STUDY OF TRANSIENT STABILITY USING MACHINELEARNING METHODS

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***Abstract*— Transient instability is one of the most severe types of power system instability, which have serious socioeconomic consequences if avoided. Fast on-line transient stability assessment in modern power systems is limited by traditional methods such as time-domain simulations and direct methods. The invention of phasor measurement units has created the path for artificial intelligence-based pattern detection and categorization for transient stability assessment. There are several categorization techniques for measuring transient stability have been documented in the literature. This research seeks to provide information on which algorithm is best for determining power system stability for a specific dataset. In a comparative examination of datasets, neural networks, support vector machines, and deep learning are evaluated for their capacity to address the binary stability classification problem. To simulate an IEEE-12 bus test system, the above datasets were constructed using MATLAB and Simulink.**

***Keywords*— Transient stability assessment, neural network, support vector machine, deep learning**

I. INTRODUCTION

The ability of a power system to maintain synchronization when subjected to large shocks is known as transient stability. The dynamic characteristics of power systems are becoming increasingly complex as big power grids are interconnected, access to high penetration renewable energy is increased, and power markets are built. As a result, the danger of transitory instability rises. Therefore, for power system security, real-time and accurate assessment of post-disturbance transient stability is critical. Prediction of stability status of a power system in real-time is important in preventing blackouts. In case of a disturbance leading to transient instability, to empower a safer operation, early corrective control methods and stabilization methods should be operated to ensure the stability of the power system. There are number of approaches to identifying the stability of a power system. A time-domain simulation which is solving the differential equations can represent power system dynamic behavior. After a disturbance, an excess of energy that must be absorbed by the grid in order to maintain the stability. This energy will be referred to here as transient energy which can be found by analyzing the difference between the kinetic energy and potential energy after a disturbance and used to determine the stability status. The equal area criterion is another method which presents another direct approach to evaluating the transient stability of a power system. This method is a graphical technique used to examine the transient stability of a multi machine system with an infinite bus without solving time domain differential equations, here an equivalent machine is created from all the existing generators by considering the dynamic parameters.

Apart from these methods, machine learning methods are useful methods for solving complex problems related to power systems. In the proposed method support vector machine (SVM), artificial neural network (ANN), and deep learning have been applied to transient stability assessment by using post-fault generator bus voltages and load angles of each generator as their inputs. Furthermore, this paper investigates the performance of above said machine learning method in terms of the accuracy. The proposed method is illustrated on MATLAB simulated IEEE 12-bus test system, and then, the robustness of the method is examined by applying it under different contingencies.

II. LITERATURE REVIEW

There were several studies which have been done to predict the transient stability using machine learning methods such as ANN, and SVM. Standard IEEE 39-bus system was commonly used as the test system in order to check the performance and the accuracy of the machine learning methods. In general, generator bus voltage magnitudes, generator speeds, or the rotor angles were taken immediately after the fault clearance and it was used as inputtraining data for different types of classifiers in order to predict the stability status after the fault. 97% testing accuracy of predicting the transient stability was achieved inmost of the similar studies.

III. TRANSIENT STABILITY PREDICTION APPROACH

A. Test System

To train, evaluate and compare the performance of the different machine learning methods, the IEEE 12-bus system was used. The test system includes 12 buses, 4 generating units, 5 loads, and 9 transmission lines. The single-line diagram of the IEEE12-bus test system is shown in Fig. 1.

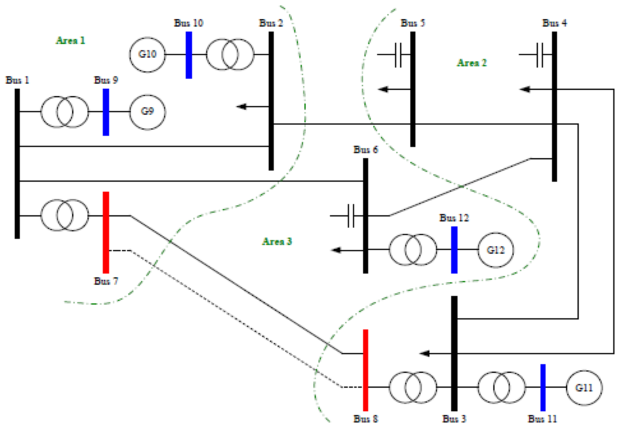

Fig. 1: IEEE 12-Bus

B. *Training Data Generation*

Data required for training the models were generated through MATLAB Simulink by modeling the IEEE 12 bus system. For the clarification of simulated bus system, whether it is running on steady state conditions, PSS/E software generated load flow analyze of same bus system was compared with it. Three-phase to ground, three phase, phase-phase-ground, phase-phase, and single phase-ground faults were the contingencies considered on each transmission line in five different locations starting at 0%, 25%, 50%, 75% and 100% of the length on each transmission line. Same contingencies were repeated on the loads by creating altogether 225 simulation cases. Until the system Fault is applied at 40^{th} second after make during it came to the steady state and fault clearing time of five cycles was assumed for all the contingencies which mean clearing the fault at 40.1s. For each case, the post-contingency variations of generator bus voltage magnitudes and load angles were taken for 1s using 0.002s sampling rate after the fault was cleared. Total number of data points for a particular data was 10 and those 10 data points were taken with 05, 07, 10, 20, 30, 40 and 50 cyclic intervals.

A class label was assigned such that ‘1’ for transient stable and ‘0’ for transient unstable for the response of each simulation case in term of the stability status by analyzing speed deviation curves and load angle curves. Fig. 2 shows the typical variations the generator bus voltage vs time graph for three phase- ground fault for a particular contingency that leads to instability. Finally, Generated data was used as input to the corresponding models and class labels of each simulation was used as the response.

Input: Training data set with m samples {x, y}, x=1894, y=80. Output: Stable (1) or Unstable (0). Given two graphs shows the variations of the generator load angles and speeds deviations during a contingency that leading to instability

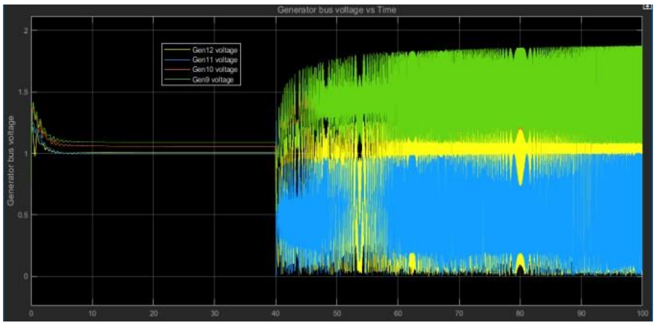

Fig. 2: Generator bus voltage vs Time graph

Similar to the training data set, testing data set also generated by considering contingencies on each transmission line in four different locations. In order to avoid the regeneration of same data, different fault locationswere selected. Faults such as three-phase to ground, three phase, phase-phase-ground, phase-phase, and single phase- ground were created at 15%, 40%, 60% and 80% of the length on each transmission line. For each case, generator bus voltage magnitudes and load angles were taken for 1s using 0.002s sampling rate after the particular fault cleared.

C. *Data Augmentation*

Increasing the size of data needed to train a machine learning model is known as data augmentation. Deep learning models frequently demand a large amount of training data, which is not always available. As a result, existing data is supplemented to produce a more comprehensive model. Initially we were able to generate 225 data from our 12-bus system owing to the number of buses are limited, which is not enough to train a machine learning model in order increase the accuracy of the output of the model. So, additionally 1894 data was generated using data augmentation technique.

IV. MACHINE LEARNING METHODS FOR TRAINING

A. *Artificial neural network*

Artificial neural networks (ANN) have become one of the most commonly utilized machine learning technologies in recent decades. The structure of the artificial neural network was inspired by the neuronal structure of the human brain. Multilayer perceptron (MLP), radial basis function (RBF) network, and self-organizing maps (SOM) are few examples of ANN structures. The MLP neural network structure is used in this study.

For neural network-based classification problems the cross-entropy cost function combined with the SoftMax activation function is preferred for training the network, since they have a good probabilistic interpretation. Cross-entropy cost function is used for optimizing the weights of the neural network. While training we randomly divide the total data set into three groups as for training, validation, and testing during the training process. We decided to proceed with following sets percentages to divide the total training data set,

TABLE 1: DATA SET ALLOCATION FOR TRAINING

	Train (%)	*validation (%)*	*test (%)*
1	70	15	15
2	60	20	20
3	50	25	25
4	40	35	35

After dividing each set of data, we developed the classifier model. We created the classifier with three layers, and they are the input layer, hidden layer, and output layer. In the input layer, we made eighty neurons, in the hidden layer we made ten neurons, and finally, in the output layer, we made two neurons. The reason why we decided to make eighty neurons is that the number of input data count for one fault is eighty and the reason for two neurons in the output layer is to get the output as a one-hot vector which is more reliable than using a single neuron.

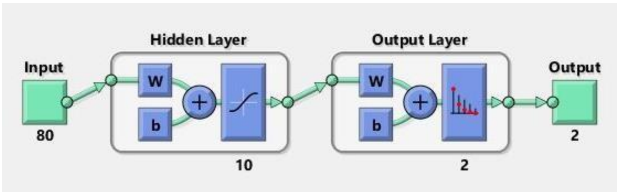

Fig. 3: Artificial Neural Network

Fig. 4: Confusion matrix of 10 cycle

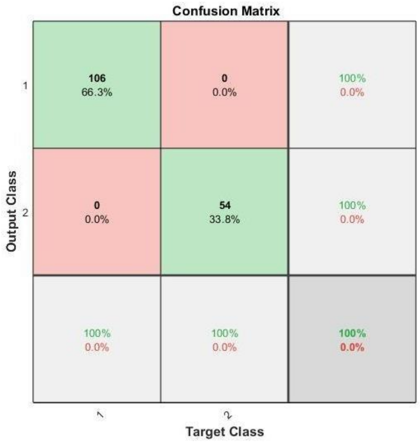

Fig. 5: Testing confusion matrix of 10 cycles

The training accuracies are tabled under Table 2 for each number of cycles.

TABLE 2: TRAINING ACCURACIES OF ANN

No of Cycles	Accuracy	
	70%,15%,15%	*60%,20%,20%*
	Training (%)	*Training (%)*
05	87.5	86.3
07	87.1	86.8
10	99.2	99.3
20	98.9	97.8
30	99.6	100.0
40	100.0	100.0
50	100.0	100.0

No of Cycles	Accuracy	
	50%,25%,25%	*40%,30%,30%*
	Training (%)	*Training (%)*
05	88.2	87.8
07	87.2	88.4
10	98.9	98.9
20	99.6	99.6
30	100.0	100.0
40	100.0	100.0
50	100.0	100.0

The trained model with the data obtained from five and seven cycles, the training accuracy percentage which was substantially low compared to other models. Therefore, we decided not to test those two models.

B. Support vector machine classification

Support vector machines (SVM) is a better method for classification-related problems. The basic concept of the

SVMs is creating a hyperplane by mapping the input data into a higher dimensional space using the kernel functions that make it linearly separable for the classification.

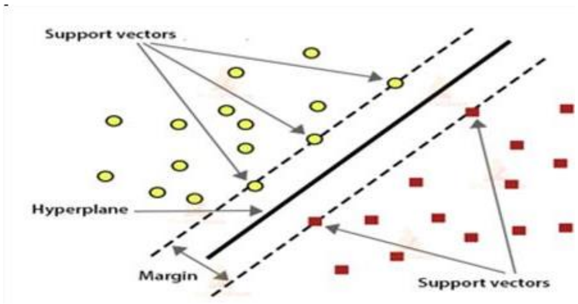

Fig. 6: SVM hyperplane

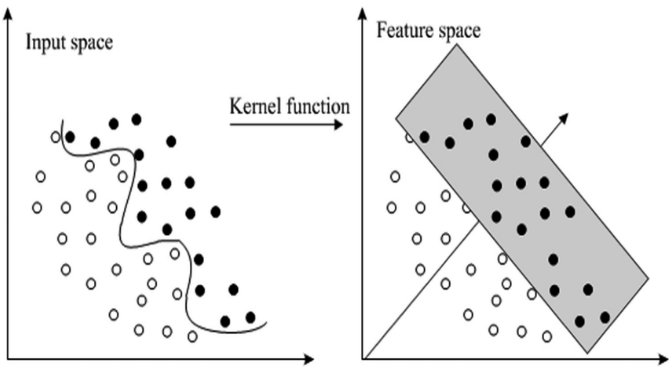

Fig. 7: Allowing linearly separable in higher dimensional spaces using Kernel functions

Training the data set was done by an inbuild app in Matlab known as classification learner app. This is generally used for training classification related problems by various types of machine learning methods. The classification learner app has the ability to train data with SVM by using various kernel functions simultaneously and ultimately calculate their training accuracies which gave the chance for selecting the optimum SVM which has the highest. In the training procedure, the K-fold cross validation method has been used to partition the data which split data into K partitions of equal sizes. Training and testing are repeated, randomly selecting the data set until all K partitions were taken to the validation. Different cross validations were used in order to figure out the best model.

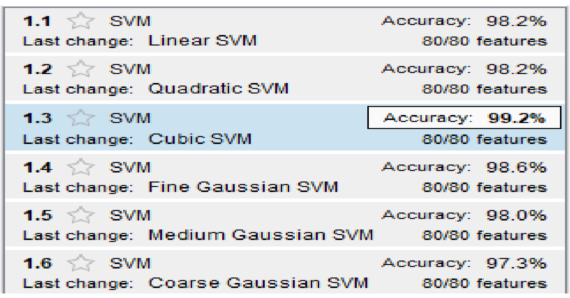

Fig. 8: SVM Model Accuracy

The testing accuracies are tabled under Table 3 for each number of cycles.

TABLE 3: TRAINING ACCURACIES OF SVM ACCORDING TO THE CROSS-VALIDATION

No of Cycles	Accuracy	
	75%, 25%	*80%,20%*
	Training (%)	*Training (%)*
05	95.1	94.1
07	93.7	94.7
10	98.7	99.1
20	98.4	98.8
30	99.6	99.4
40	100.0	99.8
50	100.0	100.0

No of Cycles	Accuracy	
	50%, 50%	*67%, 33%*
	Training (%)	*Training (%)*
05	95.7	95.7
07	95.5	95.3
10	98.3	99.2
20	98.7	98.9
30	99.6	99.5
40	100.0	100.0
50	100.0	100.0

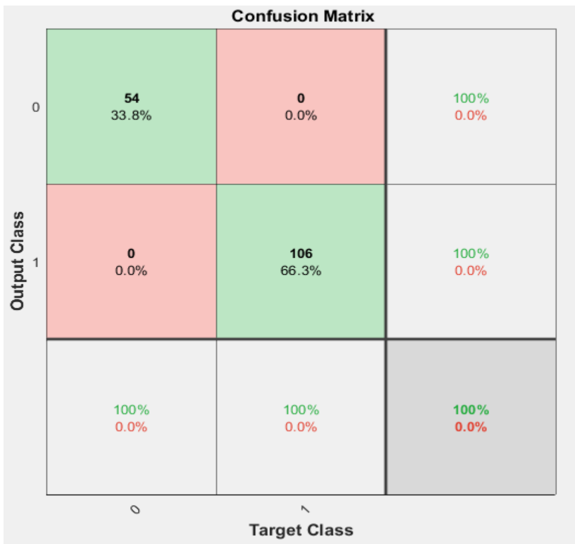

Fig. 9: Testing – Confusion Matrix for 5 fold cross validation

Every trained model in each cross validation gave substancial accuracy and each of these trained model have been used for to predict the new set of data by using another test data set. The training accuracy percentage of the data set which was gained from five and seven cycles was substantially lower than the training accuracy percentages of other cycles. Therefore, we decided not to test those two models as.

C. *Deep learning method*

Deep learning neural networks are an example of a multi-label classification problem solving system. Multi-label classification is a type of predictive modeling that entails predicting zero or more mutually non-exclusive class labels. deep learning-based classification, we used LSTM architecture for our training. Because our system is time series classification. Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. LSTM networks are well-suited to classifying, processing, and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. In the deep learning model, we have used the 'binary cross-entropy function for loss calculation and as the activation function, we have used the 'ReLU' function.

The control flow of an LSTM is comparable to that of a recurrent neural network. It processes data and passes the information on as it moves along. The operations within the cells of the LSTM differ. The LSTM uses these procedures to remember or forget information.

In binary cross-entropy function is the projected probabilities are compared to the actual class result, which can be either 0 or 1. The score is subsequently calculated, which penalizes the probabilities based on their deviation from the expected value. This refers to, how close or far the value is to the real one.

The rectified linear activation function, is a piecewise linear function. Here, if the input is positive, output is equal to the input otherwise, the output is equal to zero.

ReLU formula is : $f(x) = \max(0,x)$

Compared to the previous machine learning methods (ANN and SVM) here we were able to pass 90% testing accuracy for both five and seven cycles. The training accuracy for each cycle is tabled in Table 4.

TABLE 4: TRAINING ACCURACY OF DEEP LEANING MODEL WITH NO OF CYCLES

Cycles	Training Accuracy (%)
5	91.3
7	91.9
10	98.8
20	94.4
30	95.6
40	97.5
50	98.1

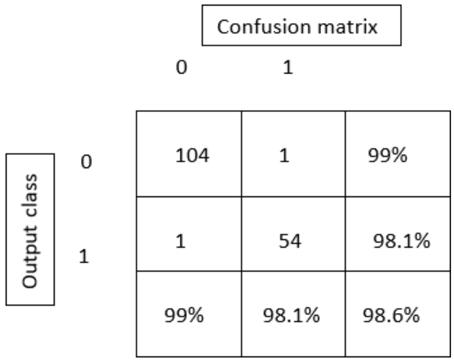

Fig. 10: Testing-Confusion matrix for cycle 50

V. CONCLUSION

This paper discussed the comparation between three different machine learning methods, SVM, ANN, and Deep Learning in order to find an accurate and fast way to predict the transient stability status in terms of the performance efficiency of a power system after being subjected to a transient disturbance. All three methods were fed by sampled values of generator bus voltage magnitudes and load angles which were taken immediately after the fault cleared in five cycles as input data. After the training the model, they were tested using different set of data. After the models were developed the over fitting problem was identified which is a general problem when training. Since our bench mark was to get more than 98% testing accuracy, we were able to achieve the training accuracy target by using 10 cyclic intervals to collect the data points. The aim is not only to make the transient stability predictions but also to evaluate the best model in terms of accuracy and performance. From the results, even though ANN, SVM and Deep learning have different training accuracies for the data collected with 10 cyclic interval their training accuracy was above the benchmark. Therefore, we can conclude that for IEEE 12 bus system either ANN, SVM or Deep learning can be selected to predict the transient stability with generator bus voltage magnitudes and rotor angles as the input which has to collected only for first 0.2 seconds form the time the fault is cleared in order to get more than 98% training accuracy.

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