Genetic Algorithm based Artificial Neural Network model for Voltage Stability Monitoring

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Abstract—**In this paper, hybrid Artificial Neural Network and Genetic Algorithm (ANN-GA) approach for online monitoring of long-term voltage instability has been proposed. Thegenetic algorithm (GA) has been used to improve the accuracy of ANN by tuning its meta-parameters such as number of nodes in hidden layer, input and output activation function and learning rate. The proposed approach uses the voltage magnitude and phase angle obtained from phasor measurement units (PMUs) as the input vectors and the outputs is the Voltage Stability Margin Index (VSMI)vector. The effectiveness of the proposed approach is testedon New England 39-bus test system. The results of the proposed ANN-GA approach for voltage stability monitoring is compared withANN model on same data set.**

Keywords--Artificial Neural Network (ANN), Genetic Algorithm (GA), Phasor Measurement Units (PMUs), Voltage Stability Margin Index (VSMI).

I. INTRODUCTION

Earlier, the electric power systems were limited to relatively small geographical regions but today the connection of regional power network forms a highly interconnected large system. Such large power system leads to complexity in the monitoring and operation, as disturbance in one part of the system may adversely impact the entire system. The power system observability is a necessary condition for real-time power system monitoring, protection and control for effective implementation of Wide Area Monitoring Protection and Control Systems (WAMPC). The Phasor Measurement Unit (PMU) is the main technology enabler of WAMPC. PMU measures voltage phasor at the installed bus and current phasors to all connected buses [1]. PMU provides synchronized voltage phasors, current phasors, frequency and rate of change of frequency. Synchronization in PMU is achieved through a common referenced clock of Global Positioning System (GPS) [2].

In recent years, voltage collapse is a major cause for many power system blackouts [3] around the globe. The traditional method for voltage stability analysis relied on static analysis using the conventional power flow method such as Gauss-Seidel or Newton-Raphson method. In references [4]-[8], numerous voltage stability indexes based upon conventional power flow have been proposed. The main drawback of these techniques is the singularity of the Jacobian matrix at maximum loading point. To overcome this problem, Ajjarapu, and Christy has proposed Continuation Power Flow (CPF) method to compute voltage stability margin [9]. Gao et al. [10] has proposed the modal analysis technique to compute the voltage stability level of the system. The aforementioned techniques require comparatively large computations and are not efficient for on-line applications.

In recent years, the machine learning techniques such as ANN, fuzzy logic, pattern recognition, support vector machine etc. has been used for power system analysis. Reference [11] introduces a method of using the ANN model for predicting the voltage stability margin of a power system. The author has proposed artificial feed forward neural network (FFNN) approach for the assessment of power system voltage stability [12]. Zhou et.al. [13], proposed a new online monitoring technique for voltage stability margin using synchrophasor measurement.Usually, ANNs are considered to be more powerful, flexible method known for performing nonlinear regression. However, ANNs suffer from the amount of training time and the scores of the learning parameters, if the ANN meta-parameters are not selected optimally.

In this paper ANN–GA approach, which not only relieve the user from choosing thesemeta-parameters but also find out the optimum valuesof these parameters to minimize the generalizationerror. The approach uses an ANN as the nonlinear processmodeling paradigm, and the GA for optimizing themeta-parameters of the ANN model such that animproved prediction performance is realized. ANN-GA is used to emulate the continuation power flow for estimation of voltage stability margin index (VSMI) for steady state voltage stability analysis. The input features of ANN-GA are formed by voltage magnitude and voltage phase angle obtained from PMUs. The effectiveness of the proposed method is presented using the New England 39-bus test system and the performance indices of ANN-GA are also compared with ANN model.

II. PROBLEM FORMULATION

A. Volatge Stability Assessment (VSA)

The main objective of voltage stability analysis is to determine whether the current operating point of power system is stable, meeting various operational criteria. The voltage vs real power curve (P-V curve) [6] as shown in Fig. 1 can be used directly to obtain voltage stability margin. Considering if at the current operating point the total active power delivered to the load is $P_{current}$ and the

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maximum active power transfer is $P_{\max}$, then the Voltage Stability Margin (VSM) for each load bus can be calculated as

$$VSM_i = P_{\max,i} - P_{current,i}, where\, i = 1, 2....l \qquad (1)$$

Where, l is the total number of load buses in the power system. The Voltage stability margin index (VSMI)for the network is given by:

$$VSMI = \min(\frac{VSM_i}{P_{\max,i}}) \qquad (2)$$

VSMI is an indicator of voltage collapse in the power system. The VSMI varies in a range between 1 (no load) and 0 (maximum loadability).

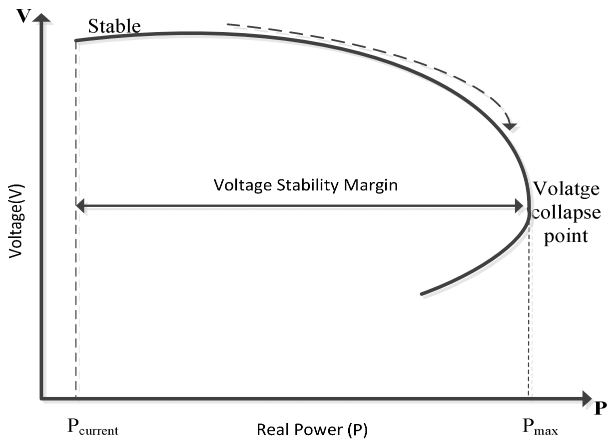

Figure 1: P-V Curve

To determine the collapse point, PV curve is drawn using the CPFbecause conventional power flow (Gauss-Seidel or Newton-Raphson) method fails to converge as the operating point reaches the nose point of PV curve[7, 14].

The CPF program calculates the voltage stability limit starting from a specified initial operating point. The flow of the procedure involved in the determination of VSMI is shown in Fig. 2. Every power network has different types of nodes. For PV-node, real power and voltage magnitude are known and for PQ-nodes, real and reactive power is specified.Therefore, this known parameter is fed to conventional power flow to calculate the current values of voltage magnitude ($V_{current}$), voltage phase angle ($\theta_{current}$), real power ($P_{current}$) and reactive power ($Q_{current}$) at the current operating condition. With these calculated values, the CPF is used to trace the PV-curve and to determine the parameters corresponding to voltage collapse point $V_{\max}, \theta_{\max}$, $P_{\max}$ and $Q_{\max}$. Then these parameters are used to calculate VSM and VSMI using (1) and (2).

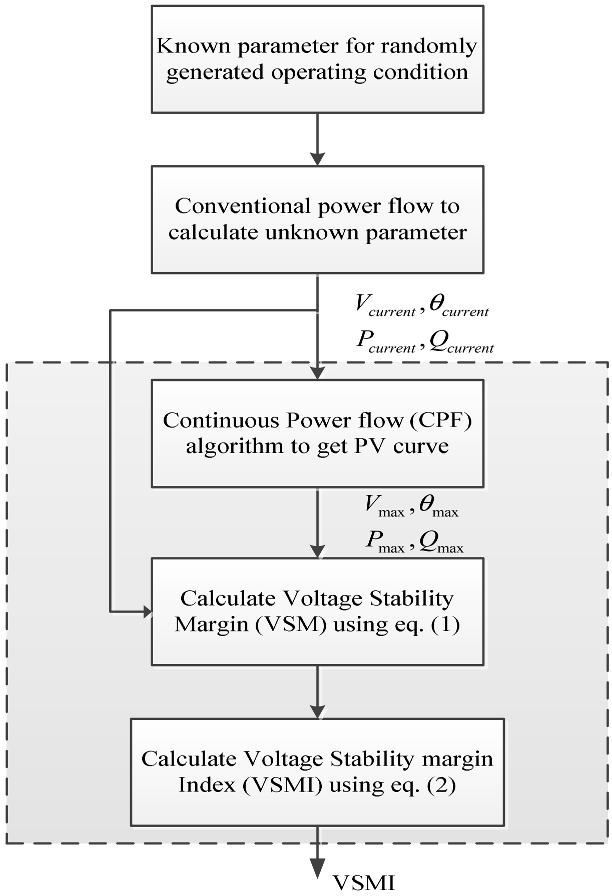

Figure 2: Procedure to calculate VSMI

To predict the voltage stability margin index, the computations shown inside dotted area in Fig 2 is replaced by ANN-GAmodel. The major advantage of using ANN-GAis that it avoids the traditional iterative procedure to find VSMI and can be used for real time application. The input to ANN-GAis voltage magnitude and voltage phase angle which is assumed to be obtained from PMUs.

III. Artificial Neural Network

Artificial Neural Network (ANN) can be defined as union of simple processing units based on neurons that are connected to each other to obtain a performance similar to a human's performance when solving problem. These connections contain the “knowledge” of the network and the patterns of connectivity express the objects represented in the network. And the knowledge about the network is obtained through a learning process. ANN is an effective alternative to solve the problem where mathematical description of the process is impossible but it is possible to obtain the data describing the problem.

Among the several artificial neural networks which have been proposed, the most widely used type of neural network is the multilayer perceptron (MLP) networks, also known as the multilayer feed-forward network [15]. The ANN structure and learning process is shown in Fig. 3. The ANN consists of an input layer, hidden layers and an output layer of neurons.

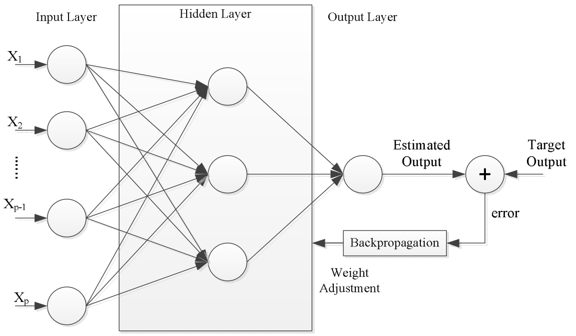

Figure 3: ANN structure and learning process

A. ANN-GA approach for Regression

The selections of meta-parameters are very important in ANN modeling to get better estimation accuracy. The tuning meta-parameters of ANN are listed below:

1. Number of nodes in hidden layer: The number of nodes in hidden layer has a profound effect on ANN performance. Too few nodes cannot learn the relationship in data properly and too large number of nodes increases the network complexity and execution time.
2. The activation functions in input layer: Each hidden node and output node applies the activation function to its input. Five type of activation function are available and are shown in table I. Y_i is the output from node i and inp_i is the input to node i.

TABLE I: DIFFERENT ACTIVATION FUNCTIONS

Case	Activation function	Equation
1	Log sigmoid (logsig)	$Y_i = \frac{1}{(1+\exp(-inp_i))}$
2	Tan hyperbolic (tansig)	$Y_i = \tanh(inp_i)$
3	Linear function (purelin)	$Y_i = (inp_i)$
4	Radial basis(radbas)	$Y_i = \exp(-inp_i \wedge 2)$
5	Triangular basis (tribas)	$Y_i = \begin{cases} 1-abs(inp_i) & if\ -1 \le inp_i \le 1 \\ 0 & otherwise \end{cases}$

3. The activation function in output layer: same activation function are applied as shown in table I.
4. The learning rate: The performance of the back propagation algorithm can be improved by estimatingoptimal learning rate. The learning rate is multiplied with the negative of the gradient to determine the changes to the weights and biases. The larger the learning rate, the bigger the step. If the learning rate is made too large, the algorithm becomes unstable. If the learning rate is set too small, the algorithm takes a long time to converge.

In this paper genetic algorithm is used to optimize the meta-parameters to inprove the accuracy of ANN model.

B. GA-based optimization of ANN model

In Hybrid Artificial Neural Network and Genetic Algorithm (ANN-GA) model, genetic algorithm is used for tuning ANN meta-parameter. The objective is to minimize mean square error (MSE) and the optimal problem of ANN model is represented as follows:

$$\min f = MSE(X)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2$$

$$X \in \{x1, x2, x3, x4\}$$

Where,X1 is Number of nodes in hidden layer and varies from $1 \le x1 \le 50$, x2 and x3 are input layer and output activation function and can have values between 1 to 5 corresponding to five activation function as shown in table I and x4 is learning rate which is varied between 0 – 5. A_i and P_i are the actual and predicted values and n is the number of training data samples.The above-formulated problem has been solved for optimal solution using GA [16].Table II gives the list of GA parameters setting used for the tuning of ANN meta-parameters.

TABLE II: GENETIC ALGORITHM PARAMETER SETTING

Generations	100
Population size	1000
Selection type	Standard roulette wheel
Crossover type	Simulated binary
Mutation type	Polynomial method
Crossover probability	0.8
Mutation probability	0.05

C. ANN-GA performance measures

To evaluate the performance of the ANN-GA model following indices have been evaluated

1. Mean Absolute percentage Error (MAPE)
2. Maximum Percentage Error (MPE)
3. Willmott's Index of Agreement (WIA) [17]

TABLE III: PERFORMANCE INDICES AND THEIR EXPRESSIONS

Indices	Expressions
Mean Absolute percentage Error (MAPE)[a]	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{A_i - P_i}{A_i}\right\rvert * 100$
Maximum Percentage Error (MPE)	$MPE = \max(\left\lvert\frac{A_i - P}{A_i}\right\rvert) * 100$
Willmott's Index of Agreement (WIA)	$WIA = 1 - \frac{\sum_{i=1}^{n}(A_i - P_i)^2}{\sum_{i=1}^{n}\left(\lvert A_i - \overline{A}\rvert + \lvert P_i - \overline{A}\rvert\right)^2}$ $\overline{A} = \frac{1}{n}\sum_{i=1}^{n} A_i$

[a] A_i and P_i are the actual and predicted values

Table III shows the Performance indices and their expressions to find the deviation between actual output and predicted output. The smaller the value of MAPE and MPE, closer the predicted value to actual value. The WIA measures the regression degree and varies from 0 (complete disagreement) to 1 (perfect agreement). WIA close to 1represents more accurate predicted value.

IV. RESULTS

The proposed hybrid ANN-GA based method for online voltage stability monitoring is applied to the New England 39-bus test system [18]. It consists of 20 load buses, 10 generator buses and 35 transmission lines. Selection of input feature for voltage stability margin can be expressed as a function of the four variables i.e. voltage magnitude, voltage phase angle, real power and reactive power that define the system operating point. In the proposed work, voltage magnitude and voltage phase angle obtained are taken as the input to the ANN-GA model. It is assumed in this work that the value of voltage magnitude and phase angle is the output of PMUs. These PMUs are installed in the system for complete observability. This means that all the data are available for all the load buses.

In ANN-GA model, GA is used to determine the optimal values of ANN meta-parameter i.e. number of nodes in hidden layer, input layer and output layer activation function and learning rate. Within the overall searching process, the optimal fitness value is 0.202% and table IV shows the optimal values of ANN meta-parameter for New England 39-bus system.

TABLE IV: ANN META-PARAMETER OPTIMIZED BY GENETIC ALGORITHM

ANN meta-parameters	Optimum values
Number of nodes	22
Input activation function	Linear function(purelin)
Output activation function	Linear function(purelin)
Learning rate	1.12

. For generating sample data for the ANN-GA, active and reactive powers at the load buses are varied randomly within ±30% of the base case values. In the present work 2500 random operating points are generated for training and another 100 operating points were used to verify the performance of proposed ANN-GA method.

The plot shown in Fig.4 is the regression plot of Target VSMI against output VSMI by the ANN-GA, for the 100 unseen test cases. Table V lists the performance indices of both training data used as input and 100 unseen test cases for New England 39-bus system.

TABLE V: ANN-GA PERFORMANCE INDEX FOR TRAINING AND TESTING DATA FOR NEW ENGLAND-39 BUS SYSTEM

Performance Indices	Training Data	Testing Data
Mean Absolute percentage Error (MAPE)	0.1849	0.1486
Maximum Percentage Error (MPE)	9.38	0.784
Willmott's Index of Agreement (WIA)	0.9976	0.9988

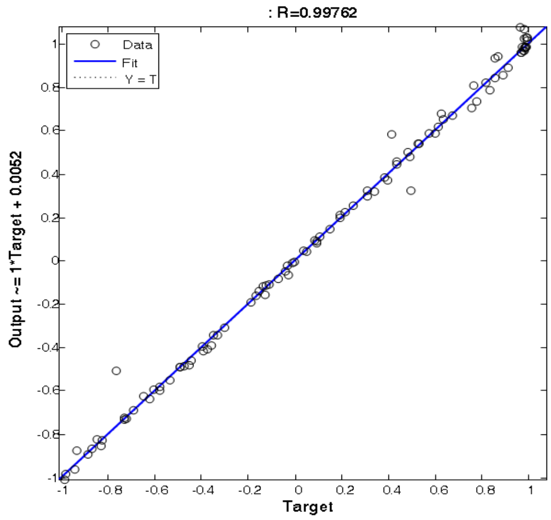

Figure 4: VSMI estimation for New England 39-bus system

To find the effectiveness of the ANN-GA model presented in this paper, comparison of hybrid ANN-GA model with ANN model is carried out. In both the model the same data set is taken for analysis. The meta-parameter considered and the performance indices calculated for ANN-GA and ANN are shown in table VI.

TABLE VI: COMPARISON OF PERFORMANCE OF ANN-GA MODEL VS ANN MODEL

	ANN-GA model	ANN model
Mean Absolute percentage Error (MAPE)	0.1486	0.1821
Maximum Percentage Error (MPE)	0.784	5.0343
Willmott's Index of Agreement (WIA)	0.9988	0.98624
Number of nodes	22	20
Input activation function	Linear function(purelin)	Tan hyperbolic function (tansig)
Output activation function	Linear function(purelin)	Linear function(purelin)
Learning rate	1.12	1.12

Table VI shows that ANN-GA model is superior to ANN model. The performance indices MAPE and MPE with smaller values indicate small deviation between the predicted and the actual values. The higher value of WIA rating indicates that VSMI predicted by ANN-GA have more precision as compared to ANN model.

A. Computation Time

Computation time is also an important aspect when applying machine learning techniques to a practical system. Table VII list the ANN-GA and ANN model training and testing time for New England 39-bus system. The computation time is estimated by matlab inbuilt function tic/tac and the computer specification used is Intel® Core ™ i7-2600 CPU @ 3.40 GHz. The experiment is conducted on the same machine using 2500 sample training set, 100 unseen test cases for both models. The result shows that selecting ANN meta-parameter using genetic algorithm reduces computational complexity when compared with ANN model.

TABLE VII: COMPARISON OF TRAINING AND TESTING TIME OF ANN-GA VS ANN MODEL

Model	Training time (sec)	Testing time (sec)
ANN-GA	6.7069	0.0254
ANN	8.1237	0.0262

V. CONCLUSION

An online voltage stability monitoring scheme has been proposed in this paper. The proposed technique is based on hybrid ANN and genetic algorithm (ANN-GA) model. The ANN-GA has been used to estimate voltage stability margin index (VSMI) under normal operating condition. The inputs to ANN-GA are considered as the voltage magnitude and phase angles. The effectiveness of the proposed approach has been illustrated on New England 39-bus system. The performance indices calculated shows that the proposed technique for estimating the VSMI can be used for online voltage stability monitoring in practical system.

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