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Artificial Neural Network Approach for Under Frequency Load Shedding

Manoj Kumar.N **M.S.Sujatha** **T.Devaraj** **N.M.G.Kumar**

Abstract— Different short circuits, load growth, generation shortage, and other faults which disturb the voltage and frequency stability are serious threats to the system security. The frequency and voltage instability causes dispersal of a power system into sub-systems, and leads to blackout as well as heavy damages of the system equipment. This paper presents a fast and optimal adaptive load shedding method, for power system using Artificial Neural Networks (ANN). The proposed method is able to determine the necessary load shedding in all steps simultaneously and is much faster than conventional methods. The simulation results show that the proposed algorithm is fast, robust and optimal values of load shedding in different loading scenarios are obtained in comparison with conventional method.

Index Terms— Artificial Neural Networks, Blackout, Load- Shedding, Power System Stability.

I. INTRODUCTION

It is an elementary case of power economics', load demand versus generation supply. When a power system is in stable operation at normal frequency, the total mechanical power input from the prime movers to the generators is equal to the sum of all running loads, plus all real power losses in the system.

The frequency conditions [3] of the overall system will directly depend on the amount of active power that the generator prime movers could deliver to the system. Also, the stored energy of the prime movers plays an important role on the system behavior. This stored energy varies drastically from gas, thermal, to hydro units.

For gradual increases in load, or sudden but mild overloads, unit governors will sense speed change and increase power input to the generator. Extra load is handled by the unused capacity of all available generators operating and synchronized to the system. If all generators are operating at maximum capacity, the spinning reserve is zero, and the governors may be powerless to relieve overloads [2].

Sudden and large changes in generation capacity through the loss of a generator or main inter-tie impacts the dynamic response of the prime mover and can produce severe generation and load imbalance, resulting in rapid frequency decline. For some switching disturbances (that results in a loss of generation or system islanding condition), the cascading effects may be of the primary concern if the load shedding action is not set and timed correct.

For instance, a short-circuit at the power station bus bar may result in acceleration of the generator prime movers. When this occurs the speed regulator will then initiate closing of the fuel or gas inlet valve. After the fault has been cleared, the turbines face the impact of the load still connected. At this time the fuel or gas valves are closed resulting in difficult reacceleration conditions. Furthermore, system generation and stability are at risk as the frequency drops. This is specially the case for a thermal generation plant where power output mostly depends on motor-driven auxiliary loads, such as boiler feed water pumps, coal pulverizing, and draft fans. The drop in system frequency instigates a rapid fall of power output to the auxiliary loads [7] [8], causing further reduction of the energy input to the turbine generator. This sequence of events further deteriorates the system frequency endangering the entire plant stability.

To halt the drop in frequency, it is necessary to intentionally, and automatically disconnect a portion of the load equal to or greater than the generation deficiency in order to achieve balanced power economics while maintaining system stability.

II. LOAD SHEDDING

As already mentioned, when a power system disruption creates a large generation load imbalance, resulting in a frequency decline, emergency action such as under frequency load shedding may be needed. If system frequency reaches a given threshold, even for a short amount of time, power stations may trip off resulting in further load imbalance which may lead to a global system collapse.

When there is a rapid decline in frequency, simple governor response may be neither sufficient nor quick enough to stop the frequency excursion before it reaches the protection threshold of frequency relays in other power plants. Thus, there is a need for a complementary emergency action in order to assure that the declining frequency is stopped before reaching this threshold. Many Algorithms are found [4][6][9][10].

III. CONVENTIONAL LOAD SHEDDING APPROACH

This section is a review of load shedding techniques that have been devised over a number of years each having its own set of applications and drawbacks.

A. Breaker Interlock Load Shedding

This is the simplest method of carrying out load shedding. For this scheme, the circuit breaker Interdependencies are arranged to operate based on hardwired trip signals from an intertie circuit breaker or a Generator trip. This method is often used when the speed of the load shedding is critical. Even though, the execution of this scheme is fast, breaker interlock load shedding possesses a number of inherent.

Drawbacks:

- Load shedding based on worst-case scenario
- Only one stage of load shedding
- Almost always, more loads is shed than required
- Modifications to the system are costly

B. Under-Frequency Relay (81) Load Shedding

Guidelines for setting up a frequency load shedding are common to both large and small systems. The design methodology considers fixed load reduction at fixed system frequency levels

[12]. Upon reaching the frequency set point and expiration of pre-specified time delay, the frequency relay trips one or more load breakers. This cycle is repeated until the system frequency is recovered, e.g., 10% load reduction for every 0.5% frequency reduction. Since this method of load shedding can be totally independent of the system dynamics, total loss of the system is an assumed possibility. Additional drawbacks of this scheme are described below.

- Slow Response Time.
- Incorrect / Excessive Load Shedding
- Analysis Knowledge Is Always Lost

C. Programmable Logic Controller-Based Load Shedding

With a Programmable Logic Controller (PLC) scheme, load shedding is initiated based on the total load versus the number of generators online and/or detection of under-frequency conditions. Each substation PLC is programmed to initiate a trip signal to the appropriate feeder breakers to shed a preset sequence of loads. This static sequence is continued until the frequency returns to a normal, stable level.

A PLC-based load shedding scheme offers many advantages such as the use of a distributed network via the power management system, as well as an automated means of load relief. However, in such applications monitoring of the power system is limited to a portion of the network with the acquisition of scattered data. This drawback is further compounded by the implementation of pre-defined load priority tables at the PLC level that are executed sequentially to curtail blocks of load regardless of the dynamic changes in the system loading, generation, or operating configuration. The system-wide operating condition is often missing from the decision-making process resulting in insufficient or excessive load shedding. In addition, response time (time between the detection of the need for load shedding and action by the circuit breakers) during transient disturbances is often too long requiring even more load to be dropped.

IV. PROPOSED METHOD

The procedure to be followed in this case involves four main steps.

1. Identification of input / output relevant variables
2. Data set generation
3. Design of the NN
4. Performance evaluation of the neural nets

1. Identification of input / outputs

The identification of the variables that are going to characterize a given operating scenario is an important step for a successful application of these techniques. Sometimes a pre-processing stage is needed to select the most relevant variables to be used as inputs of a NN. In this work, we decided by just selecting a set of meaningful variables have been used as inputs of the NN.

- Actual real power generation;

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- Active load generation level prior to disturbance;
- Amount of active load being shed;
- Percentage of exponential type Loads being shed.

These variables provide the NN with valuable information, such that it can make the needed assessment with respect to how much the generation-load imbalance has been corrected and the influence each load type has on the resulting frequency response.

2. Generation of the Data Set

The replication of a given power systems response through any machine learning technique, like a NN, can only be accurate if the data used to train these structures describes with enough coverage and quality the different operating conditions. Optimally. This data set would include all possible system scenarios; however this would require unrealistic hours of computational time. Therefore the objective of the data generation stage is to capture the breadth of the system operating conditions and behavior, while limiting computational and engineering efforts. This data set includes the data used for training a NN and the test data for evaluation purposes.

3. Design of NN

The first step in the design of a NN is to determine an architecture that will yield good results. The idea is to use the simplest architecture while maximizing performance. Usually, NN architecture is determined [5] based on subjective assessment on the part of the engineer.

Within this work it was concluded after a few trials that architecture of 2 hidden layers, the first with 14 nodes and the second with 10 nodes, was best suited for this application.

An LEVENBERG – MARQUARDT Back Propagation technique was used to train the NN[11] . This consists of the same routine as typical back propagation with the exception that instead of one learning rate for all the NN nodes, a learning rate was assigned to each of the nodes in order to speed up convergence. The activation function used within this work was a hyperbolic tangent function and the inputs were normalized to have a mean of zero and a variance of one.

4. Evaluation of NN performance

In order to get an idea for what kind of performance is to be expected from NN architecture, a preliminary evaluation is needed of its capabilities. The “training set” data, typically composed of % of the OPs from the overall data set, is used to teach the NN and give a relative inclination as to its suitability for that particular application. The “test set,” which is comprised of the remaining data, is used to evaluate the prediction capabilities and generalization performance of the structures.

If the training set provides good results, in

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terms of accuracy, and the test set does not, this generally indicates over-fitting in the learning stage and/or that the current NN structure is too complex and needs to be simplified. On the other hand if the training set and test set provide comparable results, but not satisfactory ones regarding the user this generally implies that a more complex structure should be tried. Once desirable results are attained from both the training and test data, a comparative evaluation can be made with the Conventional Method.

In addition, power system modeling and simulation software tools have been significantly improved to perform various system analyses from a simple load flow study to more advanced studies such as transient stability analysis. In recent years, modern system analysis software programs have been designed as a component of a larger power management system in order to perform system analysis using real-time data.

In addition, techniques such as Neural Network (NN), Generic Algorithms (GA), Simulated Annealing (SA), Fuzzy Logic (FL), Expert Systems (ES), etc, have emerged in the field of power systems offering more effective problem solving, knowledge representation and reasoning, search, planning and action, for some highly non-linear problems, which often cannot be solved using conventional techniques. With the combination of such technological advances in power systems, an automated, intelligent, load shedding system can be designed to meet the following objectives:

- Map a complex, highly nonlinear, nonparametric, load shedding problem, to a finite space with a limited number of data collection points
- Automatic recall of system configuration, operating condition, and system response to disturbances
- Pattern recognition capability to predict system response to disturbances
- Systems knowledgebase trainable by user defined cases
- Self-learning capability to new system changes
- Make prompt decisions regarding which loads to shed based on the online status of sheddable Loads.
- Shed the minimum amount of load to maintain system stability

V. SIMULATION RESULT

Here considering 10000Mw as generation capacity of a whole state and the frequency deviations of system is observed and the values are noted. Observing generation, load and frequency deviations actual values are obtained. all these values are obtained from load dispatch centre and it is compared with the neural network output values.

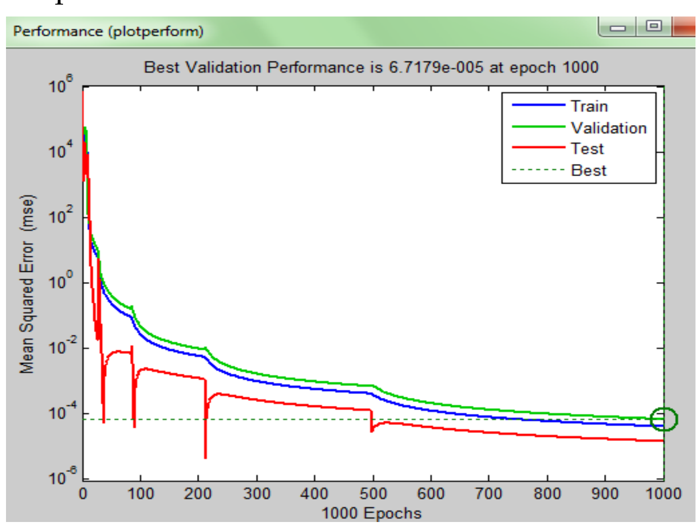

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Figure 1: performance plot of system

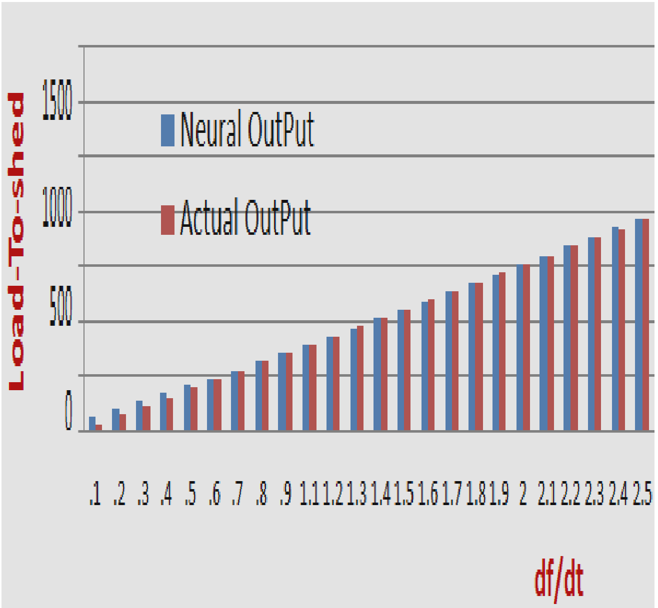

Figure 2: comparison of actual values and neural network values

df/dt	Actual Value (Mw)	Neural Network Value(Mw)
-0.5	200	212
-0.8	320	320
-0.9	360	355
-1.4	560	554
-1.7	680	678
760	760	748
-2	800	781

Table 1: Actual Value Vs Neural Network Value

VI. CONCLUSIONS

This paper described the application of a NN to make a fast prediction of the system behavior for a load imbalance disturbance followed by a load shedding control action. The excellent results obtained in an isolated system show the applicability of this method for the purpose of evaluating the quality of different load shedding schemes for a pre-specified disturbance. Due to the fast prediction of system behavior, the dispatch Center can select the feeders **to** be disconnected in emergency conditions (meaning the amount of load to disconnect). This can be done by adapting the settings of the feeder UFLS relays periodically.

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