Approximate Loading Margin Methods Using Artificial Neural Networks in Power Systems

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***Abstract*—This paper proposes approximate loading margin methods using Artificial Neural Networks (NN) for static voltage stability in power systems. Two methodologies, namely Actual LM with NN (ALM-NN) and Maximum Loading Margin with NN (MLM-NN), are proposed for finding NN training data sets. Artificial Neural Network is used to approximate the loading margin at particular generation direction. The proposed methods are validated and compared with the Maximum Loading Margin method in the modified IEEE 14-bus test system. The methods will help system operators to approximate voltage stability margin or loading margin of the system in a short period of time.**

***Index Terms*—Loading margin, maximum loading margin method, neural networks, generation direction.**

I. Introduction

Voltage instability has been a major concern in power systems, especially in planning and operation, as there have been several major power interruptions associated with this phenomenon, in the past [1]-[2]. Voltage instability due to the lack of the ability to foresee the impact of contingencies is one of the main reasons for the worst North American power interruptions on August 14th, 2003 [2]. Hence, many electric power utilities have been devoting a great deal of efforts in voltage stability assessment and margin enhancement.

Major contributory factors to voltage instability are power system configuration, generation pattern and load pattern [1], [3]-[6]. Generation pattern is easier to control by system operators compared to other factors, as long as there is enough margin left in the generators [4]-[5]. Conventionally, in typical voltage stability studies, generation of participating generators are raised at the same rate or predefined rate. Increasing generation at this rate may not lead to highest voltage stability margin.

Maximum Loading Margin (MLM) approach, which provides the maximum Loading Margin (LM) or static voltage stability margin is proposed in reference [5]. An approximate and simple model representing the relationship between the generation direction (GD) and the loading margin is used to obtain the maximum loading-margin point. Although, MLM method can provide maximum LM in the generation direction space, it approximate LM based on curve fitting methods. In addition, reactive power of all generators except the swing generator is at the limits for all cases at the LM point [5]. Alternatively, one may be interested in approximating the LM directly from the actual LM with corresponding generation direction from exhaustive simulation. This can be done by using a heuristic approach such as Artificial Neural Networks (NN) [7].

Based on the above observation, attention drawn in this paper is to propose a simple simulation approach that provides an approximation of LM in the generation direction space using Artificial Neural Networks. If the LMs at various generation directions are trained using Neural Networks, operator can approximate LM of the system at a particular generation direction in a fast and simple way. It may be useful in the real-time Energy Management System at the load dispatching center or System Operator.

The rest of the paper is organized as follows: Section II presents static voltage stability. Existing Generation Direction methods are summarized in Section III. New simulation approaches are proposed in Section IV. In Section V, numerical results are presented. Finally, in Section VI, major contributions and conclusions are given.

II. Static Voltage Stability

Voltage stability is the ability of power system to maintain adequate voltage magnitude so that when the system nominal load is increased, the actual power transferred to that load will increase [1]. It is mainly associated with reactive power imbalance. In static voltage stability study, Continuation Power Flow (CPF) and optimization methods are the main analysis techniques that are used to find voltage stability margin or loading margin of the system [1], [4]-[6], [8].

Major contributory factors to voltage instability are power system configuration, generation pattern, and load pattern. The generation pattern is easier to control by system operators compared to load pattern. Customarily, the generation of each participating generator is raised at the same rate, at a pre-defined rate, or according to their spinning reserves. In the following section, existing methods of generation directions are summarized.

III. Generation Direction

Generation pattern or "direction" is defined as the portions of generation increase in each participating generator to serve

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the desired load increase and losses in the system. Let K_{Gi} be the factor for active power increase at generator *i* and $P_{Gi,o}$ be the generation at the base case, then, the generation P_{Gi} at a higher loading point can be written as

$$P_{Gi} = P_{Gi,o}\left(1+K_{Gi}\right) \tag{1}$$

where *i* = 1, 2, …*n*, for all participating generators.

The factor K_{Gi} can be viewed as the generation direction (GD_i) and is very crucial to voltage stability. Generation Direction can be worked out by finding the slope of generation increase for individual generator. Existing methods to identify generation directions in voltage stability study are summarized below.

A. Conventional Approach

Conventionally, the generation for a system is increased by fixed percentage as pre-specified in the planning stage, e.g., according to the spinning reserve [1], [4]. The power generation of generator *i* after the load increase can be written as

$$P_{Gi} = P_{Gi,o}\left(1+K_{Gi}\right) = P_{Gi,o} + \Delta P_{Gi} \tag{2}$$

and

$$\sum_{NG} \Delta P_{Gi} = \Delta P_D + \Delta P_{loss} \tag{3}$$

where
- P_{Gi} is the power generation of generator *i*,
- $P_{Gi,o}$ is the generation of generator *i* at base load,
- ΔP_{Gi} is the increase of power generation at generator *i*,
- ΔP_D is the total load increase,
- ΔP_{Loss} is the total loss increase,
- NG is the number of generators.

B. Optimal Power Flow Approach

Traditional Optimal Power Flow (OPF) can be formulated to include voltage stability criteria as follows [8]:

Minimize
$$C\left(P_{Gi}\right) = \sum_{NG}\left(a_{Gi}P_{Gi}^2 + b_{Gi}P_{Gi} + c_{Gi}\right) \tag{4}$$

subject to

$$P_{Gi} - \left(1+\lambda\right)P_{Di,o} - \sum_{j=1}^{n}\left|U_i\right|\left|U_j\right|\left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) = 0 \tag{5}$$

$$Q_{Gi} - \left(1+\lambda\right)Q_{Di,o} - \sum_{j=1}^{n}\left|U_i\right|\left|U_j\right|\left(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}\right) = 0 \tag{6}$$

$$\left|P_{Gi}\right|_{\min} \le \left|P_{Gi}\right| \le \left|P_{Gi}\right|_{\max} \tag{7}$$

$$\left|U_i\right|_{\min} \le \left|U_i\right| \le \left|U_i\right|_{\max} \tag{8}$$

$$S_{ij} = \sqrt{P_{ij}^2 + Q_{ij}^2} \le S_{ij,\max} \tag{9}$$

Where
- C is total operating cost of the system,
- a_{Gi}, b_{Gi}, c_{Gi} are cost coefficients of generator *i*,
- λ is load incremental parameter or loading factor (L.F.),
- P_{Gi}, Q_{Gi} are real and reactive power generation at bus *i*,
- $P_{Di,o}$, $Q_{Di,o}$ are real and reactive power demand at bus *i* at base load,
- n is number of buses in the system,
- $|P_{Gi}|_{min}$, $|P_{Gi}|_{max}$ are lower and upper power limits of generator *i*,
- $|U_i|_{min}$, $|U_i|_{max}$ are lower and upper limits of voltage magnitude at bus *i*,
- P_{ij} , Q_{ij}, , S_{ij} are the real, reactive and apparent power in line *ij*,
- $S_{ij,max}$ is the MVA (Thermal) limit of line *ij*.

Generation direction, in this approach, can be worked out by subtracting the new dispatch from the old dispatch for individual generators.

C. Cost Participation Factor Approach

Cost participation factor is viewed as the easiest method to identify amount of power generation with economic load dispatch consideration. It is calculated based on generators' incremental cost [8]:

$$\Delta P_{Gi} = \frac{\left(1/C_i^{''}\right)}{\sum_{j=1}^{NG}\left(1/C_j^{''}\right)}\Delta P_D \tag{10}$$

where
- C_i is the cost function of generator *i*,
- $C_i^{''}$ is the second derivative of the cost function *i*,
- ΔP_{Gi} is the increase in power generation for generator *i*,
- ΔP_D is the total load increase.

Among the existing methods, very few of them can provide the highest LM of the system. Hence, in the following section, the Maximum Loading Margin method is presented to maximize the LM by searching in the "generation direction space."

D. Maximum Loading Margin Method

The MLM method identifies a vector of the GDs of generators that gives maximum LM by approximating the surface of the LM as a function of the generation directions. If one can approximate the LM surface as a function of all generation direction variables (K_{Gi}), optimization technique can be used to provide the highest LM point. Mathematically, the method can be formulated as follows:

$$LM = B_0 + \sum\left(\sum_{p=1}^{n} B_{i,p}K_{Gi}^{p}\right) \tag{11}$$

subject to

$$\sum_{i=1}^{NG} K_{Gi} = 1 \tag{12}$$

$$0 \le K_{Gi} \le 1 \tag{13}$$

where K_{Gi} is the generation direction for generator *i*, $B_{i,p}$ are the coefficients terms, B_o is a constant term, *p* is the power term and *n* is the number of terms of the polynomial approximation. If generation is increased according to this direction, the system will have the maximum loading margin.

The MLM method provides a good approximation of the GD, which would give the maximum LM for a given case. Since LM surface may have multiple maximum, as it can be approximated by polynomial equations, MLM method may be required to find the global maximum.

E. Other Existing Methods

Linear and quadratic estimates of the LM with respect to system parameters, including power generation, are computed by using sensitivity method to locally predict the new location of the maximum loading margin points [9].

From the existing methods, only MLM method can provide maximum loading margin in the generation direction space. This method requires an approximated LM surface equation based on the two-dimensional LM curves in each generation direction. This may be useful when one would like to find the maximum LM point based on an optimization technique.

At the load dispatching center or System operator, however, one may be interested in finding the LM of the system in a short period of time when some generation directions are considered. Instead of approximating LM in an equation as proposed in the MLM method, one may suggest to use some heuristic methods such as Artificial Neural Networks to approximate the LM surface. In the following, new LM approximation methods are proposed based on the actual LM, MLM method and Neural Networks.

IV. PROPOSED METHODOLOGIES

A. Artificial Neural Networks [7]

Neural network is a collection of interconnected neurons that incrementally learn from their data to capture essential linear and nonlinear trends in complex data. Neuron networks perform a variety of tasks such as approximation, prediction, etc.

There are several NNs suitable for nonlinear analysis, including multilayer perceptron (MLP) networks, radial basis function (RBF) networks, etc. MLP is the most popular and widely used nonlinear networks for solving many practical problems. The reason for the popularity is that it is flexible and can be trained to assume the shape of the patterns. The MLP can be called universal approximators due to their ability to approximate any nonlinear relationship between inputs and outputs to any degree of accuracy. The power comes from the hidden layer of neuron located between the input layer and output layer of neurons. The hidden layer may consist of one or many nonlinear neurons and it performs continuous, nonlinear transformations of the weighted input. Nonlinear activation function transforms the weighted input of a neuron nonlinearly to an output. Sigmoid activation function is the popular one. The most widely used sigmoid activation functions are logistic function and hyperbolic tangent function. Output of each neuron is given in Equation (14), where the weighted sum of inputs is passed through a sigmoid function as

$$\sigma\left(\sum_{j=1}^{n}\omega_j x_j + b\right) \tag{14}$$

B. Proposed Methodologies

The simulation method is presented in two steps: *Step I-Obtaining Training Data Set* and *Step II-Approximation of LM Using NN.*

Step 1: Obtaining Training Data Set

Two methodologies for finding training data set, namely Actual LM Method with NN (ALM-NN) and Maximum LM Method with NN (MLM-NN) are proposed. The methodologies are described as follows:

- *Actual LM Method with NN (ALM-NN):* The actual loading margins and corresponding generation directions are found from exhaustive simulation using any voltage stability software to calculate loading margin of the power system for a given generation direction [5]. The actual LM and corresponding GD are used as a training data set.
- *Maximum LM Method with NN (MLM-NN):* The relationship of LM with respect to GD of each generator is found from a single dimensional space as only one generator is considered, except the swing bus. The LM surface is approximated for multi-dimensional case based on the separability condition and MLM method presented in Section III.D.

Step 2: Approximation of LM using NN

After LM and all possible GDs are found, the training data set is then used to train the NN. From the NN, the approximated LM can be found from any generation direction value.

Fig. 1 summarizes the process of the proposed approximated LM methods. In the beginning, generation direction is firstly set for the CPF process. Then the training data set is found. For ALM-NN method, the completed PV curve is plotted to obtain the LM of the particular generation direction. The process is then repeated until enough training data are obtained. For MLM-NN, the LM surface is approximated for all possible GDs. The training data is then used in NN process by introducing GDs as inputs and LM as an output. After the NN is trained to find the appropriate weights and other NN parameters, one can use the trained NN to approximate the LM at the GDs of interest. The proposed method is validated in the following section.

V. NUMERICAL RESULTS

A. Test Power Systems

The modified IEEE 14-bus test system [5] is used to validate the proposed method. Its single line diagram is depicted in Fig. 2, which consists of five synchronous machines, including one synchronous compensator used only for reactive power support and four generators located at buses 1, 2, 6 and 8. The modification from the original IEEE 14-bus test system is that generators located at buses 6 and 8 were changed from synchronous compensators to generators. In the system, there are twenty branches and fourteen buses with eleven loads totaling 259 MW and 81.4 Mvar. The value of 259 MW is used for the base MVA of the IEEE 14-bus system.

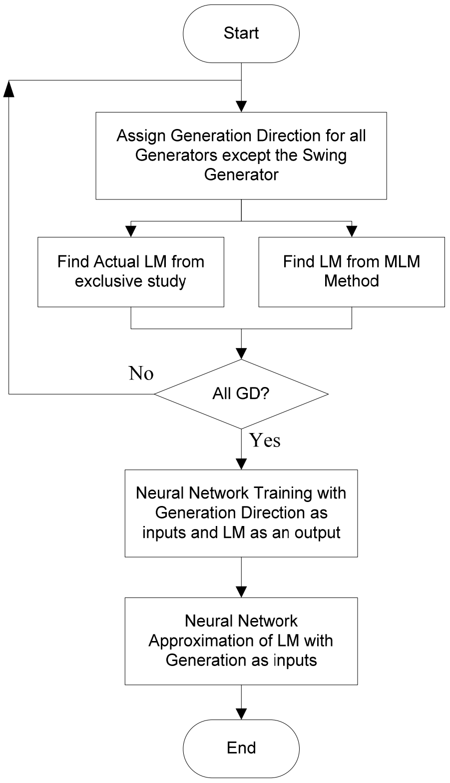

Fig. 1. LM Approximation Using Artificial Neural Networks.

Results presented in the paper were produced with the help of UWPFLOW [10] and another Neural Network Software. The UWPFLOW is a research tool that has been designed to calculate loading margin of the power system for a given load and generation direction. In the following section, simulation results are presented.

B. Training Data Set

The size of generation direction space is in proportion to the number of dispatchable generators considered in the study. To limit the number of generators in this study, a total of four generators are used for the IEEE 14-bus test system. Three cases of three generators are used throughout the paper.

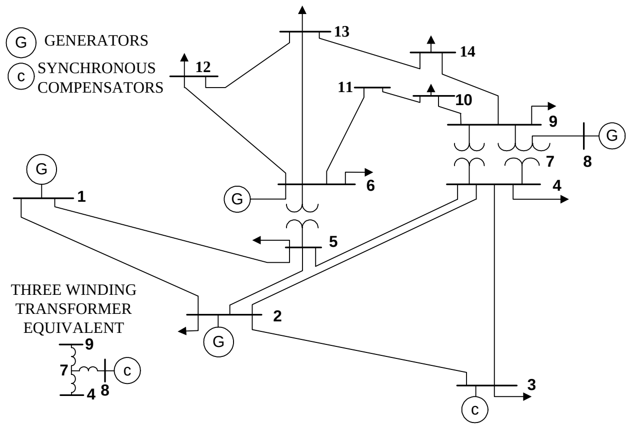

Fig. 2. Single line diagram of the modified IEEE 14-bus test system.

1. ALM-NN

Three cases of generator locations are considered: generators are located at buses 1, 2 and 6 (Case G126); at buses 1, 2 and 8 (Case G128); and at buses 1, 6 and 8 (Case G168). The actual LM is found with the help of UWPLOW program based on the methodology presented in Section IV. The actual data of LM and GDs are plotted in Figs. 3, 4 and 5 for the G126, G128 and G168 cases, respectively. These LM plots are obtained from PV at all possible GDs in the GD space with 0.1 GD step. The maximum LM and corresponding GD of each case are shown in Table I. From Table I, the maximum LM of G126, G128 and G168 cases are 1.1655, 1.0286 and 1.0686, respectively.

2. MLM-NN

The MLM method is based on the loading margin of the system at various possible generation directions in the generation direction space. The approximate plots obtained from MLM method for G126, G128 and G168 cases are shown in Figs. 6, 7 and 8, respectively. Clearly, the plots obtained from the MLM approach are almost the same as those obtained from the actual LM plot.

The LM obtained from actual LM and MLM methods are used to train NN in the following subsection.

C. Approximation of LM using NN

From LM and GD data obtained in previous subsection, one may use GDs as inputs and LM as an output to train the NN. Multilayer perceptron with activation functions and black propagation are used to capture nonlinearity of the training data. There are 66 training data used in the training process. Table II shows the summary of the training data and results for each case. The result is obtained from the best solution of 30 training results that provide the minimum training error. From the table, about 7-47 neurons are used in the hidden layer. Number of neurons and types of activation function are obtained from the best solution using NN software. The training times are only few minutes and testing time for each Gxyz case is less than 1 second.

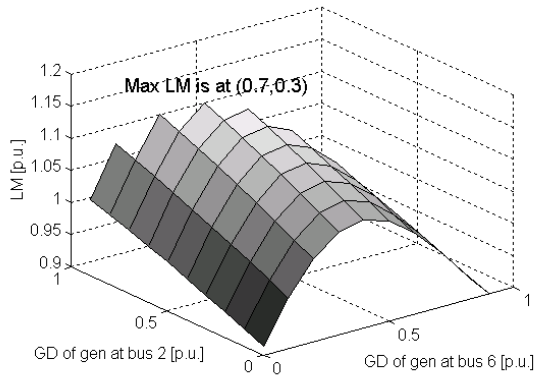

Fig. 3. Actual LMs in case G126.

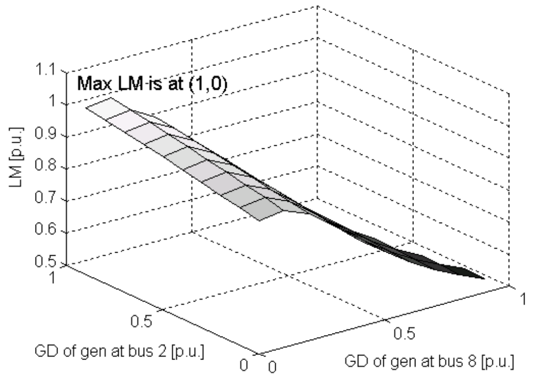

Fig. 4. Actual LMs in case G128.

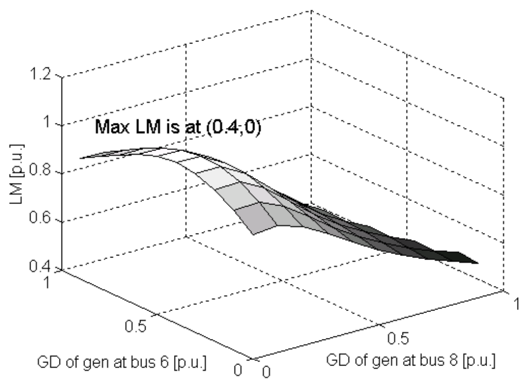

Fig. 5. Actual LMs in case G168.

TABLE I. COMPARISON OF GENERATION DIRECTIONS AND LM.

Cases	Solutions obtained from the Actual LM plot	
	LM (p.u.)	GDs
G126	1.1655	(0,0.7,0.3)
G128	1.0286	(0,1,0)
G168	1.0686	(0.6,0.4,0)

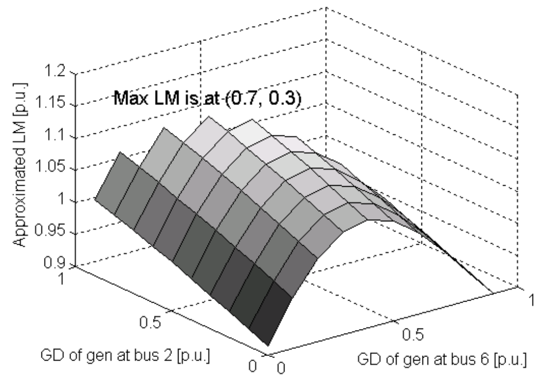

Fig. 6. Approximated LMs in case G126 using the MLM approach.

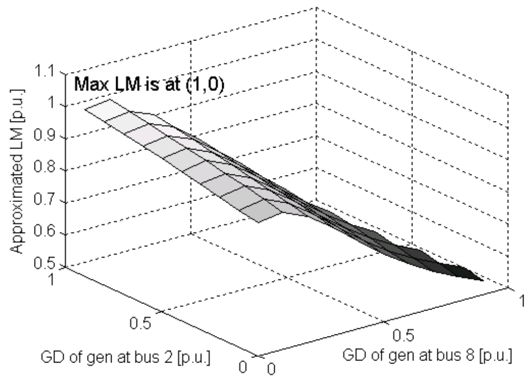

Fig. 7. Approximated LMs in case G128 using the MLM approach.

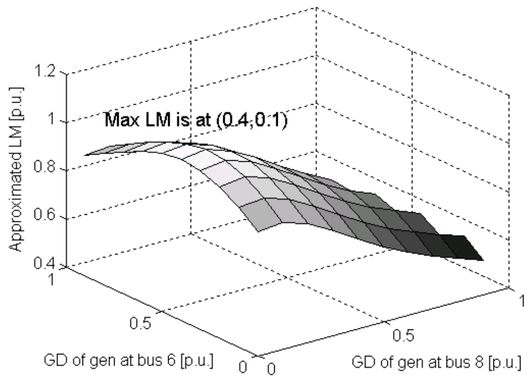

Fig. 8. Approximated LMs in case G168 using the MLM approach.

The numerical solutions of each method are given in Table III for all the cases. The GD data used for testing has 0.25 interval where those for learning has 0.1 interval. From the table it can be seen that neural networks can capture nonlinearity of LM surface. The approximated LM solutions are very close to the actual LM value as shown in Figs. 3-5 and to approximated LM from MLM method [5]. The proposed method provides a good approximation of LM, which may help System Operator to obtain LM at some generation direction points in a short time. The methodology may be applied to EMS system at load dispatching center or System Operator.

TABLE II. TRAINING RESULT INCLUDING HIDDEN LAYER, OUTPUT LAYER, ACTIVATION FUNCTION AND NUMBER OF NEURONS.

Case	Hidden Layer		Output Layer	
	Activation Function	No. of Neurons	Activation Function	No. of Neurons
	For ALM-NN/ MLM-NN			
G126	Tanh/Tanh	15/7	Sine/Sine	1/1
G128	Tanh/Sine	15/37	Tanh/Logistic	1/1
G168	Tanh/Exp	12/47	Exp/Identity	1/1

TABLE III. NEURAL NETWORK OUTPUT AT DIFFERENT GDS

GD for Gxyz case			ALM-NN for Gxyz			MLM-NN for Gxyz		
x	y	z	126	128	168	126	128	168
1.00	0.00	0.00	0.913	0.916	0.931	0.913	0.973	0.908
0.75	0.00	0.25	1.047	0.864	0.867	1.047	0.871	0.862
0.50	0	0.50	1.057	0.712	0.710	1.056	0.713	0.714
0.25	0	0.75	0.968	0.595	0.598	0.968	0.592	0.591
0.00	0	1.00	0.859	0.515	0.547	0.859	0.539	0.523
0.75	0.25	0.00	0.946	0.964	1.038	0.946	0.985	1.049
0.50	0.25	0.25	1.087	0.889	0.958	1.080	0.897	0.999
0.25	0.25	0.50	1.094	0.729	0.753	1.089	0.744	0.849
0.00	0.25	0.75	0.996	0.604	0.613	1.000	0.609	0.718
0.50	0.5	0.00	0.976	0.990	1.052	0.976	0.994	1.057
0.25	0.5	0.25	1.124	0.907	0.969	1.110	0.920	1.004
0.00	0.5	0.50	1.129	0.744	0.753	1.119	0.776	0.858
0.25	0.75	0.00	1.003	1.012	0.967	1.003	1.002	0.979
0.00	0.75	0.25	1.157	0.944	0.902	1.138	0.941	0.925
0.00	1	0.00	1.029	1.025	0.866	1.028	1.008	0.846

VI. CONCLUSION

This paper proposes new methods, namely ALM-NN and MLM-NN, for approximating loading margin or voltage stability margin of the system using Artificial Neural Networks. Loading margins in generation direction space are used to train neural networks. Multilayer perceptron with activation functions and black propagation are used to capture nonlinear relationship of the training data. The proposed methods are validated and compared with Actual LM and MLM methods in the three generator cases in the modified IEEE 14-bus test system. The results show that the proposed method is able to find the result in a short period of time. It can be used in the EMS system to help System Operator to approximate voltage stability margin based on generation directions in a simple and fast way.

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