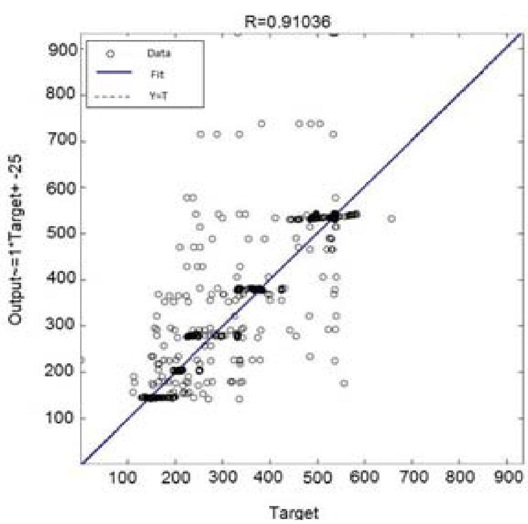

Figure 6. Neural network regression gragh

the amount of objective and the output of network. Figure 6 shows the regression criterion for the proposed neural network of this paper. As can be seen from Figure 6, the fulfilled test has 91% of precision which is a relatively acceptable one. It should be noted that the precision will increase by increasing the number and the diversity of the operating points.

The GA population size and the number of algorithm iterations are considered equal to 50 and 200, respectively. The convergence manner of the GA is shown in Figure 7. As it can be seen from this figure the algorithm is converged in 59th iteration and the total objective function is fixed at the value of 04575.

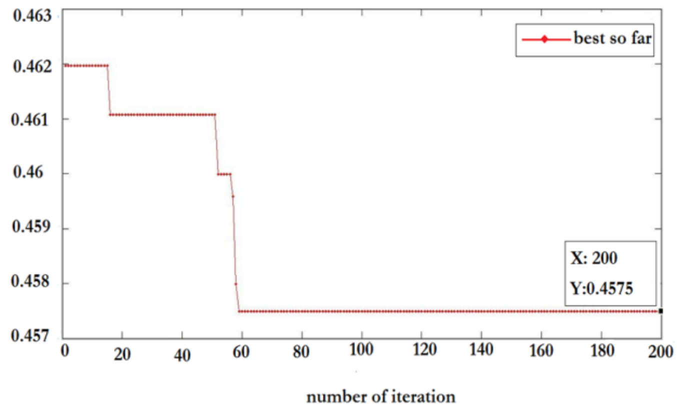

Figure7. GA convergence manner

The weighting coefficients of k_1, k_2 and k_3 are considered equal to 2/3, 1/6 and 1/6 (the importance of economic objective function is four times of security objective functions and the importance of EIC and transient stability is the same). By preparing the data set using the simulation environment of Dig silent software, then training the neural network using the obtained data set and finally running the GA, the optimal solution of scenario based OPF is obtained. Table 1 presents the generation schedule of the generating units. As it can be seen from Table 1, all available units are almost fully committed due to the outage of unit located on Bus 38. The load shed at the buses are presented in Table 2. As it cab ne concluded from Table 1 and Table 2, the total generating active power of the units and the total load shed at the buses are respectively obtained as 3910.31 MW and 2370 MW, using the proposed scenario based OPF. From Table 2, it also can be seen that the loads located on the buses next to Bus 38, which includes the outage, are considerably shed. That is to compensate the lost power of the interrupted unit. Table 3 shows the values of the objective functions associated with the obtained solution by the GA. The normalized values of the objective functions and the total fitness value are also shown in this table.

Table 1. Generation schedule of units

Unit No	Bus No	Active Power (MW)
1	30	437.91
2	31	439.7
3	32	437.38
4	33	428.1
5	34	427.21
6	35	431.72
7	36	429.79
8	37	434.29
9	38	0
10	39	444.21

Table 2. Load shed at the buses

Bus No	Load Shed (MW)	Bus No	Load Shed (MW)
1	35.06	21	104.85
3	131.09	23	116.12
4	81.37	24	149.32
7	85.58	25	105.86
8	173.23	26	24.59
9	0.069	27	136.65
12	0.012	28	60.71
15	145.29	29	125.67
16	142.47	31	3.75
18	17.68	39	462.42
20	268.21	-	-

As in power system the relays function time is 100 *ms*, for maintaining the system stability, clearing time must be more than this interval, so that relays and breakers can see and clear the fault. As it can be seen from Table 3, CCT is more than relays' function time in this study, which demonstrates the system stability.

Table 3. The results of objective functions of the solution obtained by the GA

Objective	OC ($)	ENS (MW)	CCT (*ms*)	Total fitness value
Real value	18167.43	331815.7	356.49	-
Normalized value	0.534	0.105	0.5022	0.4572

Since, the scenario based OPF is run 24 hours prior to the real happening time, it is vital to use a fast method. The proposed scenario based OPF problem with about 200 iterations, takes about 17 min of the CPU time in a PC computer (2.13-GHz) processor with 2 GB of RAM, which is an acceptable time. This is because of using the offline MLFFN training in the proposed scenario based OPF method than the traditional method.

6. Conclusion

Power system operation in contingency condition is of great importance and needs proper decisions in order to maintain system stability and prevent system black out. In this paper, a scenario based OPF including load shedding and generation rescheduling is proposed to maintain the system stability in contingency condition. The operation cost, ENS and transient stability are the objective functions of the problem. A generator outage is simulated by Dig silent software and data set are provided for CCT calculating. The a neural network is employed to train the obtained data set. The genetic algorithm is used as the optimization tool. The proposed method are tested on the IEEE 39-bus test system. The following results are concluded:

- Combination of load shedding and generation rescheduling in OPF scenario based problem may result in a more secure and economic system in contingency conditions.
- Using off line training of neural network for specifying the transient stability criteria of power system decrease the computational burden of the scenario based OPF problem and leads to a faster OPF.

The research work is under way in order to include a stochastic framework for OPF problem. Besides, more advanced neural networks such as ANFIS can be used for training the data set.

7. References

[1] P. Kundur, N. Balu, and M. Lauby, Power System Stability and Control, NY, USA: *McGraw-Hill*, 1994.

[2] Fang, D.Z., Sun, W., Xue, Z.Y, Optimal generation rescheduling with sensitivity-based transient stability constraints, *IET Gener. Trans. Distrib*., 2010, 4, (9), pp. 1044–1051.

[3] Shen, C. M. U. o. L, Power-system load scheduling with security constraints using dual linear programming, *Electrical Engineers, proceeding of the institution of*, 2010, 117 (11): 2117 - 2127.

[4] N. Yorino, H. Q. Li, S. Harada, A. Ohta, and H. Sasaki, A method of voltage stability evaluation for branch and generator outage contingencies, *IEEE Transactions on Power Systems* 2004, 19(1): 252-259.

[5] G. Caj, Y. Zhang, Z. Cai, T. Yu,A corrective load shedding control scheme to prevent voltage collapse, *Power Engineering International Conference*, 2007.

[6] Y. Ohsaki, S. Aikawa, S. Iwamoto, H. Hosogoe, Tie-line ATC calculation method using CCT with transient stability constraints, *Power and Energy Society General Meeting*, 2010 IEEE.

[7] A. L. Bettiol, A. Souza, J. L. Todesco, J. R. Tesch, Estimation of critical clearing times using neural networks, *Power Tech Conference Proceedings*, 2003 IEEE Bologna.

[8] Sunitha R, R. Sreerama Kumar, S. M. Abraham, T. Mathew, Online Static Security Assessment Module Using Artificial Neural Networks, *IEEE Transactions on Power Systems*, 2013, 28(4).

[9] A. Hoballah and I. Erlich, Online market-based rescheduling strategy to enhance power system stability, *IET Generation, Transmission & Distribution* 2011, 6(1): 30–38.

[10] J. Aghaei, N. Amjady, A scenario-based multi objective operation of electricity markets enhancing transient stability, *Electrical Power and Energy Systems* 2012, 35 (1) : 112–122.

[11] P. Wang, Y. Ding, L. Goel, Reliability assessment of restructured power systems using optimal load shedding technique, *IET Generation, Transmission & Distribution* 2009, 3(7): 628-640.

[12] A. Hoballah, I. Erlich, Transient stability assessment using ANN considering power system topology changes, ISAP 2009, *Power & Energy Society*, Curitiba, Brazil.

[13] N. Amjady, J. Aghaei, H.A.Shayanfar,Stochastic Multiobjective Market Clearing of Joint Energy and Reserves Auctions Ensuring Power System Security, *IEEE Transactions on Power Systems* 2009, 24(4): 1841 - 1854.

[14] M.El-werfelli, J. Brooks, R. Dunn, An optimized de ence plan or a power system, *Universities Power Engineering International Conference*, 2008.

[15] M.A. Pai, Energy Function Analysis for Power System Stabilit, Boston, *MA: Kluwer*, 1989.

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