Stability Analysis of Power System Based on GA-SVM

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Abstract. Aiming at the problems of long calculation time and stable stability of power system stability analysis, a GA-SVM algorithm is proposed to analyze the stability of power system. Firstly, the mathematical model is used to describe the power system. The GA algorithm is used to optimize the nonlinear regression SVM parameters. The stability of the power system is simulated and the accuracy and speed under different load levels are verified. The simulation results show that the proposed algorithm has good efficiency, good reliability and high engineering practicability.

Introduction

Nowadays, as the scale of power networks is growing and the structure is becoming more complex, the issues of security and stability are becoming more prominent. At the same time, the rapid development of intelligent algorithms provides a broader choice for power system stability analysis \cite{1-3}. In this paper, GA algorithm optimizes power system stability parameters, and uses support vector machine (SVM) to improve the accuracy and efficiency of power system stability analysis. A GA-SVM-based model can be used to evaluate the stability of power system in real time. The simulation results prove the effectiveness of the algorithm.

Power System Mathematical Description

The power system is characterized by nonlinearity, poor tolerance and lack of effective models. It is a typical nonlinear system, which can be described by the following high-dimensional nonlinear differential algebraic equations with parameters\cite{4}: \begin{align}
\dot{x} &= f(x, y, z) \\
0 &= g(x, y, z)
\end{align}

Where $x$ is the state variable of the system, such as the motion variable, the rotor angle and the rotor angular velocity, and may also include the controlled internal electromotive force $E'd$, $E'q$, etc.; $y$ is an algebraic variable, such as the current $I_d$ in the generator, $I_q$, voltage amplitude and phase angle of other busbars, etc.; $z$ is a parameter, which can be a device parameter, or an operating parameter, such as the active power or reactive power of the load. Differential equations describe the dynamic behavior of dynamic components, and algebraic equations reflect the interaction between dynamic components and network topology constraints. When considering the role of the digital controller and the discrete behavior of other components of the power system, it must also be described by a difference equation, so the power system becomes a hybrid system, which can be described by a nonlinear differential-differential-algebraic equation system.

GA Algorithm Optimization Parameters

The calculation process of the standard genetic algorithm is shown in Fig. 1. The genetic algorithm utilizes randomization technology to efficiently search the coded parameter space, which has strong robustness and strong autonomy\cite{4-5}.\hspace{1cm} 278
Coding

Binary coding is used. The discrete scope is set to be 3~8, 3 binary is used to express from 000 to 111. Suppose a total of 6 input-output variables \((x_1, x_2, x_3, x_4, y_1, y_2)\), then the binary string: 011,010,001,101,100,000 respectively indicates that the partition number of \(x_1\) is bin2dec(011) +2 = 5, (bin2dec() is a function which binary string converted to a decimal number), similarly, the partition number of \(x_2\) is 4, the partition number of \(x_3\) is 3, the partition number of \(x_4\) is 7, the partition number of \(y_1\) is 6, the partition number of \(y_2\) is 2, the discretization degree of input-output is recorded as [7 6 3 4 5 2].

Fitness function

Each chromosome (binary string) corresponds to a fuzzy neural network, the generalization results \(J(s)\) of the neural network is used to construct a fitness function which measures the fitness of chromosome. Set the fitness function \(f(s)=1/ J(s)\), and \(s\) is a binary string, \(J(s)\) indicates the binary string corresponding to the generalization results of neural network. \(J(s)\) is defined as follows:

\[
J(s) = \frac{1}{\sqrt{N_T} \sum_{i=1}^{N_T} (y_i - \hat{y}_i)^2}, \quad (x_i, y_i) \in S_{test}
\]  

(2)

In the formula, \(S_{test} = \{(x_i, y_i), i=1,2,\cdots, N_t\}\) is the test sample sets; \(N_t\) is the test sample number; \(y_i\) is the actual value; \(\hat{y}_i\) is the output of neural networks.

Evolutionary process

Firstly, generate randomly initial population. Calculate each individual's fitness of the initial population, then obtain breeding population through the competitive strategies of survival, that is, choose two individuals randomly from the initial population, individuals who have large fitness will join the breeding population with probability of \(P\), individuals who have small fitness will join the breeding population with probability of \(1 - P\) (0.6 < \(P\) < 1).

Termination criterion

When the fitness of the generated individual reach the intended value, or when the number of iteration reach a predetermined value, the evolutionary process will terminate.
Stability Analysis Based on Non-Regression SVM

The nonlinear data is mapped to the high-dimensional space by the kernel function, and the linear regression is performed in the high-dimensional space. Similarly, the quadratic programming optimization form as follows:

$$\min w(\alpha, \alpha^*) = \frac{1}{2} \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)^T K(x_i, x_j)(\alpha_j - \alpha_j^*) + \varepsilon \sum_{i=1}^{n} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{n} y_i(\alpha_i - \alpha_i^*)$$

(3)

the support vector regression estimation function is

$$f(x) = \sum_{i=1}^{n} (-\alpha_i + \alpha_i^*) K(x_i, x) + b$$

(4)

$$\begin{cases}
    b = y_i - \varepsilon - (w \cdot x) & \text{if } \alpha_i \in (0, C) \\
    b = y_i + \varepsilon - (w \cdot x) & \text{if } \alpha_i^* \in (0, C)
\end{cases}$$

(5)

In the support vector regression estimation of real-valued functions, the number of support vectors is value-controlled. Suppose that the function is approximated by precision, that is, the function is described by an estimation function, so that the function is in the pipeline. To construct such a function, you can take an elastic pipe (the pipe always tends to be flat) and put the function into the pipe. The kernel function describes the elastic law of the pipe. The axis of this pipe defines the approximation of the function. Since the support vectors are those in which the Lagrangian multiplier is not zero in the KKT condition, and this multiplier defines the boundary point in the optimization problem of the inequality type, that is, the point at which the function touches the pipe, so The coordinates of the point at which the pipe encounters the function can be considered to define the support vector. The larger the value, the wider the pipe and the fewer contact points, i.e. the fewer support vectors.

If a training sample set is given, \( T = \{(x_i, y_i) \in \mathbb{R}^n \times \mathbb{R} \mid i = 1, \ldots, n \} \), suppose \( R_{epr}(w, b) = \frac{1}{n} \sum_{i=1}^{n} |y_i - (w \cdot x) - b| \), then the empirical risk minimization under constraints \( R_{epr}(w, b) \) is equivalent to:

$$F(\xi, \xi^*) = \sum_{i=1}^{n} \xi_i + \sum_{i=1}^{n} \xi^*_i$$

\[ ((w \cdot x) + b) - y_i \leq \varepsilon + \xi_i \]
\[ y_i - ((w \cdot x) + b) \leq \varepsilon + \xi^*_i \]
\[ s.t \quad \xi_i, \xi^*_i \geq 0, \quad i = 1, \ldots, n \]

(6)

Construct a Lagrangian function for the above formula:

$$L(w, \xi, \xi^*, \alpha, \alpha^*, \gamma, \gamma^*) = \sum_{i=1}^{n} (\xi_i^* + \xi_i) - \sum_{i=1}^{n} \alpha_i [y_i - ((w \cdot x) + b) + \varepsilon + \xi_i] - \sum_{i=1}^{n} \alpha_i^* [y_i - ((w \cdot x) + b) - \varepsilon + \xi^*_i] - \frac{C^*}{2} (\varepsilon - (w \cdot x))^2$$

(7)

Solve the above formula, and find the minimum point \( w, b, \xi^*, \xi \), find the maximum point for the Lagrangian multipliers \( C^* \geq 0, \alpha_i^* \geq 0, \alpha_i \geq 0, \gamma_i \geq 0, \gamma_i^* \geq 0 \). The solution of the above formula is a complex optimization problem, which can be converted to a given regularized parameter C value to solve the convex optimization problem below, that is, to find the minimum value of the following formula as follows:
The first item on the right side of the formula is to improve the generalization ability of learning, the second item is to reduce the error, and the constant C makes a compromise between the two. According to the definition of the insensitive loss function $\varepsilon$, when the difference between $f(x_i) = (w \cdot x_i) + b$ and $y_i$ is not greater than the error $\varepsilon$, that is zero, when it is greater than $\varepsilon$, the error is: $|f(x_i) - y_i| - \varepsilon$, it can also be seen that the optimization problem obtained at this time also has sparse characteristics.

**Simulation**

To test the effectiveness of the proposed algorithm, all experimental data was generated using the Power System Analysis Software Package (PSASP) for power system stability analysis. 90 and 120 samples were taken to form two sets of samples, and Figure 2 shows the actual training results. Figure 2 (a) and (c) are the fitness optimization changes when the sample data is 120; (b) and (d) are the number of fitness optimization changes from 90 samples to 120 samples. It can be seen in Fig. 2 that the optimal fitness of (a) and (b) is 0.9342 to 0.9948, respectively. It can be seen that the GA algorithm can reduce the optimal algebra and obtain better fitness value because the initial value of fitness is high. It helps the subsequent rapid optimization, and the GA algorithm prevents the irrelevant features from being repeatedly compared in the feature optimization process, and the fitness upward trend is stable, and the system optimization is very small.

The support vector machine kernel function $\text{Errormax}=0.2$, $\Delta=0.025$, $t_{\text{max}}=2000$. Judging the anti-interference ability of the support vector machine in the stability analysis of the power system, introducing Gaussian noise of different noise rates into the training set, and the test vector set does not contain noise. BP neural network was used to predict power system stability under the same conditions. The prediction results of power system stability are shown in Table 1.
Table 1. GA-SVM and BP neural network prediction results of power system stability.

| Noise Variance | 0.2   | 0.4   | 0.4   | 0.8   |
|----------------|-------|-------|-------|-------|
| GA-SVM σ rms  | 0.562 | 0.652 | 0.674 | 0.688 |
| BP Network rms| 0.0476| 0.1121| 0.1323| 0.2331|

From the analysis results of power system stability of GA-SVM and BP neural network, it can be concluded that for Gaussian distributed noise, with the increase of noise variance, the accuracy of GAS-SVM power system stability analysis is significantly higher than that of BP neural network. It shows that GA-SVM has good anti-noise ability and function estimation and prediction performance.

Fig. 3 shows the power system voltage stability index values for different load levels.

Summary

In this paper, a GA-SVM method is proposed to study the stability of power system. In this method, GA algorithm is used to adaptively set the parameters of nonlinear regression SVM to improve the accuracy of SVM and improve the validity of calculation results. Compared with BP neural network, the calculation accuracy and efficiency of GA-SVM are better than BP neural network. The voltage stability index of power system under different load levels is also verified, which indicates that the proposed algorithm has a great application prospect.

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