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Fast and Accurate Estimation of Power System Loading Margin using Extreme Learning Machine with Reduced Input attributes

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ABSTRACT

This paper presents an Extreme Learning Machine (ELM) approach for a fast and accurate estimation of the power system loading margin for multiple contingencies with reduced input attributes. Active and reactive power flows of all load buses are chosen as the input features to the ELM. The training data for the ELM model are generated by using the Continuation Power Flow (CPF) method. The proposed method is Mutual Information (MI) based dimensionality reduction technique to reduce the input dimension and for improving the performance of the developed network with less training time, which makes ELM approach applicable to large scale power system. IEEE 30-bus system and IEEE 57-bus system are considered for the demonstration of an effectiveness of the proposed methodology under various loading conditions on the single line contingencies. Simulation results validate the proposed ELM with reduced input features for fast and accurate on-line voltage stability assessment.

Keywords: Extreme learning machine, voltage stability assessment, loading margin, mutual information based feature selection

1. INTRODUCTION

For online applications, a fast and accurate estimation of the power system loading margin is required to take decisive actions to avoid voltage collapse in the power system. Voltage stability may be assessed using static and dynamic methods. Many analytical methods [1–12] have been proposed for the static and dynamic method of voltage stability assessment that is time-consuming and limits their application for on-line. Alternatively, many authors [13-19] have proposed Artificial Neural Network (ANN) for an on-line monitoring of voltage stability. Because of slow gradient-based learning algorithms with all parameters tuned in an iterative manner, the training time of a feed forward neural network goes higher. Also, traditional ANN learning algorithms usually suffer from excessive training and/or tuning burden leads to the unsatisfactory generalization performance.

This paper contributes an accurate and valid prediction model for loading margin estimation that can overcome the limitations of conventional ANN learning algorithms. In this paper, ELM model [20] is developed for power system loading margin estimation for multiple contingencies with reduced input features. For large power systems, the training ELM with all input features consumes large training time. MI-based feature selection technique is used to reduce the input variables for reducing the training time without compromising the accuracy. IEEE 30-bus system and IEEE 57-bus system are considered for a demonstration of an effectiveness of the proposed methodology under various loading conditions on single line contingencies.

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2. LOADING MARGIN ESTIMATION FOR VOLTAGE STABILITY ASSESSMENT

Voltage stability is concerned with the ability of the power system to maintain acceptable voltage levels at all buses in the system under different loading conditions, where the system can work normally or subjected to disturbance, to ascertain the stability limit and margin. Voltage stability is commonly analyzed and applied either through time-domain (dynamic) simulation or through steady-state analysis to predict voltage collapse between these two approaches. Time-domain system influencing voltage stability is usually slow. Therefore, many aspects of the problem along with a wide range of system condition's examination can be effectively analyzed by using static methods which can provide a better insight into the nature of the problem and identifying the key contributing factors. For static voltage stability, system load is increased incrementally and slowly (in certain directions) to the point of voltage collapse. This condition is called loading margin, which is the best measure of system voltage stability limit (Fig. 1). At the load-ability limit, or at the tip of the nose curve, the power flow equations of the Jacobian system will become singular as the slope of the nose curve becomes infinite. Thus, the traditional Newton-Raphson method of obtaining the load flow solution will break down and the modification is employed using this Newton-Raphson continuation method [9]. This method introduces an additional equation and unknown into the basic power flow equations, an additional parameter is chosen specifically as a continuation parameter to ensure that the augmented Jacobian is no longer singular at the load-ability limit.

3. PROPOSED APPROACH FOR LOADING MARGIN ESTIMATION

Extreme Learning Machine (ELM) with reduced input features is developed for a fast and accurate estimation of loading margin on the multiple contingencies. The various steps involved in this proposed approach using voltage stability assessment are given below:

3.1. Generation of training data

The ELM training data are obtained using the following procedure:

- First, the real and reactive powers of all load buses are randomly varied from the base case value with proportionate change in real power generation.
- Next the loading margins are obtained by running CPF routine for the specified contingencies.

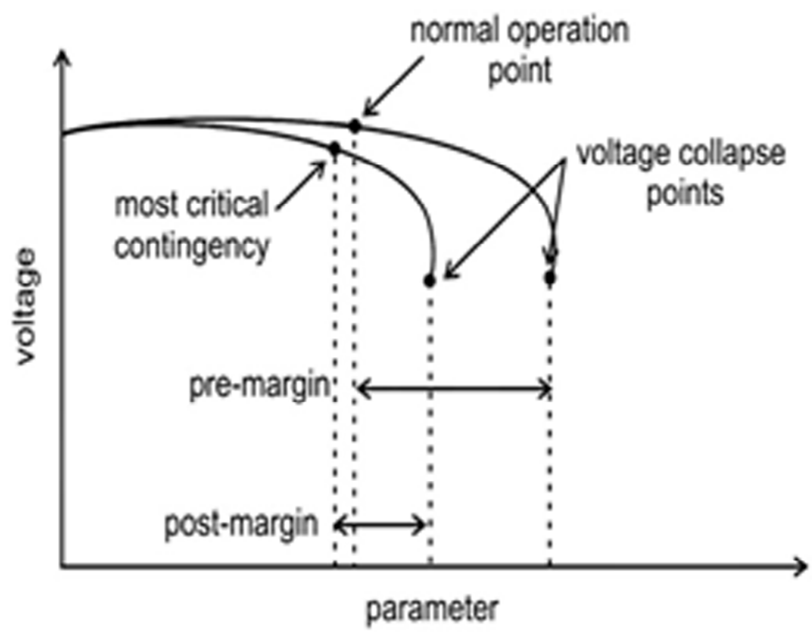

Figure 1: Loading margin

3.2. Mutual Information based dimensionality reduction

Dimensionality reduction technique is mandatory to reduce the input variables and thus reduces the measurement cost. If all the input variables are considered for training the developed network, then the system size grows larger [18] that results in large training time leading to large scale power system problems. The main aim of dimensionality reduction is to make the ELM applicable for large scale power systems. This is done by reducing the number of input measured variables from the actual measured variables to reduce the size of the network otherwise there is a possibility of the larger size network resulting in more variable data to be processed by ELM. Since the contingencies are localized nature, all the input variables cannot provide equal influence over the network and these redundant attributes may complicate the ELM network structure and they also degrade the performance of the ELM networks. Thus, by selecting the relevant variables as input features and with smaller computational efforts, higher performance is expected. With too many input variables, the ELM network suffers from the curse of dimensionality. This paper proposes a mutual information based feature selection to reduce the dimensionality of the input variables. The MI-based feature selection method [18] is used to achieve the dimensionality reduction by selecting a subset feature from an initial set of available features, thereby reducing several network input features. Thus the MI-based feature selection technique can improve the estimation speed and accuracy.

According to Shannon's information theorem, the random variable Y uncertainty can be measured using entropy $H(Y)$. Thus, for these two variables X and Y, conditional entropy $H(Y/X)$ measures the uncertainty of variable Y, when the variable X is known. Thus, the mutual information $I(Y; X)$ measures the certainty of the variable Y by resolving the variable X. The relation between $H(Y)$, $H(Y/X)$, $I(Y; X)$ is given by

$$H(Y) = H\left(Y/X\right) + I\left(Y;X\right) \tag{1}$$

The main objective of proposing a training classification model is to reduce the uncertainty predictions on output variable Y, for the given input variable X. Thus, training a classifier is to improve the MI $I(Y; X)$ as required. If $I(Y; X) = 0$ then the information contained in the observations may not be useful for determining the output Y. The goal is to achieve naturally the feature selection process for classification in order to obtain higher values with the smallest possible size of feature subsets. The prior entropy in the following section is defined based on Shannon capacity, which is defined as follows.

Consider a stochastic system with input variable X and output variable Y. Let the discrete variable with variable X has N_x number of possible values and the variable Y has N_y number of possible values. Now the initial uncertainty about the variable Y is defined by the entropy H(Y),

$$H(Y) = -\sum_{j=1}^{N_y} P(Y_j) \times \log\left(P(Y_j\right) \tag{2}$$

Where $P(Y_j)$ is the probability of the different value of the variable Y. The remaining amount of uncertainty about the system output variable Y after knowing the input variable X is defined by its conditional entropy $H(Y/X)$,

$$H\left(Y/X\right) = -\sum_{i=1}^{N_x} P\left(X_i\right) \times \left(\sum_{j=1}^{N_y} P\left(Y_j/X_i\right) \times \log\left(P\left(Y_j/X_i\right)\right)\right) \tag{3}$$

Where $P(Y_j/X_i)$ is the conditional probability for output variable Y_j given the input variable X_i. Now the difference between $H(Y) - H(Y/X)$ represents the uncertainty of the system's output, which can be resolved by knowing the input. Thus from eqn. (2) we may thus write,

$$I(Y;X) = H(Y) - H\left(Y/X\right)) \tag{4}$$

Thus the mutual information is therefore the amount by which the input variables provided by X reduces the number of uncertainties about the random variable represented by Y. Mutual information, also called as a symmetrical measure, which represents the information gained from the output variable Y after observing the input variable X is equal to the information gained about the variable X after observing Y. For the contingency selection problem, variable X at load buses refers to the real and reactive power loads and variable Y represents the post-contingency loading margin.

3.3. Data normalization

To avoid the dominance of higher valued input variables over the smaller ones and to prevent the saturation of simulation neuron, the input data are normalized by using the following expression:

$$x_n = \frac{(x - x_{\min}) \times range}{(x_{\max} - x_{\min})} + \quad starting \quad value \tag{5}$$

where, x_n is the normalized value and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the data.

3.4. Network training and testing

The normalized input features are presented to the ELM network for training and tested with a new input data, which is not previously used for training. The accuracy is evaluated by calculating the root mean square error (RMSE). Once the network is trained and tested, the developed network is ready for estimating the loading margin values at different operating conditions.

4. REVIEW OF EXTREME LEARNING MACHINE

The conventional Back Propagation (BP) learning algorithm suffers from slow convergence, local minima and over-fitting problems as it is a first order gradient method. It also involves too many parameters which are needed to be tuned randomly. Extreme learning machine (ELM) [20, 21] is a new and promising three-step tuning free learning algorithm used for training the single hidden layer feedforward neural networks (SLFNs). Empirical risk minimization theory is adopted in ELM. The whole learning process is done within a single iteration. The proposed algorithm is able to provide good generalization performance, robustness, controllability and fast learning rate. ELM is remarkably efficient and tends to reach a global optimum. The input weights and hidden layer biases of ELM can be assigned randomly. In ELM, the hidden nodes are randomly initiated and then fixed without iteratively tuning. The weights of the output layer are calculated using the Moore-Penrose (MP) generalized inverse. ELM uses non-differentiable or even discontinuous functions as an activation function. Different from traditional learning algorithms, the proposed learning algorithm not only tends to reach the smallest training error but also the smallest norm of weights. Therefore, the proposed learning algorithm tends to have good generalization performance for feedforward neural networks.

4.1. Algorithm of ELM

The steps of ELM algorithm are briefly given below:

Step 1: Random assignment of input weights and bias for the given activation function and hidden neurons.

Step 2: Calculation of the hidden layer output vector.

Step 3: Calculation of the output weight vector β:

$$\beta = H^{\dagger} T$$

$H^{\dagger}$ Moore–Penrose generalized inverse of matrix H.

5. PERFORMANCE EVALUATION

In this section a detailed simulation study is carried out on both IEEE 30-bus system and IEEE 57-bus systems. Based on contingency analysis conducted at varying load conditions, severe line outages could be identified and the ELM model is developed for estimating the loading margin analogous to these contingencies.

5.1. Voltage stability assessment in IEEE 30-bus system

IEEE 30–bus system consists of 41 transmission lines, 6 generator buses and 24 load buses. For this test system, severe cases based on the contingency analysis conducted at different loading conditions were identified, the seven single line outages were 1-2, 2-5, 4-12, 9-10, 27-29, 27-30, and 28-27. To generate the ELM training data, generator real power outputs and reactive and active powers at the load buses are varied randomly between the operating conditions that vary between 75% and 125%. Based on the algorithm given in Section 4.1, thousand input output pairs were generated, with 250 for testing and 750 for training. Using a data set, a single network for all contingencies is developed.

For illustration, the overall mutual information between the input variables and the output for severe contingencies is shown in Fig. 2. From this figure, it is evident that only few variables are having necessary information and the remaining variables have insignificant information. Few variables with overall high MI values are selected as features for training this proposed ELM, and the remaining variables are neglected from further observations. The selected features of the ELM model are real power demand at bus 30 and reactive power demand at buses 3, 4, 18, 20 and 29. The selected seven variables after normalization are presented to the network. After training, the networks are tested with the test data set to assess the generalization capability of the developed network.

The performance evaluation of the proposed ELM model is shown in Table 1. From this evaluation it is clear that the proposed ELM algorithm takes lesser time for training and exhibits better generalized performance of RMSE with 0.0002 after feature selection.

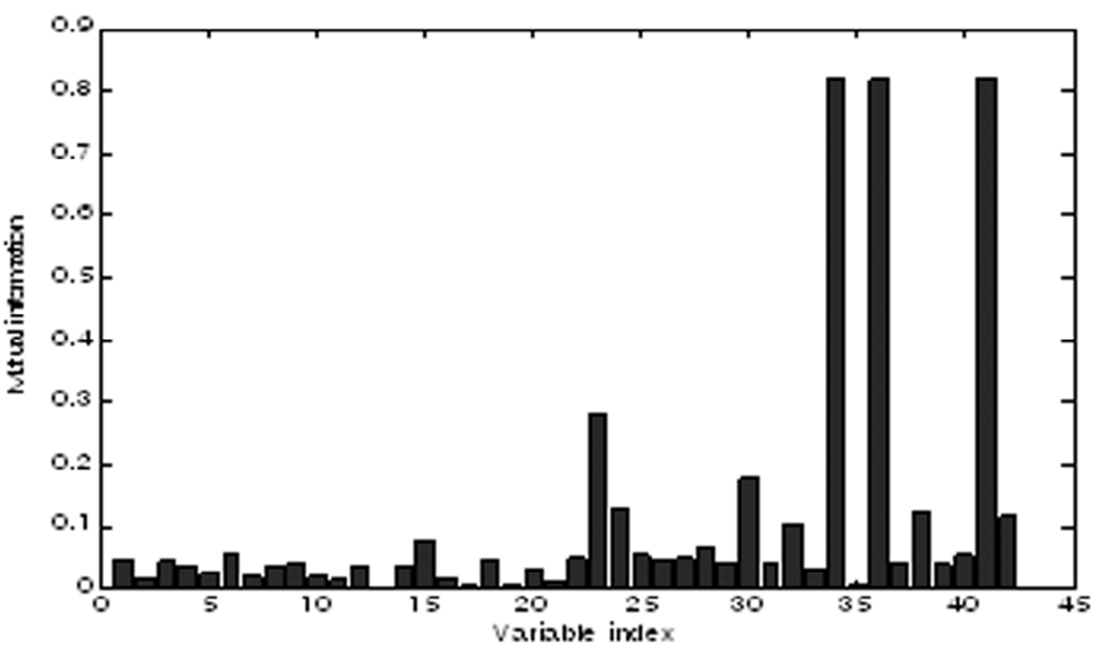

Figure 2: MI between input and output variables in IEEE 30-bus system

Table 1
Performance Comparison of ELM before and after Feature Selection

Parameters	*With all input features*	*With MI-based feature selection*
Number of input variables	42	7
Number of output variables	7	7
Training data	750	750
Testing data	250	250
Training accuracy (RMSE)	0.0029	0.0001
Testing accuracy (RMSE)	0.0035	0.0002
Training time (s)	0.1875	0.0781
Testing time (s)	0.0313	0.0313

Comparison of ELM output with CPF result is presented in Table 2 which shows an agreement between the rankings based on the output and the actual ranking of the ELM. After providing necessary training, the voltage stability index is estimated accurately within short duration of time, i.e., 0.0313 seconds, compared to conventional power flow method which takes 12.575 seconds. This clearly reveals that the proposed method can provide efficient training in large scale power systems for on-line voltage stability assessment.

Table 2
Comparison of ELM output with CPF result

Line outage		*ELM output*		*CPF result*	
		Loading margin in p.u	*Rank*	*Loading margin in p.u*	*Rank*
1	2	0.2612	I	0.2612	I
2	5	2.0411	V	2.0410	V
4	12	2.7010	VII	2.7010	VII
9	10	2.4207	VI	2.4207	VI
28	27	1.4144	II	1.4144	II
27	29	2.0143	IV	2.0143	IV
27	30	1.8089	III	1.8089	III

5.2. Voltage stability assessment in IEEE 57- bus system

Next, the proposed approach was applied for voltage stability assessment in IEEE 57-bus system. The considered system consists of 80 transmission lines, 7 generators and 50 load buses. The training and test data required to develop the ELM are generated by adopting the procedure given in Section 3.1. A single ELM model was developed for ten severe single line outages (22–23), (24–25), (26–27), (27–28), (28–29), (7–29), (30-31), (36-37), (37-38) and (22–38). Input features of the network are selected using the mutual information based method.

The overall mutual information between the input variables and the output for severe contingencies is shown in Fig. 3. Table 3 shows the performance of ELM before and after feature selection. The results presented in the tables show the ability of the proposed model to estimate the voltage stability level even for a larger test system.

Table 4 shows the comparison between the conventional CPF and ELM load flow for ranking of contingencies with one particular condition and the result provides an agreement between ELM ranking and CPF ranking. This clearly proves that ELM is computationally efficient for on-line voltage stability for multiple contingencies.

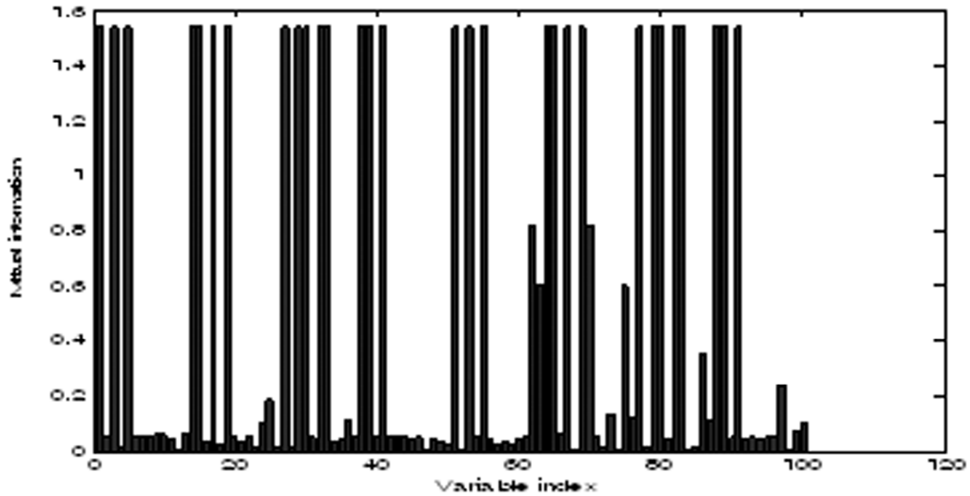

Figure 3: Mutual information between input and output variables in IEEE 57-bus system

Table 3
Performance Comparison of ELM before and after Feature Selection

Parameters	*With all input features*	*MI-based feature selection*
Number of input variables	100	36
Number of output variables	10	10
Training data	750	750
Testing data	250	250
Training accuracy (RMSE)	6.7635e-004	9.9704e-006
Testing accuracy (RMSE)	0.0040	6.8198e-004
Training time (s)	0.1250	0.0938
Testing time (s)	0.0313	0.0313

Table 4
Comparison of ELM output with CPF result

Line outaged		*ELM output*		*CPF result*	
		Loading margin in p.u	*Rank*	*Loading margin in p.u*	*Rank*
37	38	0.8934	VII	0.8934	VII
36	37	0.9420	VIII	0.9421	VIII
07	29	0.3314	I	0.3314	I
30	31	1.1210	X	1.1210	X
28	29	0.4376	III	0.4375	III
27	28	0.5084	IV	0.5084	IV
22	38	0.5105	V	0.5105	V
24	25	1.1116	IX	1.1117	IX
22	23	0.3819	II	0.3818	II
26	27	0.6027	VI	0.6027	VI

6. CONCLUSION

This paper presents a single ELM model for power system loading margin estimation for multiple contingencies with reduced input features. For large power systems, training ELM with all input features consumes large training time. Thus, MI- based feature selection technique can reduce the input dimensionality thereby the training time could be reduced without compromising the accuracy. This proposed ELM model can be used for fast and accurate contingency ranking and the network training time is reduced considerably after applying MI dimensionality reduction techniques. IEEE 30-bus system and IEEE 57-bus system are considered for a demonstration of an effectiveness of the proposed methodology under various loading conditions on single line contingencies. Finally, our proposed learning algorithm provides extreme fast learning phase than the conventional feed forward networks using classic algorithms. Also, this proposed method provides a better generalization performance and easy learning compared with a conventional CPF algorithm by the factor of a thousand, which is the gradient- based and can face severe issues like learning rate, over-fitting and local minima. Finally, this work has demonstrated that extreme learning machine can be used in many applications effectively and thus proving the performance of ELM in high dimensional network applications. Also loading margins computed using CPF and proposed ELM algorithm is compared of which ELM provides better results than conventional continuation power flow algorithm.

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