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Probabilistic Transient Stability Assessment of Power Systems Using Artificial Neural Network

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***Abstract* – With the evolution of renewable energy sources, such as wind and photovoltaic generators (PVGs), the present electric power systems will transform into systems, possessing various amounts of uncertainties. These systems will be dominated by an unparalleled combination of a variety of generation and power transmission technologies, accompanied by flexible load and storage devices, and possessing spatial and temporal uncertainties. In this regard, the significance of probabilistic transient stability cannot be overlooked. The inherent methods to determine power system transient stability, such as Lyapunov direct method (based on transient energy function), and time-domain simulation method (based on numerical integration and algebraic-differential equations), have proven to be very computationally intensive. Novel soft computing techniques, such as machine learning and neural networks, provide promising results for tackling such kind of issues. Therefore, this paper aims to describe and discuss the framework for probabilistic transient stability in electric power systems and the application of artificial neural network to enhance its evaluation process. Various uncertain factors such as faulted line, fault type, fault location, and fault clearing time are incorporated in the analysis. Time-domain simulation, using DIgSILENT PowerFactory software, are used to obtain training data for the proposed neural network. The neural network toolbox of MATLAB is used to apply the proposed algorithm. Levenberg-Marquardt backpropagation algorithm is used for training purpose. The approach of probabilistic transient stability is demonstrated using the standard IEEE 39-bus test system. The results obtained indicate the effectiveness of the proposed algorithm such that it can be applied to transient stability prediction of large-scale practical power systems. Finally, a direction for future research in this growing area is identified.**

Keywords-Artificial neural network; machine learning; probabilistic transient stability; renewable energy sources; uncertainty

I. Introduction

Since the early 20th century, power system stability has been documented as a significant issue in securing power system planning and operation [1-2]. Most blackouts caused by power system instability have demonstrated the significance of this phenomenon [3-4]. Traditionally, transient stability has been the leading stability issue in most power networks. However, with the introduction of novel technologies and increasing load demands, several kinds of instability have appeared. For instance, voltage stability, frequency stability and interarea oscillations have gained importance. This has necessitated an understanding of the basics of power system stability. A lucid concept of various kinds of instability is significant for the acceptable operation of power systems. Reference [5] has broadly classified power system stability into three major kinds: frequency, voltage, and rotor angle. This is pictorially shown in Figure 1. A brief description of these classifications follows.

Frequency stability is the ability of a power system to maintain steady frequency after a severe system stress causes a substantial disparity between generation and load. It relies on the ability to maintain equilibrium between system generation and demand, with minimum inadvertent loss of load.

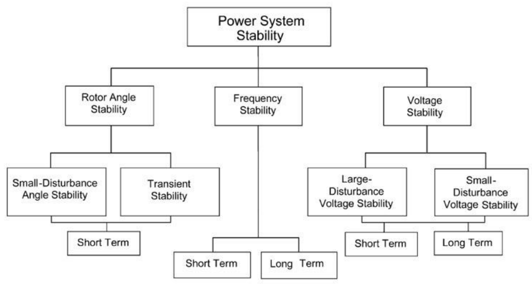

Figure 1. Classification of power system stability

An example of this phenomenon is the forming of an undergenerated island with inadequate under frequency load shedding such that frequency declines swiftly resulting in an island blackout within a few seconds. Longer-term phenomena, with the period of interest ranging from tens of seconds to several minutes, include situations in which steam turbine overspeed controls cause frequency instability.

Voltage stability is the ability of a power system to maintain steady voltages at all buses in the system, after being subjected to a disturbance from a given initial operating condition. The culprit for voltage instability is typically the loads. Large-disturbance voltage stability is the ability of a power system to maintain steady voltages after the occurrence of large disturbances, such as three-phase faults. The inherent features of system and load are major determinants of this ability. The period of interest typically ranges from a few seconds to tens of minutes. Small-disturbance voltage stability is the system's ability to maintain steady voltages when small disturbances, such as steady changes in network load, take place.

Rotor angle stability is the ability of synchronous machines in a power system to maintain synchronism when a disturbance is applied. Instability can result when the angular swing of generators causes a loss in synchronism. Small-signal rotor angle stability deals with stability under small disturbances, such as minor load variations. Large-disturbance rotor angle stability, or much more commonly called transient stability, focuses on the ability of the power system to maintain synchronism when a severe disturbance, such as a three-phase short circuit on a transmission line, is applied. The resulting system response constitutes large excursions of generator rotor angles and is affected by the nonlinear association between load angle and active power. The time range for transient stability studies is about 3 to 5 seconds after the disturbance has occurred.

The focus of this paper is probabilistic transient stability in electric power systems. Traditionally, transient stability analysis has been conducted using a deterministic approach, such as equal area criterion, and a direct method using the Lyapunov function [6]. This method is normally founded on a worst-case scenario, for instance, a three-phase fault at the terminals of a generator. In real systems, this situation seldom occurs. Hereafter, the results attained are conservative which increases the cost. Also, the approach cannot determine the system deviation from the stability state. These inadequacies of the deterministic method drove research in favor of the probabilistic approach for analyzing the transient stability of an electric power system. The probabilistic approaches to transient stability of power systems were first assessed in [7-9]. These approaches utilized the conditional probability method to formulate a single stability index for any system fault. Reference [10] further enhanced the concept of probabilistic power system stability. This technique incorporated a compound analytic transformation. In [11], the joint probability distribution function for the critical clearing time (CCT) was computed. References [12-14] have made some progress in stochastic modeling and have applied the bisection approach to decrease the computation time for CCT. The major shortcomings in these works is the use of conventional methods to assess transient stability. These methods may be suitable for offline (planning) phase as they are time-consuming, but are inappropriate for fulfilling the online (operational) requirements. Therefore, a faster method (based on artificial intelligence and neural network) can fulfil this significant requirement, and is the need of the hour.

The remainder of this paper is organized as follows. Section II discusses the need for probabilistic transient stability in power systems. Section III discusses the framework for probabilistic transient stability in power systems, and the associated random variables involved. Section IV gives a brief background of artificial neural networks (ANNs). Section V demonstrates the application of probabilistic transient stability using simulations on the IEEE 39-bus test system. Section VI presents the results and associated discussion. Finally, Section VII concludes the paper with recommended directions for future research.

II. The Need for Probabilistic Transient Stability in Power Systems

Conventional power systems are gradually evolving in terms of operation, planning, and design criteria. The future power systems will be categorized by an extraordinary mix of a variety of energy sources, such as wind, photovoltaic generators (PVGs), tidal, and gas, and effective power transmission technologies, such as high-voltage direct current (HVDC) and flexible AC transmission system (FACTS) devices. These evolved power systems will possess the following features: (1) new structures for liberalized electricity markets; (2) novel generation and storage technologies, most of which interface with power electronics (PEs), including wind farms and grid-connected photovoltaic (PV) technologies, that are sporadic and stochastic in nature, and result in large operation uncertainty; (3) propagation of PE-based efficient transmission technologies, and growing use of multimodal converters (MMC), and (4) novel kinds and diverse operational loads with better flexibility, including PE-interfaced loads and electric vehicles (EVs). One of the salient features of these systems is the upsurge in the level of uncertainties related to system modeling and operation. The main sources of uncertainties in a typical modern power system are: (1) network-based uncertainties, including network topology and settings of network elements, such as transformer tap settings and line parameters; (2) generation-based uncertainties including the output power uncertainty of PV and wind sources owing to forecasting errors; (3) load-based uncertainties, including uncertainty in load forecasting techniques and spatial variation in load, specifically the location of EVs; (4) uncertainties due to operating conditions, including the type, location, duration and impedance of a fault occurrence, and (5) weather-related uncertainties, including wind direction, wind velocity, solar irradiation, etc. [15].

A deterministic analysis of transient stability in a power system is based only on a specific case. It disregards the uncertainties in various system states and parameters as discussed above. Basically, deterministic analysis supposes that all system states are identified and do not vary over time. Traditionally, it has been conducted with a three-phase fault as this is the most severe example. This worst-case scenario gives conservative results and ignores the probability of events occurring. On the contrary, probabilistic transient stability considers the stochastic and probabilistic behavior of power system parameters. Thus, it can determine the risks for a given unforeseen event. Although, it was recognized that the deterministic approach does not accurately represent the system dynamic behavior, the framework for probabilistic transient stability has not been used extensively in recent times. Therefore, it is important to describe the methodology for probabilistic transient stability, as it can enable an enhanced comprehension of the system behavior during transient events [15-16].

III. Framework for Probabilistic Transient Stability in Power Systems

Conventional power system transient stability analyses have been deterministic. A specific procedure exists in which the system parameters, such as the fault type, fault location, fault clearing time (FCT), etc., are pre-selected, according to the worst-case scenario. Probabilistic studies, however, consider the stochastic features of the power system. Attention is given to the credibility and probability of a certain event happening. The framework for probabilistic transient stability in electric power systems is described in Figure 2 [16].

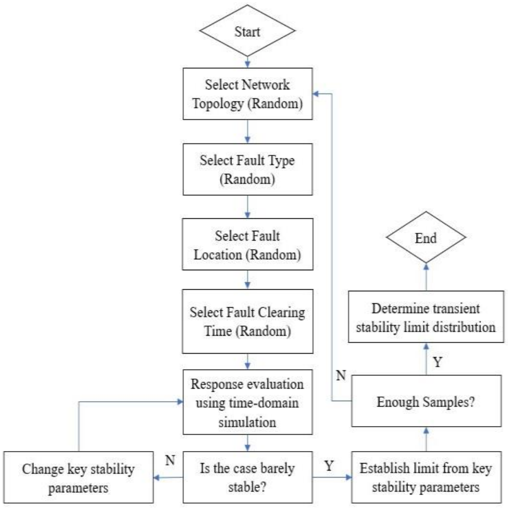

Figure 2. Framework for probabilistic transient stability

In the probabilistic approach, the procedure to include various system uncertainties is repeated many times. For instance, in deterministic transient stability, a specific network configuration is used, but for probabilistic analysis, a determination for forced transmission outages is required. In the next step, fault type, fault location and FCT are randomly chosen based on suitable probability distributions. Barely stable indicates a case where increasing the stability parameter above the threshold level will cause an unstable case [16].

Common distributions, which are used to model the probabilistic factors in transient stability, are outlined below [17-21].

A. Fault Type

Generally, shunt faults, such as three-phase (LLL), double-line-to-ground (LLG), line-to-line (LL) and single-line-to-ground (LG) short circuits, are considered for evaluating probabilistic transient stability. A discrete distribution is normally used to model the fault type. Based on past system statistics, the common practice is to select the probability of LLL, LLG, LL and LG short circuits, as 0.05, 0.1, 0.15, and 0.7 respectively [22].

B. Fault Location

The probability distribution of fault location on a line is usually assumed to be uniform or can be predicted from the actual fault statistics. This implies that a fault may occur with equal probability at any line of the power system and at any point (0-100%) along the line [20]. Let $\Pr(F_{loc})$ denote the probability of fault location on a line.

$$\Pr(F_{loc}) = \begin{cases} \dfrac{1}{N_d}, \text{ for } 0 \le i \le N_d \\ 0, \text{ otherwise} \end{cases} \tag{1}$$

where N_d=100.

C. Fault Clearing Time

The procedure for fault clearing is comprised of three stages: fault detection, relay operation and breaker operation. If the primary protection and breakers are fully reliable, only the clearing time is the uncertain factor. A normal (Gaussian) distribution is generally used to model this time [20]. Let $f(T_C)$ denote the probability density function for clearing time, T_C.

$$f(T_C) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(T_C - \mu)^2}{2\sigma^2}} \tag{2}$$

IV. Artificial Neural Networks

An ANN normally consists of a set of connected nodes (known as artificial neurons), which replicate the features of the biological neurons [23]. Each neuron can communicate a signal to other neurons, which, in return, processes it. A simple diagram of feedforward neural network is shown in Figure 3.

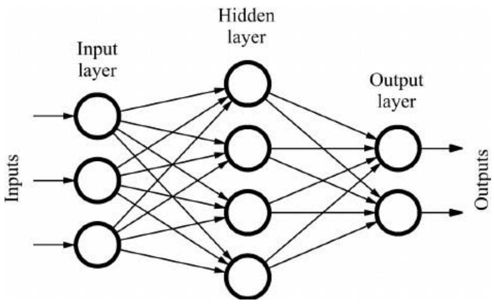

Figure 3. Feedforward ANN

ANN is usually used to predict the values for a set of new inputs, when the network is trained for existing data. To quantify the performance of the prediction, mean squared error (*MSE*) is usually used. Mathematically, it is given by

$$MSE = \frac{\sum_{i=1}^{N} (f_i - y_i)^2}{N} \tag{3}$$

where N denotes total number of data points; f_i and y_i denote the predicted and actual value of output, respectively.

Backpropagation algorithm is normally used to adjust weights and biases of neural network. This algorithm is perhaps the most central building block in a neural network. It was first introduced in 1960s, and almost 30 years later, it was disseminated by Rumelhart, Hinton and Williams. The algorithm is essentially used train a neural network through a technique called chain rule. In simple words, after each forward pass through a network, backpropagation performs a backward pass while adjusting the weights and biases of the model. The detailed discussion of the algorithm is beyond the scope of this paper.

The activation function of the artificial neurons in ANNs implementing the backpropagation algorithm is a weighted sum (the sum of the inputs x_i multiplied by their respective weights w_{ji}):

$$A_j(\bar{x},\bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \tag{4}$$

As evident, the activation depends only on the inputs and the weights. If the output function would be the identity (i.e. output equals activation), the neuron would be called linear. The most common output function is the sigmoidal function:

$$O_j(\bar{x},\bar{w}) = \frac{1}{1+e^{A_j(\bar{x},\bar{w})}} \tag{5}$$

The goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and there is a need to adjust the weights to minimize the error. The error function for the output of each neuron can be defined as:

$$E_j(\bar{x},\bar{w},\bar{d}) = (O_j(\bar{x},\bar{w}) - d_j)^2 \tag{6}$$

In the next step, the backpropagation algorithm computes how the error depends on the output, inputs, and weights. After determining this, the weights can be adjusted using the method of gradient descent:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \tag{7}$$

Although, ANNs have been applied to transient stability assessment in [24-27], but most works neglect the stochastic dynamics and uncertainties of the power system. Hence, this works attempts to apply ANN to predict transient instability parameter, considering uncertainties.

V. CASE STUDY AND SIMULATIONS

To quantify the output for the probabilistic transient stability approach, researchers have proposed different indices. These indices include probability of instability of different lines [13], probability of system instability [18], and expected frequency of transient instability [8]. In recent years, the Transient Stability Index (*TSI*) has been used to assess system transient stability in the presence of conventional synchronous generators [22, 28-31]. This index uses maximum rotor angle separation between any two synchronous generators, after a fault has occurred. Mathematically, it is given as (8).

$$TSI = \frac{360-\delta_{\max}}{360+\delta_{\max}} \tag{8}$$

where $-1<TSI<1$

The maximum rotor angle separation between any two synchronous generators in the system after a fault is represented by $\delta_{\max}$. A negative value of *TSI* indicates that the system is unstable. The larger the *TSI* value, the greater the system stability. The same index is used in this section to demonstrate the application of probabilistic transient stability on a standard test power system.

Let N_s denote the total Monte Carlo (MC) iterations for random sampling of distributions of faulted line, fault type, fault location, and FCT.

Let N_u denote the number of iterations which cause instability (i.e., when $\delta_{\max i} > 360$). Let N_{st} denote number of iterations which cause stability (i.e., when $\delta_{\max i} < 360$). Thus,

$$N_s = N_u + N_{st} \tag{9}$$

Let P_{LG}, P_{LL}, P_{LLG}, and P_{LLL} denote the probability of instability for LG, LL, LLG, and LLL faults, respectively. Mathematically,

$$P_{LG} = \frac{N_{u1}}{N_s} \tag{10}$$

$$P_{LL} = \frac{N_{u2}}{N_s} \tag{11}$$

$$P_{LLG} = \frac{N_{u3}}{N_s} \tag{12}$$

$$P_{LLL} = \frac{N_{u4}}{N_s} \tag{13}$$

where N_{u1} , N_{u2} , N_{u3} , and N_{u4} denote the number of unstable samples for LG, LL, LLG and LLL faults, respectively.

Let P_{SYS} denote the probability of system instability, i.e.,

$$P_{SYS} = \frac{N_u}{N_s} \tag{14}$$

where N_u denotes the total unstable samples, irrespective of the fault type.

The computation procedure is outlined in Figure 4. Symbol *i* denotes the iteration number of the MC simulation. The number of samples N_s selected for the MC simulation are limited to 1,000. This number has been established based on the observance of suitable convergence. Faulted line, fault type, fault location, and FCT are selected based on distributions described in Section III. For defining the FCT, Normal distribution, with various values of mean, is considered (keeping the standard deviation constant). Thus, a random fault is placed at 1 *s* on a random line with a random point (0-100%) on the line. The fault is cleared based on the normal distribution of FCT. The process is repeated for N_s MC simulations. In the next step, values of P_{LG}, P_{LL}, P_{LLG}, P_{LLL}, and P_{SYS} are determined for different values of FCT mean. In the last step, ANN model is trained to predict the value of P_{SYS}, without conducting the computationally intensive time-domain simulation.

The well-known IEEE 39-bus test transmission system was used to conduct the required simulations using DIgSILENT PowerFactory. The numerical data and parameters were taken from [32]. It was assumed that the analysis was conducted for the worst-case scenario, i.e., peak load. The system one-line diagram is shown in Figure 5.

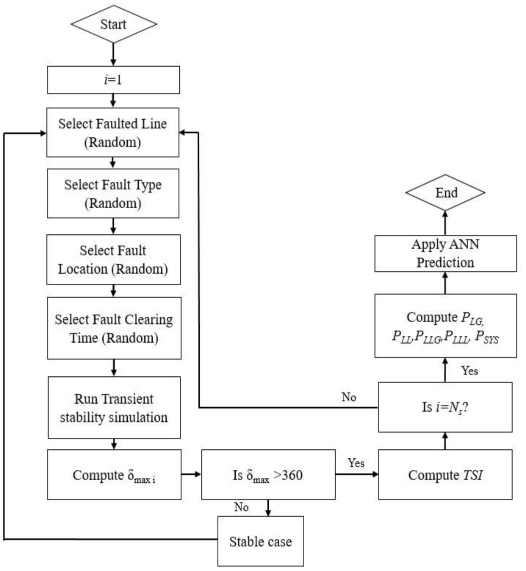

Figure 4. Probabilistic transient stability application to IEEE 39-bus system

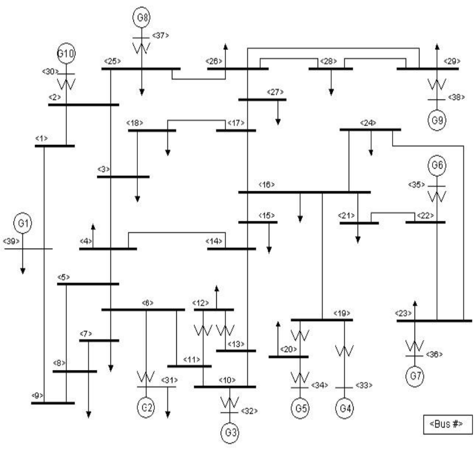

Figure 5. IEEE 39-bus test system

VI. RESULTS AND DISCUSSION

The results for variation of P_{LG}, P_{LL}, P_{LLG}, and P_{LLL} with FCT mean are shown in Figure 6. As is evident, increasing the FCT mean, increased P_{LG}, P_{LL}, P_{LLG}, and P_{LLL}. Moreover, for all situations, P_{LLL} was the highest and P_{LG} was the lowest. This is because the LLL fault was the most severe. Moreover, the LG fault was the least severe. The same trend in fault severity was observed for all variations in FCT mean. After a certain FCT mean was achieved (1.4 *s* in this case), values of P_{LG}, P_{LL}, P_{LLG}, and P_{LLL} did not alter. This is because, in this instance, the FCT became greater than the CCT of the system, hence, the number of unstable samples for each fault remained unchanged after FCT mean equals 1.4 *s*.

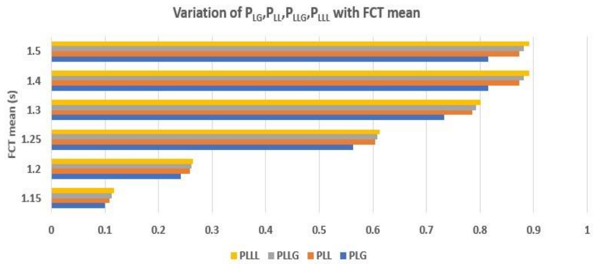

Figure 6. Variation of P_{LG}, P_{LL}, P_{LLG}, and P_{LLL} with FCT mean

It is important to observe the trend of P_{SYS} with FCT mean. The trendline is displayed in Figure 7. As is evident, P_{SYS} increased approximately linearly as FCT mean increased. The CCT was defined as the maximum time before which the fault must be cleared by the protection device to keep the system stable [18]. Thus, stability was only achieved if FCT was less than CCT. However, after a certain FCT mean (1.4 *s*), P_{SYS} remained constant. This is because system CCT was less than FCT.

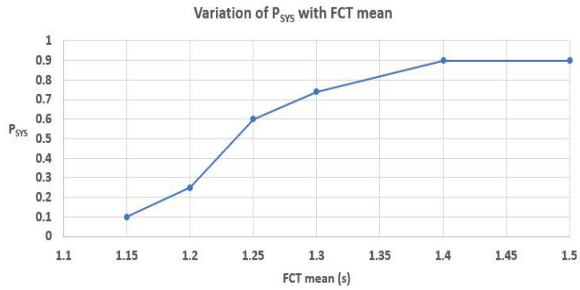

Figure 7. Variation of P_{SYS} with FCT mean

These results give the power system planner a good idea regarding selection of tripping times for circuit breakers. If slow breakers (having a larger FCT mean) are chosen, they obviously will expose the system to a greater risk of transient instability. Therefore, it is recommended that fast-operating circuit breakers be used to minimize the risk of system transient instability. Moreover, the impact of fault type is important to quantify the severity levels of different fault types. The location of fault on a line is vital. Fault near bus-ends of the line may prove more critical for the system than a fault at, say, middle of the line. Therefore, it is important to consider all probabilistic factors which can impact the assessment of transient stability in an electric power system. This analysis can be applied to a large-scale power system, and the results can be compared to analyze the transient stability performance of systems possessing diverse characteristics. These findings, regarding the significance of probabilistic methods in power systems, with increasing renewable generation penetration and the rising unexpected events, are also highlighted by [33-45].

In the second part, an ANN was used to predict the value of P_{SYS}. Application of ANN is significant in transient stability as time-domain simulation is very time-consuming, especially for large-scale power systems. The training data consisted of faulted line as inputs and value of P_{SYS} as output. The neural network toolbox of MATLAB, a part of which is shown in Figure 8, was used to train and validate the performance of the prediction accuracy. Levenberg-Marquardt algorithm was used for training purpose. The data division for training, validation and testing was chosen as 70%, 15%, and 15%, respectively. The results obtained are shown in Figure 9. As evident, the value of regression correlation coefficient, R, is very close to 1 in all phases (training, validation, testing). It means the trained model is very accurate in predicting values of P_{SYS}. The x-axis represents the target (actual) values of P_{SYS}, and the y-axis represents the predicted values of P_{SYS}. The closer the value of R to 1, the greater is the prediction accuracy. The resulting error histogram is shown in Figure 10. Also, the depiction of best validation performance is shown in Figure 11.

The results obtained by the proposed approach is comparable to the results presented by various research papers [46-48] in this field. Moreover, all these papers indicate the strong possibility of application of machine learning (including ANN) to online prediction of power system security.

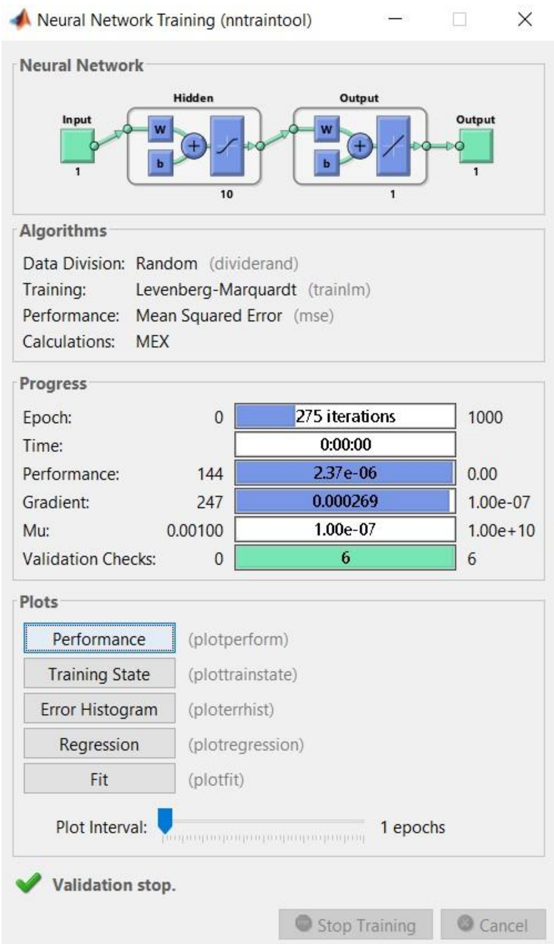

Figure 8. MATLAB Neural Network toolbox

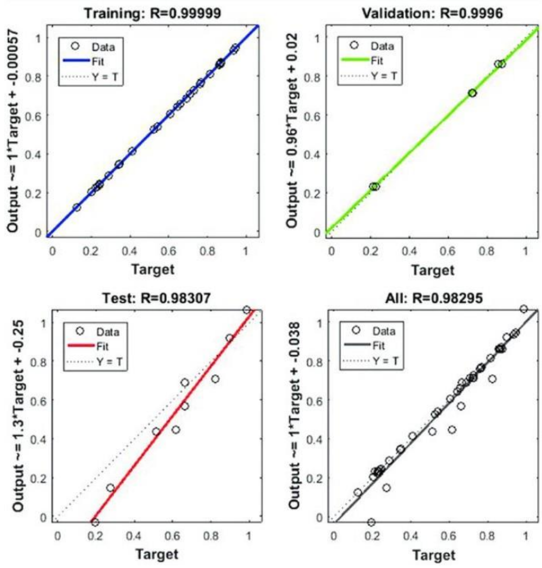

Figure 9. Regression plot (target vs predicted values) for prediction performance assessment

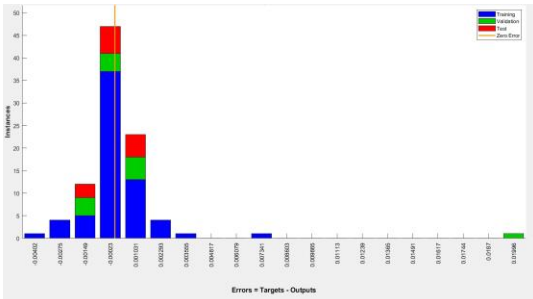

Figure 10. Error histogram of P_{SYS}

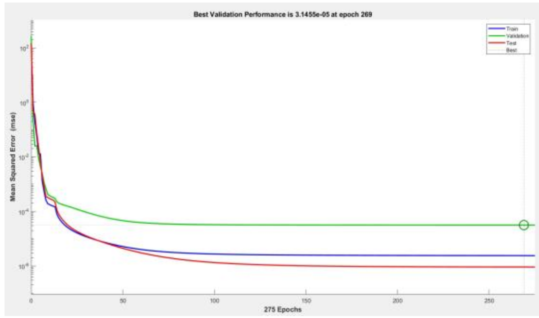

Figure 11. Best validation performance (at iteration 269) for P_{SYS}

VII. Conclusion and Future Work

This paper presented the framework for analyzing probabilistic transient stability in electric power systems. Various uncertain parameters involved were described. Moreover, the significance of the probabilistic approach was highlighted. A case study was conducted for the application of probabilistic transient stability on the IEEE 39-bus test system. ANN was applied to predict the instability probability, without having the need to solve the complex and time-consuming differential-algebraic equations of time-domain simulation approach. The main technical benefit of the proposed approach is that it gives faster prediction of transient stability status when compared to conventional methods. Moreover, the economic benefit of the proposed approach is that it allows power system planners to make rapid decisions (based on neural network-based model transient stability status predictor). This, in turn, prevents equipment damage due to delayed decision-making, thereby providing a huge economic advantage.

A possible extension of the application could be to consider various transient stability models of synchronous generation. The sources and levels of uncertainties are on the rise in electric power systems. Due to this, probabilistic transient stability will become indispensable in the future. The trade-off between modeling accuracy and computation burden is a developing research subject. Moreover, techniques need to be developed that can accurately model the correlation between various random system input variables. Other machine learning approaches, such as decision trees (DTs), random forests, and support vector machines (SVMs) can be applied for predicting probabilistic transient stability, and consequently, a performance comparison can be made with ANN.

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