DYNAMIC STABILITY RECOGNITION OF POWER SYSTEM USING GENERALIZED REGRESSION NEURAL NETWORKS

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ABSTRACT

A modern power system has faced in stress condition and its operating point is close to its stability limit, while the power system is subjected to variety large oscillation. These lead to blackout problem, so the unstable state of power system must be early detected in order to activate an emergency control system. This may be save the power system from falling into blackout. The paper presented a process to build dynamic stability recognition model of power system (DSRMPS) using Generalized Regression Neural Networks (GRNN). After trained GRNN, in operation phase, output of GRNN function yields a value that is a stable index. It can be visually expressed on a screen. The paper designed an interactive visualization tool that enables the user to monitor the stable status of power system. The study is tested on IEEE 39-bus power system network.

Keywords: *Dynamic stability recognition; Feature Selection; Power System; monitoring; Generalized Regression Neural Networks.*

TÓM TẮT

Hệ thống điện hiện đại phải đối mặt với áp lực vận hành với điểm hoạt động gần giới hạn biên ổn định, trong khi đó hệ thống điện lại luôn gặp các sự cố dao động lớn và gây nên mất ổn định. Vì vậy, trạng thái mất ổn định hệ thống điện cần phải được nhận dạng nhanh nhằm phát tín hiệu kích hoạt hệ thống điều khiển khẩn cấp. Hệ thống điều khiển khẩn cấp được kích hoạt sớm thì còn có khả năng cứu hệ thống điện tránh rơi vào tình trạng tan rã do mất ổn định gây ra. Bài báo này giới thiệu quy trình xây dựng mô hình nhận dạng ổn định động hệ thống điện ứng dụng mạng Nơ-ron GRNN. Mạng Nơ-ron khi đã được huấn luyện, trong pha vận hành, kết quả đầu ra của hàm mạng là giá trị thể hiện chỉ số ổn định. Chỉ số ổn định có thể được diễn tả một cách trực quan trên một màn hình quan sát. Bài báo đã thiết kế một công cụ tương tác trực quan, công cụ này giúp ích cho người dùng quan sát được trạng thái ổn định hệ thống điện trên màn hình. Nghiên cứu đã được thực thi trên hệ thống điện chuẩn IEEE 39-bus.

Từ khóa: *Nhận dạng ổn định động; chọn biến; hệ thống điện; giám sát; mạng Nơ-ron hồi quy tổng quát.*

1. INTRODUCTION

A modern power system is operating with a lot of changes such as continuous load growth, renewable energy resources development, which are significantly threat to operation of a power system. Power system is always subjected to serious incident such as short-circuit faults. They can harm the power system stability and may result in blackouts. To protect a power system from the blackouts, dynamic stability recognition needs to be executed to identify of power system status. Once unstable is recognized, emergency control action must be activated to drive the power system into re-stable state. So, real time stability recognition is essential to allow online monitoring system stability state against risk of blackouts.

In recent years, artificial neural network (ANN) has been emerged as a promising approach to enable the real-time dynamic stability recognition [1]–[3]. By learning from a dynamic stability database, the nonlinear relationship between the input and the output can be extracted and reformulated in ANN. In the online application phase, the system's stable state can be recognized in real-time as soon as the input is accessed [1], [4].

This paper introduces a process to build DSRMPS. The process consists of the following steps: feature selection, training, evaluation, and monitoring. In feature selection step, we present two criterions for feature selection that are Fisher and Scatter matrices criterion, and K-nearest neighbor classifier (1-NNC, K=1) firstly guides to find feature subset. With found result, the DSRMPS is built by Generalized Regression Neural Network (GRNN). After trained GRNN, in operation phase, output of GRNN function is a value that is a stable index (SI). It can be visually expressed on a screen. The paper designed an interactive visualization tool that enables the user to monitor the stable status of power system. The study was implemented on IEEE 39-bus power system using simulation software Power-World 18. The computation was implemented by the Mat-lab R2014a software

2. METHOD

2.1 Feature selection

To build DSRMPS, initial features and samples are required. A large number of samples are generated through off-line simulation and the stable status was evaluated for each fault under study. Data for each bus or line fault occurring in the test systems are recorded in which samples of dataset are kept in a database.

The input features are the vector of system state parameters that characterize the current system state. Fault-on features are variables that characterize at fault-on state of power system occur such as changes in nodal powers, in power flows in transmission line, and voltage drops in the nodes at instance of fault.

The output features represent the stable conditions of the power system. The output variables are assigned to label binary variable y {1, 0}. Class 1 {1} is stable class and class 2 {0} is unstable class.

Simulating observation results, if the angle of the relative rotor generators is larger than 180^0 then the system is 'Unstable', and less than 180^0 then the system is 'Stable'. The corresponding data will be put into unstable and stable class.

Fisher criterion: this is a criterion that was applied in many works with ranking feature selection method (RFSM) [1], [5]. By evaluating criterion of the features as (1), the features are ranked by ordering the best of them and selecting for good features. The bigger F value of feature is the more important feature.

$$F = \frac{|m_1 - m_2|^2}{\sigma_1^2 + \sigma_2^2} \qquad (1)$$

Where m_i is the mean of class C_i and σ_i^2 is the variance of class C_i.

Scatter matrices criterion: According to the scatter matrices (SM) theory, the separation of classes of feature subset is based on (2) [6], [7]. The bigger the value of J is the higher the separation of classes of feature subset will be.

$$J = \mathrm{Tr}\{S_w^{-1} S_m\} \qquad (2)$$

Where S_m is the dataset covariance matrix, S_w is within-class scatter matrix, and the trace (Tr) of matrix is the sum of the diagonal elements.

In this paper, the Sequential Forward Floating Selection (SFFS) with SM criterion and the RFSM with Fisher criterion were applied for feature selection. These were presented and applied in our previous work [8], [9], detail of the SFFS in [7], [10].

2.2 Generalized Regression Neural Network

A schematic diagram of GRNN is depicted in Fig.1 in which it consists of four layers, namely, input layer, pattern layer, summation layer and output layer [11]–[13]. The number of input units in the first layer is equal to independent factors, x. Only the pattern layer (hidden layer) has biases. The first layer is fully connected to the pattern layer, whose output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer, known as S summation neuron and D summation neuron. The S summation neuron computes the sum of the weighted outputs of the pattern layer while the D summation neuron calculates the un-weighted outputs of the pattern neurons. For D-summation neuron, the connection weight is set to unity. The output layer only divides the output of each S summation neuron by that of each D-summation neuron.

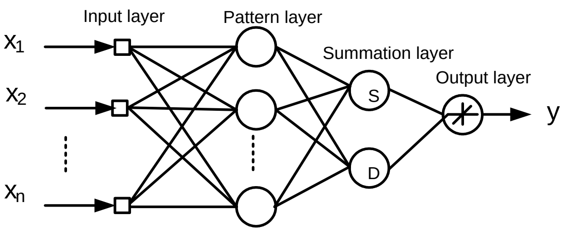

Fig. 1. *The schematic diagram of GRNN*

Once GRNN takes new input data **x** for the prediction of the output value, it calculates the Euclidean distance between the input **x** and each training data $\mathbf{x}_i$. The distance between **x** and $\mathbf{x}_i$ is calculated as (3)

$$D_i^2 = (\mathrm{x} - \mathrm{x}_i)^T (\mathrm{x} - \mathrm{x}_i) \quad (3)$$

Where each input data is defined as $x_i=(xi_1, x_{i2}, \ldots, x_{id})$, d is the number of features. A given an input, GRNN calculates the predicted output according to the equation as (4).

$$\mathrm{y}(x) = \frac{\sum_{i=1}^{N} y_i e^{(-\frac{D_i^2}{2\sigma})}}{\sum_{i=1}^{N} e^{(-\frac{D_i^2}{2\sigma})}} = \frac{\sum_{i=1}^{N} w_i e^{(-\frac{D_i^2}{2\sigma})}}{\sum_{i=1}^{N} e^{(-\frac{D_i^2}{2\sigma})}} \quad (4)$$

Where N is the total number of training patterns; σ is spread parameter, whose optimal value is often determined experimentally; y_i or w_i is the weight connection between the ith neuron in the pattern layer and the S-summation neuron.

2.3 Proposed Approaches

By learning from a dynamic stability database, the nonlinear relation between input and output can be captured and memorized in the DSRMPS, Classifier. In the online mode, the system's stability status can be identified in real time as soon as the DSRMPS receives the input signal. The architecture of proposed DSRMPS is as Fig. 2.

Fig. 2. *The architecture of proposed DSRPS model*

Necessity is to select a compact data set that is the representative of all data set with the aim of reducing memory, saving cost. To build DSRMPS, feature selection is implemented. Feature selection is actually dimensional space reduction. The design DSRMPS process is proposed as Fig. 3. This process consists of the following steps: Feature selection, Training, Evaluation, and Monitoring.

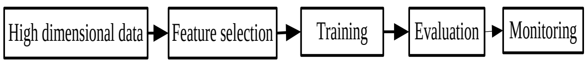

Fig. 3. *The design DSRS model process*

2.3.1 Feature selection

The ANN-based DSRMPS can be formulated as a mapping $y_i = f(x_i)$ after learning from a dynamic stability database $D = \{x_i, y_i\}_{i=1}^{n}$. Where: x_i is feature; it is n-dimensional input vector that characterizes the system operating state; and y_i is output vector. The feature subset selection consists of selecting a *d* dimensional feature vector *z, d<n;* The *d* selected features represent the original one in a new knowledge base $D_{new} = \{z_i, y_i\}_{i=1}^{d}$, and the new mapping $y_{newi}=f_{new}(z_i)$.

2.3.2 Training

A large number of samples are generated through off-line simulation and the stable status is evaluated for each fault under study. Data for each bus or line fault occurring in the test systems are recorded in which samples are kept in a database. The dataset is normalized before training. The data are split into training set (D_{tr}) and testing set (D_{te}) randomly.

In phase training, the ANN learns the input and output relationship to build knowledge. Classification is that data are classified into labeled classes basically. The classes have labeled as '1: Stable ', and '0: Unstable'. The ANN assigns each data point in the entire space of data into one of two classes.

2.3.3 Evaluation

The overall accuracy rate (*AR*) is calculated by (5).

$$AR(\%) = \frac{n}{N}.100 \quad (5)$$

Where n are a number of the correct classified samples; N are a total number of the classified samples.

Due to the computing errors, a threshold needs to be defined as the decision borderline for the ANN to classify [1], [14]. So, a typical rule for a neural network classifier to classify a new sample can be as (6).

$$\begin{cases} If \quad y \le 0.5 \quad then \quad y = 0, \text{'Unstable'} \\ If \quad y > 0.5 \quad then \quad y = 1, \text{'Stable'} \end{cases} \quad (6)$$

2.3.4 Monitoring

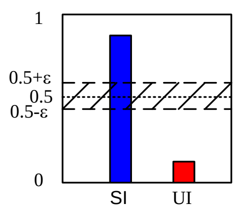

Fig. 4. *The layout of the monitor screen design.*

The paper designed an interactive visualization tool that enables the user to monitor the stable status of power system. The idea layout design of monitor tool that we engineered is shown in Fig. 4.

After trained ANN, output of ANN function yields a value that is a relative stable index. The relative stable index (SI) and unstable index (UI) represent the stable and unstable state of power system. This result can be visually expressed on a screen. Then, the SI and UI on the screen indicate the state of the power system. In order to show the recognized mode on the screen, we stipulate that the horizontal SI-bar, blue colour, is the SI level and UI-bar, red colour, is the UI level. The value of relative stable index is from 0 to 1. So, the relationship between SI and UI is expressed as (7).

$$SI+UI=1 \Leftrightarrow UI=1-SI \quad (7)$$

A trained ANN contains the knowledge of stability status of power system. The ANN decision function can evaluate the relative stable index of the stable state of power system how far from the boundary. In exceptional cases, the outputs are 0.5 or value of around 0.5. These are points that locate on the border between stability and instability. It is an uncertain zone. As illustrated in Fig. 4, the points locate on the uncertain zone, the striped area, where its width is from (0.5-ε) to (0.5+ε), ε is a slack value. In case of uncertain zone, it is advisable to put power system status into the warning mode, and emergency control action is absolutely necessary.

3. RESULTS – DISCUSSION

3.1 Features and samples

The study was tested on the IEEE 39-bus scheme. It includes 39 buses, 19 loads, 10 generators. The diagram IEEE 39-bus scheme is shown as Fig. 5. This is well-known single-line diagram. It was used in many published works [1], [5], [15]. Off-line simulation was implemented to collect data for training. Load levels are (20,30,…,120)% normal load. The setting fault clearing time (FCT) is 50ms [16]. In this paper, all kinds of faults such as single phase to ground, double phase to ground, three phases to ground and phase-to-phase short-circuit are considered. Faults are tested in any buses and in each of 5% distances of long transmission lines of the test systems. For each of considered load samples, the generator samples have been got accordingly by running optimal power flow (OPF) tool of Power-World software.

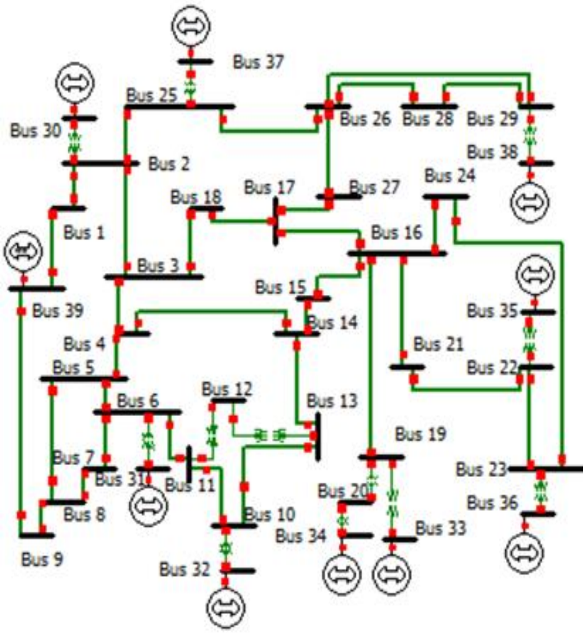

Fig. 5. *The IEEE 39-bus diagram*

The input and output feature are x{delV$_{bus}$,delP$_{Load}$,delP$_{flow}$} and y{1,0}. Total of input features is 104, x{104(39+19+46)}. The number of output feature is one, y{1,0}. From simulating results, there are 3551 samples that includes 2649 S samples and 902 U samples, D(S,U)=D(2649,902).

3.2 Feature selection results

The 1-NNC firstly used as classifier for evaluating accurate classification because of its simplicity. The dataset was randomly divided into ten sub-datasets. Each training sub-dataset had 2384 S samples, 812 U samples. Each testing sub-dataset had 265 S samples, 90 U samples. It is 10-fold cross-validation. Average evaluation result was executed by ten times on 10-fold. Results of selected feature with SFFS and RFSM are shown in Table 1.

Table 1. *The highest average AR of feature selection methods.*

Classifier	Algorithm	d (Feature)	AR (%)
1-NNC	RFSM	17	95.32
	SFFS	15	95.63
	-	104	95.60

According to Table 1, testing accurate rate of SFFS is higher than that of RFSM. So, there are the feature set of 15 selected features with SFFS.

3.3 Training

3.3.1 Classifier

The paper used the GRNN to build model. It is similar to the radial basis network except the summation layer. The training algorithm is much better than the back propagation training, which involves long and iterative training as well as facing the problem of local minima. The GRNN classifier (GRNNC) has a special property that enables the users to flexibly adjusting spread parameter. The best value of the spread parameter was chosen by trial and error experiments [12], [17]. The tool of GRNN is supported by Mat-lab R2014a software [11].

3.3.2 Data training and testing

The initial samples, D(S,U)=D(2649,902), are split randomly into a training set (75%) and a testing set (25%). The training set and testing set are D$_{tr}$(1987,677) and D$_{te}$(662,225) respectively. The Fig. 6 shows the testing experiment to find spread parameter of GRNN classifier. The results are shown in Table 2.

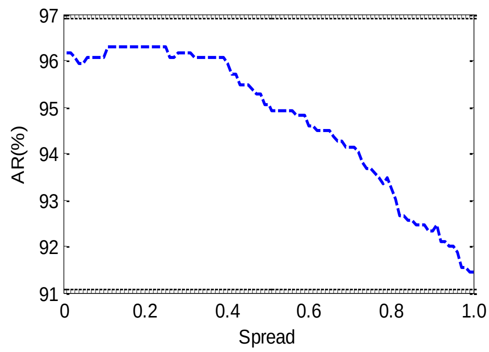

Fig. 6. *Spread parameters of experiment*

***Table 2.** The AR (%) results of GRNNC*

Classifier	Spread	Train(%)	Test(%)
GRNNC	0.15	98.0	96.3

3.3.3 Monitor screen design.

In training phase, the trained GRNNC function contains an education of the stable status of the power system. In operating phase, the output results of the GRNNC function yield values that are classified by (6). For the unstable class, the output value of the correct classified samples is less than or equal 0.5. However, in testing phase, the closest output value from the border of the misclassified sample is 0.5499. So, with ε=(0.5499-0.5)=0.0499, the uncertain zone is expanded to values from 0.4501 to 0.5499. The selected ε can be used to determine the uncertainty zone in the operating phase. The width of the uncertain zone, in Fig. 3, is {2*ε =2*0.0499 =0.0998}. From the results, the paper builds a monitor tool for monitoring the stable status of the power system. The layout of the tool is shown in Fig. 7. In the Figure, the monitor has five parts include:

- Stable and Unstable Index: this part shows the calculated SI and UI in operation phase or recognition phase.
- System Status: this part shows a result that the power system status is predicted. It is one of three modes. These are stable, unstable, and warning mode.
- Action: this shows a warning control action. The case of stable is 'NORMAL', and the cases of unstable and warning mode are an 'EMERGENCY CONTROL'.
- Window: it shows the point operation of system. The blue bar, SI level, is a relative stable index and the red bar, UI level, is a relative unstable index.
- Run and Close button: these have function in operation of the monitor tool. The selected Run means that the monitor switches to operation mode, and the selected Close means that the monitor switches to stop mode.

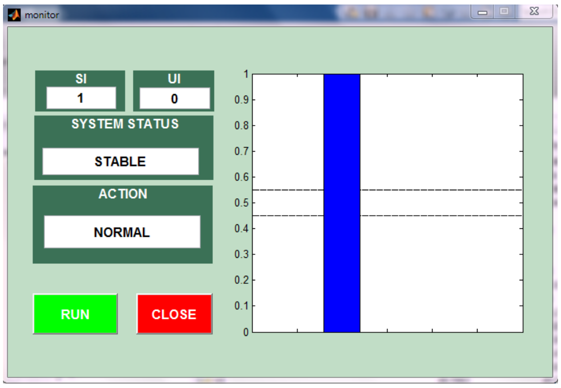

***Fig. 7.** The monitor screen design.*

In fig. 7, it is the example case of stable status of power system. SI is '1' or UI is '0', System Status is 'STABLE', Action is 'NORMAL'. For 'NORMAL' case, no emergency control actions are warned.

3.4 Discussion

In Table 1, with 1-NNC, the AR(%) was 95.63% with the 15 selected features of the SFFS, 95.32% with the 17 selected features of the RFSM. Comparing with all features set, the average classification rate of the 15 selected feature subset of the SFFS increased by 0.03%, while the number of features decreased by 6.9 times. The SFFS removed the abundant features, while recognition accuracy is still not decrease.

According to Fig. 6 and Table 2, the testing accuracy rate of GRNNC obtained 96.3%. The result was also acceptable in comparison with some previous studies applying pattern recognition for power system stability studying. For instance, the accuracy rate in [1], [5], [12], [18] is the range of (94%-97%).

This paper presents the visualization tool for dynamic stability of power system monitoring. The ANN method is used for recognizing and monitoring system stability. System status is displayed on the screen of the visualization tool. While blue represents normal conditions, red allows abnormal conditions to be instantly recognized by the user. In addition, the monitor screen tool can be used as a training tool for power system operators to handle situations based on incident scenarios.

4. CONCLUSIONS

Feature selection is aimed at reducing the number of features, reducing memory and saving cost. This paper proposed the use of the SFFS for feature selection in power system transient stability classification. The results showed that the SFFS achieved effective reduction features.

The paper presents the process to build dynamic stability recognition model of power system using GRNN. The study is tested on IEEE 39-bus power system network. The paper presents the visualization tool for dynamic stability of power system monitoring. The ANN method is used for recognizing and monitoring system stability. The monitor screen tool can be used as a training tool for power system operators to handle situations based on fault scenarios.

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