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Transient Security Assessment in Power Systems using Deep Neural Network

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Abstract—**Maintenance of power system security is a technological challenge as the power systems are now operated much closer to security limits. Conventional method of transient security evaluation involves solving full AC load flow equations and transient stability analysis of time domain simulation, which is a time consuming operation. To overcome this drawback, a faster transient security assessment of electric power systems by using Deep Neural Network (DNN) has been presented. A Deep Neural Network is a feed-forward, artificial neural network that has multiple layers of hidden units among its inputs and its outputs. DNNs are flexible in modeling of very complex and highly nonlinear relationships between inputs and outputs, which enables efficient solution for complex problems. Sequential forward feature selection (SFS) technique has been implemented to obtain the optimal feature set by reducing the size of data. This method is suitable for on-line applications and its performance is illustrated by the transient security analysis of a sample IEEE-14 bus power system using MATLAB/Simulink. The DNN transient security analysis results show that the security condition of the power system can be predicted with high accuracy and less misclassification rate.**

Keywords—Artificial Neural Network, Deep Neural Network, Pattern Recognition, Security assessment, Transient Security.

I. INTRODUCTION

Today, power systems have developed through continuing growth in interconnection, use of new technologies and controls. Power system security assessment is an important work carried out in an energy management organization to determine the security and stability of a system under unforeseen contingencies. Security assessment is the investigation done to establish whether, and to what level, a power system is practically secure from severe disturbances to its operation [1]. Referable to the increased operations which may cause power system to be in highly stressed conditions, the demand for security assessment of power systems is rising.

Transient security of a power system addresses whether, after a perturbation, the system proceeds to operate consistently within the limits imposed by system stability phenomena [1]. Transient security assessment (TSA) consists of determining, whether the system oscillations, following the occurrence of a fault or a large disturbance, will cause loss of synchronism among generators [2]. TSA may serve to decide the operating mode of a power system as an advance analysis tool in security assessment framework, and to trigger the emergency controls as a real-time stability prediction tool after faults. The traditional methods for transient security analysis, cannot well take on the requirements of the online TSA for modern complex power systems. With the speedy growth of computational intelligence, such as decision trees (DT), artificial neural networks (ANN), and support vector machines (SVM), the pattern recognition-based TSA methods have much potential for on-line application to power systems [3–6]. Pattern Recognition (PR) approaches have revealed immense importance as a means for determining the security of large electric power systems, reducing the disadvantages of conventional methods [7].

The primary process in application of PR approach for security evaluation problem is the conception of an apt data set. Off-line data simulation method is used for generation of required data sets called as patterns [7]. In this paper, Deep Neural Network based pattern recognition technique has been proposed to design classifier for security valuation. A binary logic is utilized for the definition of security which classifies a given operating state as secure (1) / insecure (0). A forward sequential selection approach has been implemented for feature selection purpose. These selected input features are utilized for classifier design which is used for accessing system security level. Application of the proposed technique is implemented on an IEEE 14 Bus system and its effectiveness has been proved by comparing the results with Back Propagation Neural Network (BPNN).

II. TRANSIENT SECURITY ASSESSMENT IN POWER SYSTEMS

Security Assessment is the procedure of evaluating the maximum limit up to which a power system is practically safe from serious interference in its performance [7]. It estimates the forcefulness of the system for a set of contingencies in its present / future state. Security assessment involves estimation of the relative security level of the current operating status of the system using available data measurements.

Transient security evaluation is a complex non-linear problem, which has a non-linear separating boundary between secure and insecure classes. Transient security generally requires repeated load flow analysis to be performed from time to time and the relative rotor angles are verified for violation limit. This usually involves more computation time and the volume of data generated needs significant human decisions to assess the security of the system. Pattern recognition techniques bypass the complete analysis procedure by learning the mapping technique of input pattern to output. Transient Security analysis is related to rotor angle stability, in which the stability criterion is distinguished by rotor dynamics during a rigorous perturbation. The status of power system is said to be Transient Secure (Binary 1) if the relative rotor angle remains less than 180° with respect to slack generator after fault clearing for a specific transient fault condition. Else the power system status is categorized as Transient Insecure (Binary 0).

III. PATTERN RECOGNITION (PR)

Pattern Recognition (PR) [8] is explained as "the act of taking in raw data and taking an action based on the category of data". The data objects are categorized into a number of classes known as Patterns. The Pattern Recognition involves three important stages of operation: generation of data, feature selection of optimum data set and design of classifier. The data generation is defined as representation of input patterns. The objective of feature selection technique is to choose best possible feature subset by processing numeric information from interpretation. A classifier is designed from the selected optimal feature subset that performs the function of categorizing, depending on selected features.

A. Generation of Data set

The performance of pattern recognition depends on the generation of an efficient training set. The training data set must sufficiently characterize the complete variety of system operating conditions that are possible. Through off-line simulation, sufficient numbers of operating points known as patterns are generated and the security status of the operating power system is calculated for all possible contingencies [8]. Every operating point or pattern is denoted by a number of parameters or attributes such as load level, voltages, power generation, etc. These parameters represent the variables of a vector known as the pattern vector, denoted by X. While estimating the security status of the operating system, every pattern is classified among the two classes, secure state or insecure state. The set of data generated during this process is split randomly as training data set and testing data set. The training data set should contain sufficient number of operating points belonging to both secure and insecure classes.

B. SFS technique based feature selection

Feature selection is defined as the process of estimating the most prominent feature subset from the initial set of features, without further alteration of features [9-10]. The reduction of features is done in such a way that the main information represented by the original set of features is not lost [11-12]. Feature extraction is utilized to reduce the data size and to improve the classification accuracy.

Sequential forward selection (SFS) is a strategy to reduce the number of features in local search area. In SFS technique, the features are sequentially added to an empty candidate set until the addition of further features does not decrease the objective function. In SFS, an initial feature set is selected which is based on the objective of the problem to be solved. In this analysis, classification accuracy is the objective function. The initial feature set is a general set of features, which is independent of data set used for training. The idea behind the first subset is to eliminate the insensitive features using knowledge base, a priori so as to avoid exhaustive search of the second stage of SFS algorithm.

The performance of the classifier is determined by assessing the parameters given below during training process and testing process.

Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{kml} (E_k)^2 ; E_k = |DO_k - AO_k| \tag{1}$$

N No. of samples in the data set

DO_k Desired Output obtained from off-line simulation

AO_k Actual Output obtained from NN trained classifier

Classification Accuracy (CA)

$$CA(\%) = \frac{\text{No. of samples classified correctly}}{\text{No. of samples classified correctly}} \tag{2}$$

C. Classifier

With the selection of input feature set using SFS technique, the subsequent process in pattern recognition is the design of an efficient classifier for solving the security assessment problem. The requirements of a good classifier are high accuracy and less misclassification [13]. Many different training algorithms have been reported in literature for the design of classifier which includes least squares, linear programming, back propagation, etc. Even though these training algorithms consume less time, they were found to provide high misclassification and low accuracy which is not acceptable in security analysis. To overcome the short comings of the above mentioned algorithms, in this paper, a Deep Neural Network based classifier model is designed for solving the transient security assessment problem with much higher efficiency and low misclassification rate.

IV. DESIGN OF DEEP NEURAL NETWORK

A Deep Neural Network is a feed-forward, artificial neural network that has multiple layer of hidden units among its inputs and its outputs [14-15]. Deep Neural Networks having many hidden layers and many units per layer are very flexible models with a very large number of parameters. This enables the modelling of very complex and highly nonlinear relationships between inputs and outputs. Every hidden unit, j, in general makes use of the logistic function to map its total input from the layer below, x_j, to the scalar state, y_j that it sends to the layer above.

$$y_j = \text{logistic}\ (x_j) = \frac{1}{1+e^{-xj}} \tag{3}$$

$$x_j = b_j + \sum_i y_j w_{ij} \tag{4}$$

where b_j is the bias of unit j,i is an index over units in the layer below, and w_{ij} is the weight on a connection to unit j from unit 'i' in the layer below. In multiple class classification, output unit 'j' transforms its total input, x_j, into a class probability, P_j, by using the "softmax" non- linearity

$$P_j = \frac{\exp(x_j)}{\sum_k \exp(x_k)} \tag{5}$$

DNNs can be discriminatively trained by back propagating derivatives of a cost function which measures the discrepancy between the target outputs and the actual outputs produced for each training case. In DNNs with full connectivity between adjacent layers, the initial weights are specified with small arbitrary values to avoid all of the hidden units in a layer from getting exactly the same gradient.

V. IMPLEMENTATION AND DISCUSSION

The design of Deep Neural Network (DNN) based classifier model for transient security assessment is implemented and tested on IEEE 14 bus standard test system and the effectiveness of the proposed classifier has been has been demonstrated by comparing with Back Propagation Neural Network (BPNN) [16]. In this analysis, the Deep Neural Network (DNN) based classifier model for transient security assessment has been assumed to have three layers of hidden units among its inputs and its outputs. The bus voltage magnitude is limited between 0.90 p.u and1.10 p.u. The MVA limits of transmission lines and generator data are provided in [13, 17]. The training data set and testing data set required for training and testing phases are obtained by off-line simulation using programs written in MATLAB 7.0 version. This data generation is obtained by incrementing the generation and load from 10% to 30% of their base case value with generation variation restricted to their minimum and maximum limits.

For transient security evaluation, the static security of the power system for all operating conditions is first predicted by using Newton Raphson load flow analysis. The operating conditions which violate the constraints are neglected from the analysis. The secure cases are considered for further transient security evaluation by simulating transient disturbances into the system. The faults are assumed to occur at zero second and the fault clearing time is assumed to be 0.2 seconds. If the relative rotor angle of any generator with respect to reference generator exceeds 180° after fault clearing instant, the corresponding data pattern is labelled as Transiently Insecure(0), else classified as Transiently Secure(1).

The load and generation of buses have been randomly changed between 10% up to 30% of their base case, resulting in 1820 different operating points. Among these operating points, 80% of resulting data, 1456 operating points were considered for training data set and the remaining 20% of data, 364 operating points were considered for testing data set. The transient security status of each operating point for each contingency has been determined. The number of each class members in the data set is given in Table 1.

TABLE I. DATA GENERATION AND FEATURES OF TSA

Test case studied	IEEE 14 bus system
Operating scenarios	1820
Transient secure (1)	1300
Transient insecure (0)	520
No. of pattern variables	218
No. of features selected	2

The parameters considered for training are voltage, angle, real power and reactive power generation, losses, mechanical power input and electrical power output. Further the operation of the system has been improved by implementing sequential forward feature selection technique which has reduced the size of the patterns from 218 variables to 2 variables. The selected features are mechanical power input of generator 1 and reactive power of generator 3.

TABLE II. CLASSIFICATION RESULTS OF IEEE 14 BUS SYSTEM

Type	Without Feature selection		With Feature selection	
	BPNN	DNN	BPNN	DNN
Classification accuracy (%)	78	84	87	92

The results of classifier obtained during testing phases for transient security assessment are compared in Table 2. The classification results of BPNN and DNN classifiers show that the DNN trained classifier gives fairly high classification accuracy compared to BPNN classifier. It has also been observed that the classification accuracy of DNN has increased significantly with the implementation of SFS feature selection algorithm.

VI. CONCLUSION

Transient security assessment is greatly important in the actual operation of a power system. In this paper, a Deep Neural Network approach to the transient security evaluation of a standard IEEE-14 bus test system has been presented. DNNs are very flexible models, which have many hidden layers and many units per layer with a very large number of parameters. This makes them capable of modelling very complex and highly non-linear relationships between inputs and outputs. Hence, the DNN can be applied to any power system irrespective of its complexity. A systematic methodology for feature selection of TSA using Sequential forward selection technique has been implemented for the selection of optimal set of training features, which has improved the performance in assessing the security of the power system. The proposed feature selection algorithm is an efficient method to cope with the problem of high dimensionality in the design of neural network. The Results obtained indicate the potential of DNN as a promising neural network technique for the transient security evaluation of power systems.

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