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Artificial Neural Network Based Load Shedding Technique for Industrial System

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ABSTRACT: In this paper an Artificial Neural Network (ANN) based adaptive and optimum load shedding scheme is designed for industrial system with in-plant generation. The proposed load shedding technique is designed based on transient stability analysis of industrial system. Load flow analysis is performed to determine steady state performance for various possible operating scenarios. Frequency stability analysis is performed for all possible load-generation scenarios. For different fault contingencies and operating scenarios data base is generated for training and testing of the ANN. To determine the optimum load-shedding amount, frequency stability analysis has been done, taking into account inertia of generator, inertia of load, load damping, spinning reserve and effect of low voltage and frequency on loads. Various combinations of the total in-plant generation, total demand, total power import, spinning reserve, and frequency decay rate have been considered for frequency stability analysis and the minimum amount of load shedding is thereafter determined to maintain the frequency stability of islanded systems.

KEYWORDS: Transient Stability, Load shedding, Artificial Neural Network.

I.INTRODUCTION

When the power system is able to maintain a stable frequency even in sever power generation mismatch condition it is called frequency stability. It depends on the system's ability how much load is loss in this phenomenon. Frequency instability may lead to undesired generation unit trips. [1]. Severe disturbance result in large deviations in frequency, voltage, power and other important variables. Failure of governor control actions may result into the formation on islands. If each island is able to prevent loss of load, the island may be said to be stable. Frequency instability leads connected equipments to get damaged, poor coordination of control and protection equipments and insufficient generation reserve.

In adaptive UFLS (AUFLS) the parameters such as load-level changes, system inertia changes, changes in load composition, governor response characteristics, or changes in system topology [2] are included and magnitude of disturbance is estimated online [3, 4]. This method is based on real time topology and communicates between remote protective relays and centralized UF appliance [5, 4]. For the design of an AUFLS plan, the behavior of multi-machine electric power systems immediately after sudden load generation imbalance is initiated [6, 7]. The Rate of change of Frequency (ROCOF) based Load Shedding is an adaptive method where the initial ROCOF following a disturbance is directly proportional to the power imbalance and also depends on the electric power system inertia [10, 12]. Power deficit can be calculated using the system frequency response model [8-10]. The model is based on largest time constants such as generation unit inertia and reheats time constant in the generation units of the isolated system [8]. SCADA Based Load Shedding enables to have a high reliability solution, without any data transfer through communication links [3].

The neural network was inspired by its inception by the recognition that the human brain computes differently than that of a conventional digital computer. The brain acts as a highly complex, non-linear and parallel computer. An artificial neural network (ANN) is a flexible mathematical structure which is capable of identifying complex nonlinear relationships between input and output data sets. A neural network is a parallel-distributed processor made up of simple

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processing units, is known as neurons, which has a tendency for storing, and making easily available, experimental information.

II.SYSTEM MODEL AND LOAD FLOW

The industrial system with in-plant generation is simulated in ETAP to analyze the load shedding schemes presented. A single-line diagram of an industrial power generation and distribution system is as shown in Figure 3.1. The system consists of 34 buses, 249 circuit breakers, and 186 cables. Three generating units rated 20MW each at 11kV are the source of supply to the entire system. The maximum power that can be generated is 60MW and minimum power import is limited to 40MW. The grid transformers GTR-01 and GTR-02 step down the voltage from the 132kV utility ties to the 33-kV level and connect it to HT-201 BusA2. Power generated is stepped up to 33kV through transformers STG-1, STG-2 and STG-3. The power is distributed at a 33-kV level from two main receiving stations to 14 substations (SS-1to SS-14) through cables. Voltage level is stepped down from 33kV to 6.6kV inside the substations. The total industrial load has been listed in Table.1.

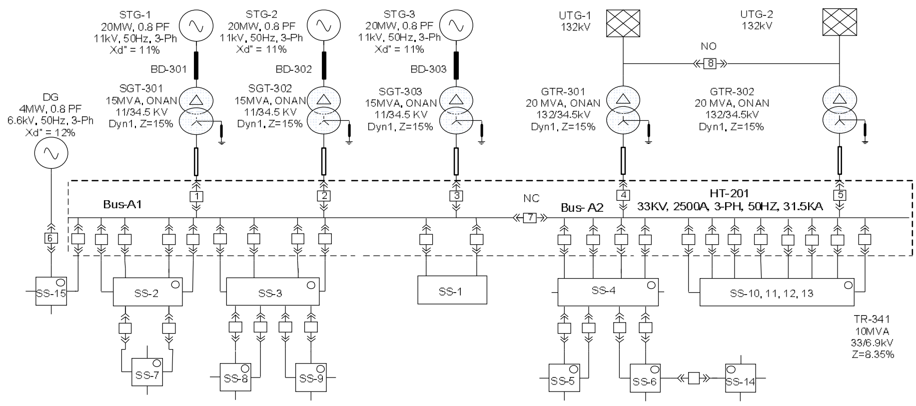

Figure 1. Single line diagram of an industrial system

Table1. Total load of industry

Substation Number	Load in MW
SS-1	7.8
SS-2,SS-7	19.5
SS-3, SS-8, SS-9	32.9
SS-4, SS-5, SS-6, SS-14	5.2
SS-10, SS-11, SS-12, SS-13	12.7

III.DESIGN OF ANN BASED LOAD SHEDDING

An ANN-based load shedding technique for industrial systems is designed. The Levenberg–Marquardt algorithm is adopted and incorporated into the back-propagation learning algorithm for training feedforward neural networks. The total power generation, total load demand, spinning reserve, tie-line power and frequency decay rate as the input neurons of the ANN, the minimum amount of load shedding is determined. The Levenberg–Marquardt Back-Propagation (LMBP) algorithm is used for training of the ANN model because of the low error and least epochs. In the LMBP training algorithm the input data is propagated from the input layer, multiplied by their respective weights, to the hidden layer before reaching the final output layer. Finally, a set of outputs is produced as the actual response of the network. The error signals between the desire output and actual output at the output layer are then propagated back to the hidden and input layer. The sum of square error is then minimized by adjusting the synaptic weights and bias in any layers during the training process of ANN model. By performing the stability analysis for various fault scenarios the

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training data set of ANN model can be created. With the derivation of ANN model, the optimal load shedding at the instant of tie lines tripping is determined according to the input neurons of the neural network.

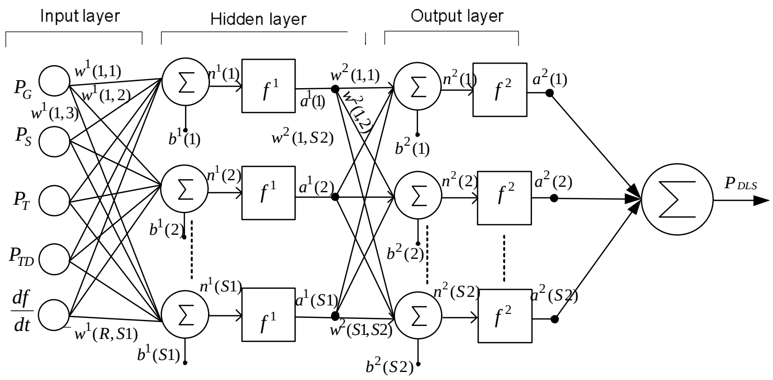

Figure 2 Three layer neural network topology

A. Back-Propagation Algorithm

The Multi-Layered Feed Forward Neural Network (MLFFNN) using back propagation training algorithm is most established neural network in pattern recognition application in power system because of its simplicity and good generalization. Standard back propagation is a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. In the BP training algorithm the input data is propagated from the input layer, multiplied by their respective weights, to the hidden layer before reaching the final output layer. Finally, a set of outputs is produced same as the actual response of the network. The error signals between the desired output and actual output at the output layer are then propagated back to the hidden and input layer. The sum of square error is then minimized by adjusting the synaptic weights and bias in any layers during the training process of ANN model. A three-layer feed-forward ANN as shown in Figure 2.

Input samples are defined as:

$$p_N = \left(P_G, P_S, P_T, P_{TD}, \frac{df}{dt} \right)$$

Required output samples are as:

$$q_N = (P_{DLS})$$

Actual output is expressed as:

$$a_N = (P_{ALS})$$

Sigmoidal and pureline activation function is considered for hidden and output layer respectively and can be given as follows:

$$f^1 = \frac{1}{1+e^{-x}}$$

$$f^2 = purelin(x)$$

The net input to unit i in layer k+1 can be represented by Equation (1) as:

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$$n^{k+1}(i) = \sum_{j=1}^{sk} w^{k+1}(i,j)a^k(j) + b^{k+1}(i) \tag{1}$$

The output of unit i can be given by Equation (2) as:

$$a^{k+1}(i) = f^{k+1}\left(n^{k+1}(i)\right) \tag{2}$$

For an M layer network the system equations in matrix form are given as:

$$\bar{a}^0 = \bar{p} \tag{3}$$

$$a^{k+1}(i) = f^{k+1}\left(W^{k+1}a^k + b^{k+1}\right) \tag{4}$$

k = 0, 1, …….M-1

The assignment of the network is to learn associations between a specified set of input-output pairs {(p_1,q_1), (p_2,q_2), (p_3,q_3), …….(p_n, q_n)}.

The performance index for the network can be expressed as:

$$V = \frac{1}{2}\sum_{m=1}^{N}\left(\bar{q}_m - \bar{a}_m^M\right)^T\left(\bar{q}_m - \bar{a}_m^M\right) = \frac{1}{2}\sum_{m=1}^{N}\bar{e}_m^T\bar{e}_m \tag{5}$$

Where, a_m^M is the output of the network, q_m is the target. The error function can be given by Equation (6) as:

$$\bar{e}_m = \left(\bar{q}_m - \bar{a}_m\right) \tag{6}$$

An approximate steepest descent rule is used in the standard back-propagation algorithm. The performance index is approximated by Equation (7)

$$\bar{V} = \frac{1}{2}\bar{e}_m^T\bar{e}_m \tag{7}$$

IV. STEP FOR ANN LOAD SHEDDING DESIGN

This section presents the process to determine the amount of load shedding for power systems by using the ANN with various training algorithms according to the transient stability analysis. Figure 6.2 shows the flowchart of the proposed adaptive minimum load shedding. It can be divided into five steps as follows:

Step 1: Identify the network configuration and prepare the data for the power system to be studied. It includes the branch and bus data for load flow analysis and the mathematical models with corresponding parameters of generators, excitation systems, governor systems and loads for transient stability analysis.

Step 2: To verify the accuracy of the mathematical models, computer simulation of the actual contingency cases is performed by the transient stability analysis. The models and parameters of the power systems are modified accordingly.

Step 3: For system contingency, the dynamic frequency response of the power system is highly dependent on the amount of load to be shed. The objective function of the ANN model is to derive the optimal amount of load shedding so that the stable operation of power system can be maintained and the economic loss can be minimized. Choose the input variables, which are highly correlated to the frequency deviation as the training data of ANN models.

The input neurons of ANN are total power generation of generating units P_G, total load demand of the system P_L and frequency decay rate df/dt. The frequency decay rate is calculated as follows.

Average rate of frequency change *R* [11],

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$$R = \frac{pL}{H} * \frac{f_2 - f_1}{1 - \frac{f_2^2}{f_1^1}}$$

Relative Load Excess Factor L is defined by [12]

$$L = \frac{P_{TD} - P_G}{P_G} \tag{17}$$

H =Aggregate inertia constant
P =Power factor
L= Relative Load Excess Factor
f_1 =Operating frequency before fault
f_2=Frequency after fault.

Step 4: To prepare the input data for the ANN, the transient stability analysis of power system for many operation conditions and fault contingencies have to be executed. The data of the selected input variables and the corresponding output are then divided into two data sets for training and testing, respectively. Before the training and testing process, all the data sets should be normalized to the same range of values. Training and testing of ANN models are executed by using the feed-forward ANN with various back-propagate algorithms as described previously until the performance index is less than the specified error tolerance. Redefine the input variables if the convergence of ANN models cannot be obtained.

Step 5: When a fault occurs, the proposed ANN controller will determine the minimum amount of load shedding quickly according to the input data captured by the SCADA system in real time. Finally, the hardware of the load-shedding scheme will trip the predetermined load to restore the system frequency. The output neuron of ANN is the amount of load to be shed.

Determination of the amount of load to be shed: Total amount of load to be shed is calculated using Equation (18)

$$LS = \frac{\frac{L}{1+L} - d\left(1 - \frac{f}{f_0}\right)}{1 - d\left(1 - \frac{f}{f_0}\right)} \tag{18}$$

Where,
LS = Total load that must be shed
L = Per unit overload
f = Minimum permissible frequency
d = Load reduction factor
f_0 = Nominal frequency

Table 6.1 presents load shedding calculation results for various operating scenarios by using LMBP-ANN. The regression plot for LMBP training algorithm is shown in Figure 3. It shows error between desired output and actual output of ANN in case of LMBP training algorithm.

It has been found that the minimum value and slop of frequency of an islanded system would be different for different combinations of in-plant generators and loads for same disturbance power as shown in Figure 5. The impact of other parameters (i.e. system inertia, magnitude of disturbance power, spinning reserve, droop, governor parameter settings etc.) on frequency is analyzed in [13]. The load shedding amount is calculated for all possible disturbances and in-plant load-generation combinations to arrest the frequency decay within 3% from its rated value. According to load flow and transient stability analysis, operating case-6 was very critical case for islanding operation. The maximum over load condition has been occurred at the time of islanding for this operating scenario. For this operating scenario load generation imbalance is 49.4 MW.

The operating condition for the case-6 is as follows:
Total in-plant generation = 19000 kW
Total spinning reserve = 1000 kW
Total demand = 66826 kW

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Total power import at the time of islanding = 47826
Total imbalance power at the time of islanding = 46826

A three phase fault is created on utility 132 kV transmission systems which is cleared by opening tie-line circuit breakers (CB-4 and CB-5) using under voltage relay. The total amount of load shedding is 46890 kW for this scenario calculated with the help of Equation (17) and Equation (18). The parameters considered are,

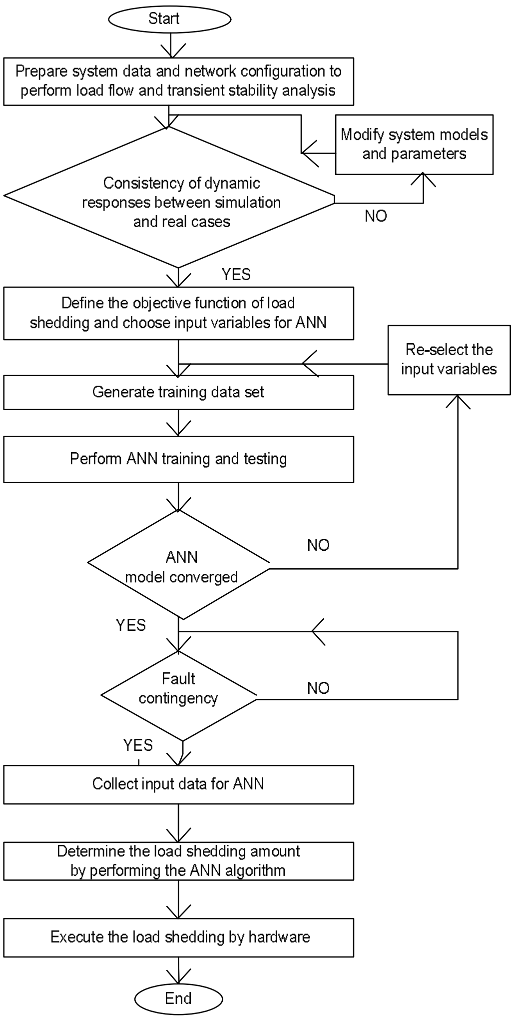

Figure 3 Flowchart of ANN Based Adaptive Minimum Load Shedding

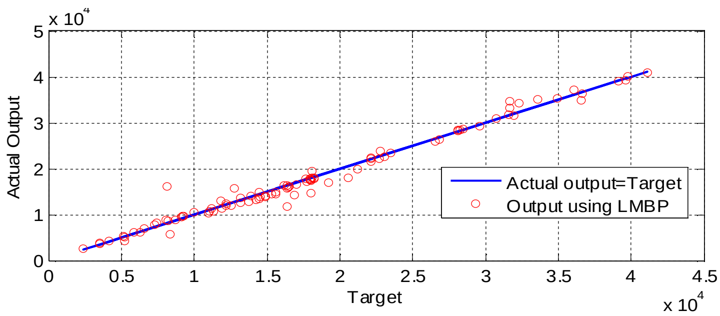

Figure 4 Regression plot for ANN output with LMBP training algorithm

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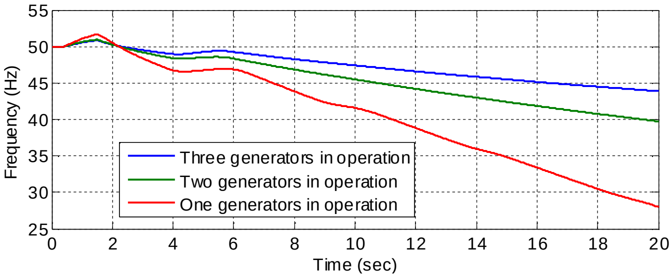

Figure 5. Frequency response of the ICP system for same disturbance power with different combinations of generators available after islanding

L = 2.51
f = 48.5 Hz
d = 1.5
f_n = 50 Hz

The transient stability has been performed to evaluate the scheme performance in terms of the maximum transient and steady-state frequency deviations for the range of systems impacts expected to be encountered. Underfrequency load shedding design, number of steps, step frequency and percentage load shedding amount for 81L relay is shown in Table 2.

Transient stability has been performed for this calculated load shedding amount and it is found that the amount 46890 kW is not sufficient to limit frequency degradation below 48.5 Hz. It is shown in Figure 6 that the minimum frequency reached for this amount is 48.37. To prevent frequency declination below 48.5 Hz using UFR based load shedding scheme, 49910 kW load has to be disconnected from islanded system. This load shedding amount has been determine by performing transient stability analysis. For the same operating scenario the load shedding amount determined by ANN is 47646 kW.

To demonstrate effectiveness of the proposed methodology, system under study has been made to undergo a fault contingency and load shedding is performed by underfrequency relay and ANN based load shedding method. The underfrequency relays settings for the step-1 load shedding is activated as the frequency decay below 49.5 Hz.

The frequency stability of islanded system for operating scenario-6 with underfrequency relay based and ANN based load shedding methods are depicted in Figure 7 At t = 0.5 sec 3-phase fault was created in utility grid which were cleared by opening tie-line circuit breaker (CB-1 and CB-2) at 0.76 sec. In the case of underfrequency load shedding, as the system frequency reached below 49.5 Hz at 1.232 sec, underfrequency relay was activated and 1-stage load shedding is implemented at 1.332 sec with 0.1 sec time delay. The system frequency still did not recover and it crossed 49.2 Hz (2-stage load shedding threshold) and 2-stage load shedding was implemented at 1.382 sec. The system frequency further decline below 48.8 Hz (3-stage load shedding threshold) and then third stage load shedding is executed at 1.501 sec. After 3rd-step load shedding system frequency improved above 49.5 Hz in 5.1 sec. It was found that the total amount of load shed using underfrequency relay method was 49910 kW. For the same contingency in case of ANN based adaptive load shedding, the entire load shedding was achieved in 0.845 sec with the calculation delay of 0.025 sec and 60 msec breaker operating time included. The amount of load shedding in case of ANN based load shedding was 47646 kW which was 2264 kW less than the conventional scheme. The system frequency decline is arrested above 49.5 Hz in case of ANN based load shedding which is shown in Figure 6.

Table 2. Summary of UFR and ANN based Load shedding scheme

Cases	P_G (kW)	P_S (kW)	P_T (kW)	P_{TD} (kW)	df/dt (Hz/sec)	LS amount UFR (kW)	LS amount ANN (kW)
Case-2	57000	3000	21284	78284	-1.33	24955	18809
Case-3	57000	3000	21321	78321	-1.33	24955	18873
Case-4	38000	2000	40000	78000	-3.86	40282	38418
Case-5	38000	2000	23896	61896	-2.22	24955	22240
Case-6	19000	1000	47826	66826	-8.51	49910	47646

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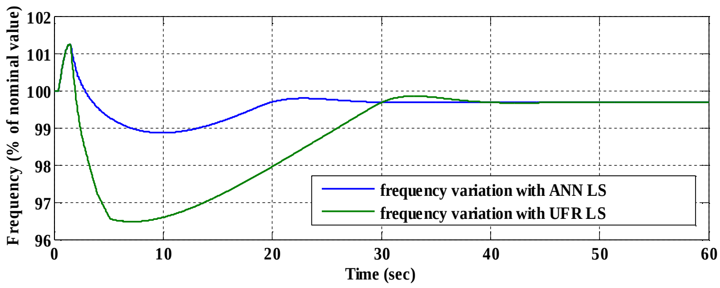

Figure 6. System frequency variation for operating case-6

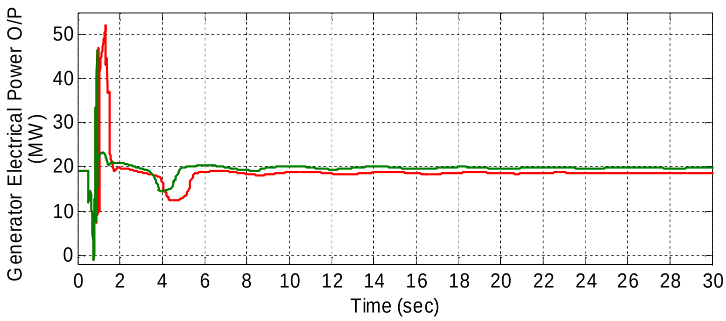

Figure 7. Generator output electrical power variation for operating case-6

Figure 6 depict frequency variation for different load shedding scheme during operating case-6. It cleared from these figures that in case of ANN load shedding scheme frequency dip is less as compare to UFR based load scheme. Figure 7 shows generators electrical power output variation. It is clear from electrical and mechanical power variation curves that in case of UFR based load shedding scheme excess amount of load is disconnected from system as required to maintain stable operation. Table 2 shows the comparison between Relay based load shedding and ANN based load shedding technique.

VI.CONCLUSION

To enhancement of frequency stability of an industrial system an ANN based adaptive load-shedding scheme is developed. By executing the transient stability analysis for various operation scenarios of the ICP system, the training data set of ANN model has been prepared. To verify the effectiveness of the proposed ANN based load shedding as compare to the present underfrequency relay based load-shedding, schemes are applied in the simulation to investigate the dynamic response of system frequency. It is concluded that the proposed ANN based methodology with two hidden layers and LMBP algorithm can achieve more effective load shedding to maintain system stability as compare to underfrequency based relay.

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