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Static Voltage Stability Margin Assessment Based on SDAE-SVM Hybrid Prediction Model

Haichao Wang[1], Xiangrong Zu[2]
[1](*School of Control and Computer Engineering, North China Electric Power University, China*)
[2](*School of Control and Computer Engineering, North China Electric Power University, China*)

Abstract: With the continuous expansion of the scale of new energy power system, voltage collapse will seriously affect the safe and stable operation of power system. To avoid voltage collapse, it is necessary to predict the distance between the system operation state and the critical point of voltage stability, that is, voltage stability margin. Through the analysis of voltage stability margin, power grid operators can judge the current operation state of power grid, and then know whether the current system is static voltage stability. Traditional static voltage stability assessment methods are mostly based on complex power flow equations. Because of manual operation, the speed of solution cannot meet the demand of online real-time prediction. In order to satisfy the rapid automatic evaluation of system voltage stability, artificial intelligence technology is introduced in the current research, but most of the research focuses on improving the speed of off-line training. When noise data is mixed into the collected samples, noise cannot be filtered well, which leads to the poor fault tolerance rate of the training model and poor power supply. Pressure stability margin is predicted. Combining the advantages of Stacked Denoising Auto Encoder (SDAE) and Support Vector Regression (SVR) classifiers, this paper proposes a hybrid prediction model based on SDA-SVR, which can reduce input dimension and filter noise to reconstruct input. Over-stacked multi-de-noising self-encoding filters the mixed noise input data hierarchically, reconstructs the input, and directly inputs the reconstructed data to the support vector regression classifier, and then obtains the static voltage stability margin. In this paper, the model is validated by the simulation data of 9-node power network of WSCC 3 generators. Experiments show that the proposed model can reduce dimension and fault-tolerant processing of large-scale power network data in high latitudes. The model trained can effectively reduce the prediction error on the test sample set and achieve accurate prediction of static voltage stability margin. It has good adaptability, generalization ability and real-time.

Keywords: Power System Static Voltage Stability; Support Vector Regression; Stacked Denoising Self-Encoder; Deep Feature Learning; Deep Learning Prediction

1. INTRODUCTION

Modern power system is a non-linear complex system, its operation is complex and changeable. With the increasing integration of unit capacity, scale, voltage level and network interconnection in power system, many large power grids at home and abroad have occurred voltage collapse accidents, even caused large-scale blackouts, inconvenience to people's lives, resulting in huge economic losses [1], voltage collapse problem day. It has gradually become an important problem threatening the safe and stable operation of power system. At present, there are two main types of research on voltage stability, one is static voltage stability analysis based on power flow equation, the other is dynamic voltage stability analysis based on state equation.

This paper mainly evaluates the voltage stability of power system from the point of view of static voltage analysis, which is to calculate how far the current system operation state is from the voltage collapse point, that is, the voltage stability margin.

The core of solving static voltage stability margin is to determine the voltage limit point. There are many methods for calculating limit points, such as direct method [2], continuous power flow method [3], non-linear programming method [4]. Among them, the continuous power flow method can overcome the ill-condition of the power flow equation near the limit point, conveniently consider some constraints of the power system, reliably track the change of the steady-state operation of the system with the load, and obtain the static voltage stability margin, which is a very effective method for voltage stability analysis. However, the application of continuous power flow method in on-line static voltage stability assessment needs manual operation, which is time-consuming and difficult to meet the requirements of automatic rapid assessment.

In order to satisfy the on-line evaluation of voltage stability, artificial intelligence technology is introduced into the research of voltage stability. Reference [5] presents a static voltage stability evaluation model based on support vector machine (SVM). Reference [6] A SIPSS-LASSO-BP network model for off-line fitting and on-line prediction of load capacity limit is proposed by combining the sample selection method of SIPSS (Similarity Index of Power System State), Least Absolute Shrinkage and Select Operator (LASSO) method and BP (Back Propagation) neural network method. Literature [7] theoretically analyzed the characteristics of local node voltage and current vectors, and then directly utilized the measured values of local voltage and current vectors collected by wide area measurement system to realize on-line evaluation and indication of voltage stability of key nodes, and studied the problem of communication interruption and phase failure of balanced nodes caused by communication system faults. Document [8] solves the problem of feature extraction with noise in sample data, and improves the classification accuracy and recall rate by using stacked denoising self-encoder to extract feature from sample data with noise. Literature [9] applies stacked denoising self-encoder to the field of intrusion detection. First, the weights of the network are initialized layer by layer through unsupervised learning, and then the whole network model is fine-tuned by supervised learning. Experiments show that stacked de-noising self-encoder has high accuracy in classifying intrusion detection data. In reference [10-11], two-stage feature selection methods based on SVM and combined SVM evaluation methods based on multi-input feature information fusion are proposed respectively to solve the problem of feature selection in power system transient stability assessment, which provides an important way for on-line fast transient stability calculation.

Aiming at the problem of processing mixed noise data sample set in static voltage stability margin assessment, a hybrid prediction model based on SDAE-SVR is proposed in this paper. The noise reduction self-encoder can reduce input dimension and filter noise to reconstruct input. By stacking multiple noise reduction self-encoders, the mixed noise input data is filtered hierarchically to reconstruct input, and the reconstructed input is reconstructed. The data are input directly to the support vector regression classifier to obtain the static voltage stability margin. At present, the research on the combination of deep learning and regression prediction is still in its infancy [12-13]. In addition, this paper draws on the achievements of deep learning algorithm in other application fields, applies stacked denoising self-encoder to feature extraction calculation, and combines the advantages of SVR, puts forward the static state of deep feature learning based on SDAE-SVR. Voltage stability margin evaluation model, in which SDAE is used to filter and reconstruct the input samples, SVR is mainly used to predict the extracted features and output static voltage stability margin, so as to achieve the purpose of online voltage stability evaluation processing. Finally, the prediction performance of SDAE-SVR model is tested by using WSCC (Western System Coordination Council) 3-machine 9-node system model. The results show that the model can maintain good prediction accuracy for both noise-free and noise-free sample sets, and has good generalization ability.

2. LOAD LIMIT OUTPUT AND ACQUISITION OF EXPERIMENTAL SAMPLE SET

a. Load Limit

OutputLoad limit refers to the total active power of load nodes when the system reaches the critical point of voltage collapse. It can effectively characterize the static voltage stability of the system. In engineering, the method of continuous power flow is usually used to calculate the ultimate load at the limit point of voltage stability.

Continuous power flow (CPF) approach the system voltage critical point by increasing the system load output gradually in a fixed direction, so as to find the load limit at the system voltage limit point.Assume that the direction of system state change [6] is:

$$\begin{cases} P_G = P_{G0} + \lambda P_{Gd} \\ P_L = P_{L0} + \lambda P_{Ld} \\ Q_L = Q_{Ld} + \lambda Q_{Ld} \end{cases} \quad (1)$$

In the model, P_G is the initial active power of the generator, P_{G0} is the initial active power of the load, Q_{L0} is the initial reactive power of the load, P_{Gd} is the change direction of the active power of the generator, P_{Ld} is the change direction of the active power of the load, Q_{Ld} the change direction of the reactive power of the load, and the growth factor. With the increase of power flow Jacobian matrix, the power flow Jacobian matrix tends to be singular. When the Jacobian matrix of the system reaches singularity, the system reaches the static voltage stability limit point. At this time, the total active load of the system is the load capacity limit of the system. It is generally believed that the greater the total load capacity limit of the system, the better the static voltage stability of the system.

b. Acquisition of Experimental Sample Set

The sample set data of this experiment is obtained by simulating the 9-node system of WSCC 3. The sample collection program is compiled and the Matpower power power power power simulation toolbox is used for sample collection. The data of 9-node test system for WSCC 3 are detailed in reference [14]. Among them, node 1 is a balanced node, node 2 and 3 are PV nodes, node 5, 7 and 9 are load nodes, WSCC 3 machine 9 node system is shown in Figure 1.

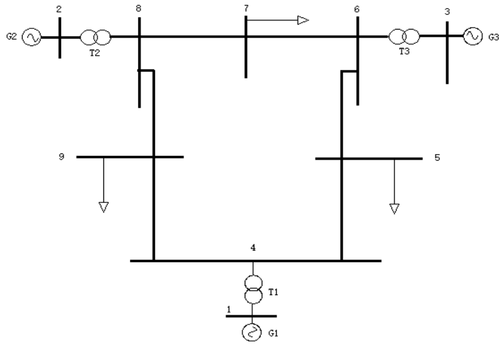

Fig.1 WSCC 3 machine 9-node test system

In this paper, the continuous power flow method is used to simulate [3], in which the power factor of the load node P and Q remain at the initial working point, and the proportion of each node does not change and keeps synchronous growth. The P on the PV node increases in the same proportion, with the synchronous growth ratio of 2.5, without considering the reactive power limitation of the PV node. With the sample acquisition program, a total of 1000 sample data were obtained by simulation.

3. Deep Learning Model Based on SDAE-SVR

The hybrid model proposed in this paper is divided into two parts: SDAE feature processing and SVR regression prediction. The SDAE part consists of three noise reduction coders stacked together. The number of hidden neurons in each denoising coder is 2000. The stacked noise reduction encoder part filters and reconstructs the input data. The whole network algorithm model architecture is shown in Figure 2.

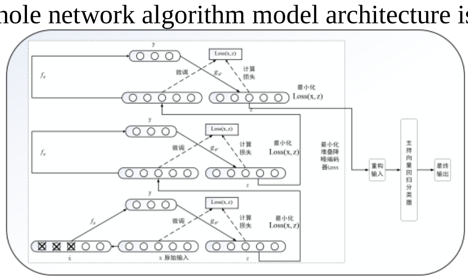

Fig.2 SDAE-SVM mixed mode

a. Feature Processing Based on Stacked Denoising Self-Encoder (SDAE)

Denoising Auto Encoder was proposed by Vincen in 2008.It is a kind of encoder that accepts damaged data as input and trains to predict original undamaged data as input. Its function is to learn the original data of superimposed noise, and the features it learns are basically the same as those that it never learns from the data of superimposed noise. Compared with the self-encoder, the features it learns from the de-noised self-encoder are more robust, and the model used in the de-noised self-encoder has more generalization ability. The structure of the de-noised self-encoder is shown in Figure 3. Among them, x is the original sample data, $\tilde{x}$ is the damaged sample data (adding noise), f_{θ} is the encoding operation, $g_{\theta'}$ is the decoding operation, z the output of the denoising encoder, and $\mathrm{Loss}(x, z)$ is the reconstruction error of the denoising self-encoder.

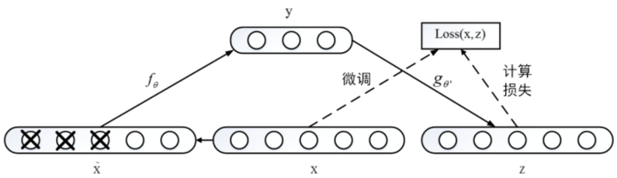

Fig. 3 Denoising Auto Encoder structure

The stacked denoising self-encoder model combines multiple denoising coders, and the minimum reconstruction error output of each denoising coder is used as the input of the next denoising coder. In the model used in this paper, a total of three noise reduction coders are superimposed. The structure of the stacked noise reduction self-encoder is shown in Figure 4.

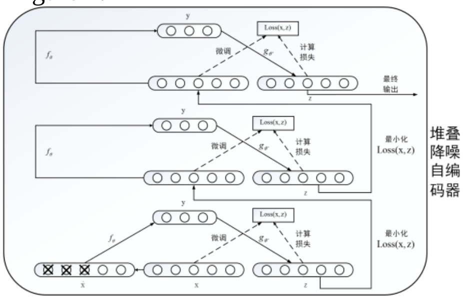

Fig.4 Stacked Denoising Auto Encoder structure

In this model, given the input data of the original sample, noise information is added to the original data to obtain the damaged sample data $\tilde{x}$ .Then, the noise reduction self-encoder training $\tilde{x}$ is input to the first layer to minimize the loss function of the first layer, and the minimized output is used as the input of the second layer noise reduction self-encoder to continue training as the first layer, and so on, until the output of the last layer noise reduction encoder. At this point, the reconstructed input is obtained. The concrete realization of the model is as follows:

Assuming that the input set of the original sample is $x = \{x^{(1)}, x^{(2)}, \cdots, x^{(n)}\}$; the corresponding hidden layer vector is $y = \{y^{(1)}, y^{(2)}, \cdots, y^{(n)}\}$; and the corresponding output layer vector is $z = \{z^{(1)}, z^{(2)}, \cdots, z^{(n)}\}$.At the same time, it is stipulated that the activation function of the noise reduction coder in each layer should be taken as a function $sigmoid$. The formula for calculating the function is shown in Formula (2).

$$f(x) = \frac{1}{(1+\exp(-x))} \qquad (2)$$

$\tilde{x}$ is the damaged sample data, noise information is randomly added to the original sample data to generate in this paper. The addition method is to generate a normal distribution random matrix with the same structure as the sample data, and add it to the original sample data to get the damaged sample data.Next is the input to the stacked noise reduction coder, the encoding operation from the input layer to the hidden layer (3), and the decoding operation from the hidden layer to the output layer (4). The objective function of minimizing reconstruction error for each layer of denoising coder and the objective function of minimizing reconstruction error for the whole stacked denoising coder are formulated (5).

$$y = f_{\theta}(W_y * \tilde{x} + b_y) = sigmoid(W_y * \tilde{x} + b_y) \qquad (3)$$

$$y = g_{\theta'}(W_z * \tilde{x} + b_z) = Sigmoid(W_z * y + b_z) \qquad (4)$$

$$\underset{Wy,by,bz}{\arg\min}[J(x,z)] \qquad (5)$$

Among them, W_y is the hidden layer weight, W_z is the output layer weight, b_y is the hidden layer bias, b_z is the output layer bias. $J(x,z)$ is the mean square error calculated for the difference between reconstructed input and original input. Finally, for the purpose of minimizing the reconstruction error objective function, the gradient descent method is used to train stacked noise reduction self-encoder to achieve the best level of training. Support Vector Regression (SVR) classifier has many superior properties and experimental performances in small sample, non-linear and high-dimensional data prediction. Combining the advantages of stacked denoising self-encoder noise filtering and reconstructing input, this paper can further improve the prediction performance of SVR model. Architecture of the whole network algorithm model is as follows:

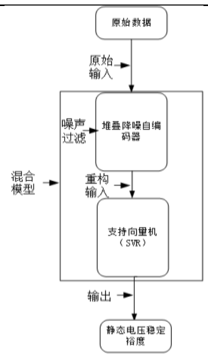

Fig. 5 Convolutional neural networks structure

4. Experimental evaluation

In this section, the static voltage stability margin is predicted using the SDAE-SVR hybrid model constructed above. The RBF Gauss kernel is used as the SVR kernel function. Firstly, the sample data of the training set (without adding noise) is input to the SDAE-SVR hybrid model for network model training, and the input is reconstructed using unsupervised learning and supervised fine-tuning characteristics of stacked denoising self-encoder. The reconstructed input is used as the input of SVR, and the final static voltage stability margin prediction value is output by SVR. After network training, the minimum Mse of the whole model in the training set is 0.0044. The change of Mse during the training process is shown in Figure 6. The final value of parameter C of SVR is 100.0.

Next is validation on the test set. The testing process is divided into original test set samples (without adding noise) testing and damaged test set samples (adding noise) testing. The test results are shown in Figure 7 (original test results) and Figure 9 (damaged test results).

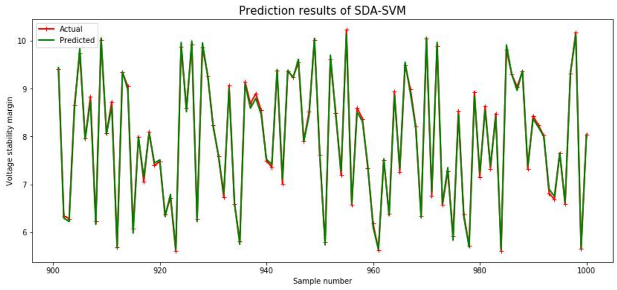

Fig.6 Original test set prediction result

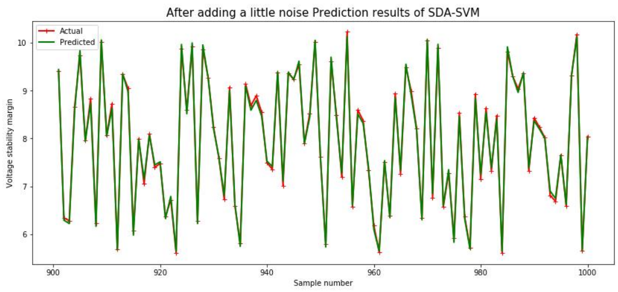

Fig.7 Damage test set prediction result

The experimental results of the two tests are compared in detail in Table 1.

Table 1 SDAE-SVR prediction resultscomparison

Test sample set	Minimum Mean Square Error	Maximum relative error	Average relative error
Original	0.00392	0.00709	0.00709
damage	0.00389	0.00706	0.00706

5. Conclusion

In this paper, by referring to the characteristics of stacked denoising self-encoder, which can filter noise and reconstruct input, multi-layer denoising self-encoder is used to filter and reconstruct the damaged data containing noise, so that the reconstructed input data can be as close as possible to the original input data set, and the reconstructed input is used as the input of SVR, and the final static voltage stability margin is output by SVR. Degree prediction value. Compared with the previous static voltage stability assessment methods, the proposed model can achieve good prediction performance when input data are mixed with noise data, and greatly improve the fault tolerance rate of the prediction model. By comparing the experimental results in Table 1, it can be concluded that the proposed model can effectively predict the static voltage stability margin. When the input value is mixed with noise, it can still maintain good prediction ability.

However, this paper also needs to consider that stacked denoising self-encoder may be time-consuming when the number of samples is very large and the dimension is high, so we can continue to study this problem in depth.

6. References

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