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Transient stability preventive control of power systems using chaotic particle swarm optimization combined with two-stage support vector machine

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ABSTRACT

This paper presents a chaotic particle swarm optimization (CPSO) algorithm combined with data mining method for transient stability preventive control. The data mining method is utilized to approximate the security region considering transient stability. Therefore, the application effects of different input features and data-mining classifiers are compared first. Then, a two-stage support vector machine (SVM) approach is proposed to generate two models, including a linear SVM model with controllable features provides preventive adjustment rules, and a more accurate SVM model to approximate the actual security region. Finally, the CPSO in combination with the two-stage SVM is proposed to calculate the optimal preventive control strategies. Comprehensive studies are conducted on a 16-machine 68-bus system and 48-machine 140-bus system to verify the effectiveness.

1. Introduction

With the continuously increase of electricity demands, integration of intermittent energy source, and the enlargement of interconnection scale, modern power systems are becoming increasingly complex and operating closer to their secure operating limits. Hence, it becomes more challenging to ensure the safe operation of power systems. Transient stability, or large-disturbance rotor angle stability, refers to the ability of an interconnected power system to maintain synchronism after a severe disturbance. Historically, transient instability has been the dominant stability issue in power systems [1]. Meanwhile, massive operation and computation data are accumulated in dispatching center every day. Rapid accumulation of data provides unprecedented rich condition for power system security and stability analysis. How to discover valuable knowledge about transient stability from massive data has become a hot spot.

Recently, decision tree [2–8], artificial neural network (ANN) [9], support vector machine (SVM) [10–12], ensemble classifiers [13,14], and other data-mining algorithms [15–17] have been applied in transient stability analysis. To sum up, there are two application scenarios of transient stability analysis including the pre- and post-fault environment [4]. For pre-fault analysis, the transient stability status is predicted under credible faults in the near future [2–4,9,12,13,16,17]. If an operating point (OP) is insecure, prevention actions should be taken to modify this OP to withstand the credible contingencies. In contrast, the post-fault analysis is to implement the transient stability analysis in real time when the fault has already occurred [5–8,10,11,14,16,18]. Once the power system is found to be loss of synchronism in the near future, emergency control should be taken to avoid the possible collapse. Since the pre-fault transient stability assessment and preventive control are implemented before the fault occurrence, they are timely and will be the main research contents in this paper.

For the pre-fault transient stability analysis based on data-mining methods, one key issue is to obtain the security boundary using a set of selected variables (or features). Generator active power outputs are widely used as the input features of transient stability classifiers [2–4,9,13,16,17]. The main reason is that these variables are adjustable therefore the generated classifier can provide useful rules for preventive control. However, the performance of the classifier just using these controllable variables is limited. In Ref. [3], the rotor angles are utilized as the input features for accurate prediction. In Ref. [12], the post-fault energy-based features are utilized for transient stability analysis and the accuracy has improved significantly. But these post-fault dynamic features can only be obtained by time domain simulation since the fault has not occurred. On the other hand, the rotor angles and the

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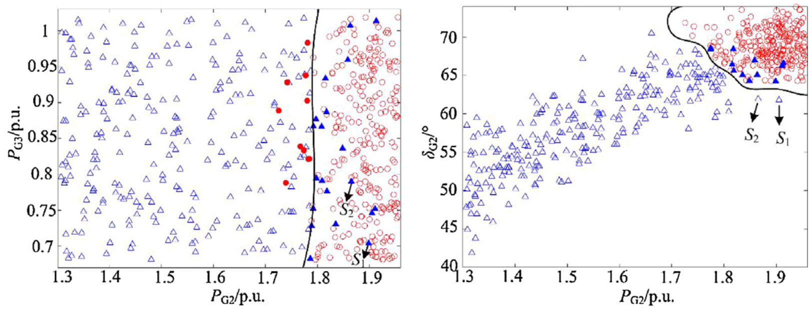

(a) Feature space of P_{G2} versus P_{G3} (b) Feature space of P_{G2} and δ_{G2}

Fig. 1. Feature space of different attributes.

energy-based features cannot be adjusted directly for preventive control. Therefore, more importance should be attached to balance the controllability versus accuracy of different input features in application.

Transient stability preventive control refers to modifying the OP of power system to withstand credible contingencies causing transient stability. The optimal preventive control strategies are often obtained by solving transient stability-constrained optimal power flow (TSCOPF). The complex differential constraints of swing equations can be converted into algebraic ones by using data-mining methods, such as decision tree [2–4] and recursive partitioning [17]. All these data-mining models are linear. In Ref. [18], the accuracy and transparency of different models are studied. The simulation results shown that, the accuracy of complex black-box models is generally higher than the simple models. Whereas the more transparent the classifier is, the easier to be understood and implemented by operators. So there is an unavoidable trade-off between the accuracy and transparency. For the preventive control, the TSCOPF with linear transient stability constraints is simple to solve, but the complex nonlinear constraints are more accurate thus the obtained prevention strategy will be more economic.

In order to take full consideration of the performance of different features and classifiers, a two-stage SVM method is proposed to obtain the approximate boundary of transient security. To ensure the economy and computation rapidity of preventive control, a chaotic particle swarm optimization (CPSO) algorithm combines the two-stage SVM is proposed to calculate the optimal prevention control strategies.

The rest of this paper is organized as follows. Section 2 introduces the approximation effect of different input features for transient secure boundary. Section 3 introduces the proposed approach using the CPSO combined with the two-stage SVM. Results and discussions of comprehensive case studies on a 16-machine 68-bus power system are conducted in Section 4. The conclusions are given in Section 5.

2. Approximation effect of different features for transient security boundary

Variety of variables can be used to establish the approximate security boundary. The pre-fault generator active power outputs are the most widely used due to their ability to provide basis for generation rescheduling or preventive control. However, the performance of the classifier merely using these variables is limited.

To illustrate the approximation effect using different features for transient security boundary, case studies are conducted on 3-machine 9-bus power system [19]. The transient stability simulations are carried out using the Power System Toolbox 3.0 [20]. Three-phase short circuit fault at line 7–8 is considered and the fault clearing time is 0.1 s. Generator active power outputs and loads are

Table 1
Two kinds of input feature sets.

Feature set	Descriptions
$\boldsymbol{F}_1$	Generator active power, generator terminal voltage
$\boldsymbol{F}_2$	Generator active and reactive power, rotor angle, terminal voltage, active and reactive power of transmission line

randomly varied by ±20% of the standard data, and the generator terminal voltages are varied by ±2%. After that, the P_{G2} and P_{G3} (G1 is the slack generator), P_{G2} and δ_{G2}, are used as the input of SVM with radial basic function to generate two security boundaries respectively. The LIBSVM toolbox [21], which is an open source MATLAB library for SVM, is used to generate all the SVM models. The feature space of different attributes and the generated secure boundary are shown in Fig. 1, the circles and triangles are unstable and stable instances respectively.

Fig. 1(a) shows that 20 stable instances are classified as unstable (filled triangles), and 9 unstable instances are classified as stable (filled circles). Whereas, only 11 stable instances are classified as stable, and none of unstable instances is incorrectly judged in Fig. 1(b). The misclassified stable instances $\boldsymbol{S}_1$ and $\boldsymbol{S}_2$ in Fig. 1(a) can be classified correctly when using the uncontrollable feature δ_{G2}. Therefore, the approximation effect of security boundary can be improved when using more features.

In this research, the variables are divided into two feature sets based on their controllability, shown in Table 1. The generator active power outputs and terminal voltages are considered as the preventive control variables, and the other variables with control variables are employed as candidate features for accurate prediction.

To further study the performance of different classifiers using different features, the original dataset is divided into training and testing sets (80% and 20% respectively) firstly. Then, C5.0, C5.0 using boosting technique, random forest (RF), LSVM, ELM and SVM with radial basic function are used to generate different classifiers based on these two feature sets in Table 1. The optimal parameters of single SVM and ELM are searched using a grid-search and cross validation process [11]. Prediction accuracy of testing set using different classifiers are shown in Fig. 2.

Following conclusions can be concluded from Fig. 2. (1) The prediction accuracy of classifiers using $\boldsymbol{F}_2$ is always higher than $\boldsymbol{F}_1$, which indicates the necessity of using more features. Nevertheless, not all the features in $\boldsymbol{F}_2$ can be adjusted directly. (2) The SVM model using $\boldsymbol{F}_2$ performs the best since its accuracy is the highest.

In order to take full consideration of the prediction accuracy and the application of useful rules for preventive control, a CPSO combined with two-stage SVM is proposed for transient instability prediction and prevention.