Power System Dynamic Analysis by Support Vector Machine

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***Abstract*—The main purpose of this paper is to utilize the method of Support Vector Machine (SVM) to assess the power system dynamics to decide which one of the loads should be tripped after the fault occurs and then is isolated to make the system stable. Because once the fault occurs the protection relay is triggered to isolate the fault point but the system may be still unstable, therefore the backup protection relays in the system are then triggered, and this may cause the outage region wider and even results in system blackout. To avoid system blackout, the suitable load is to be tripped to make the system return to another stable operating point after the fault has been isolated. The suitable trip loads are the transient stable samples which are selected by SVM, and then the load is selected which has the lowest impact on system. This paper we employs different loading conditions to increase the number of training samples to promote the accuracy rate of SVM. The results show that the accuracy rate of the purpose method can reach 70.86%.**

***Index Terms*—support vector machine, power system dynamic analysis, fault isolation, accuracy rate**

I. Introduction

The increasing load demand in power systems without accompanying investments in generation and transmission has affected the analysis of stability phenomena, there will be more challenges for the security and stability analysis of the power systems, and these traditional analysis methods such as time domain simulation has been not well meet the current needs of power grid [1]. With the development of wide area measurement system and big data methodology, using data mining methods to analysis the vast amount of data will bring new opportunities for stability assessment of power system [2].

The main purpose of this paper is to study the analysis of power system dynamics with the data mining method of big data methodology [3]. The approach of using data mining method for Transient Stability Assessment (TSA) is to train classifiers, such as Support Vector Machine (SVM), which use large amount of data to estimate the stability boundary of power system, then tries to figure out whether a new sample is in or out of the boundary, corresponding to the system is stable or not [4], [5]. The process for stability analysis of power system by SVM method can be divided into three steps: Firstly, the features that can rapidly reflect the transient process, such as generator rotor angles, are is selected for being the subsets of power system dynamic analysis. And then these feature subsets are used to train the SVM. Finally, these training data is integrated to assess the transient stability of power system.

II. Support Vector Machine Algorithm

Support Vector Machine (SVM) is based on the concept of decision planes that define decision boundaries [6]. A decision plane is one that separates between a set of objects having different class memberships. SVM performs the task of classification by first mapping the input data to a multidimensional feature space and then constructing an optimal hyper plane classifier separating the two classes with maximum margin. SVM performs minimization of error function by an iterative training algorithm to construct an optimal hyperplane [7].

SVM is a machine learning technique for classification. Given a training set of samples $\{\vec{x}_i\}$. The hyperplane is determined by an orthogonal vector $\vec{w}$ and a bias b, which identifies the points that satisfies $\vec{w}\cdot\vec{x}_i + b = 0$. By finding a hyperplane that maximizes the margin of separation $2/\|\vec{w}\|$, it is intuitively expected that the classifier will have a better generalization ability. The hyperplane with the largest margin on the training set can be completely determined by the nearest points to the hyperplane [6], [8]. To show the underlying reason for doing this, consider the fact that it is always possible to scale $\vec{w}$ and b so that:

$$\vec{w}\cdot\vec{x}_i + b = 1 \quad (1)$$

and

$$\vec{w}\cdot\vec{x}_i + b = -1 \quad (2)$$

If these data are excluded from the training set one can separate the remaining part of the training set without errors. To separate the remaining part of the training data one can construct an optimal separating hyperplane. This idea can be expressed formally as: minimize the functional [6], [8].

$$\begin{aligned} &\min && \frac{1}{2}\|\vec{w}\|^2 + C\sum_{i=1}^{N}\lambda_i \\ &\text{subject to} && y_i(\vec{w}\cdot\vec{x}_i + b) \ge 1-\lambda_i \\ & && \lambda_i \ge 0,\ i=1,\dots,N \end{aligned} \quad (3)$$

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where $\vec{w}$ is weight vector of the hyperplane, $C>0$ is penalty parameter proportional to the amount of constraint violation, λ is a slack variable, $\vec{x}_i$ is a mapping from input space to feature space, and b is threshold.

A hyperplane is used in the middle of the two classes, for the separation of these data, as shown in Fig. 1 [6].

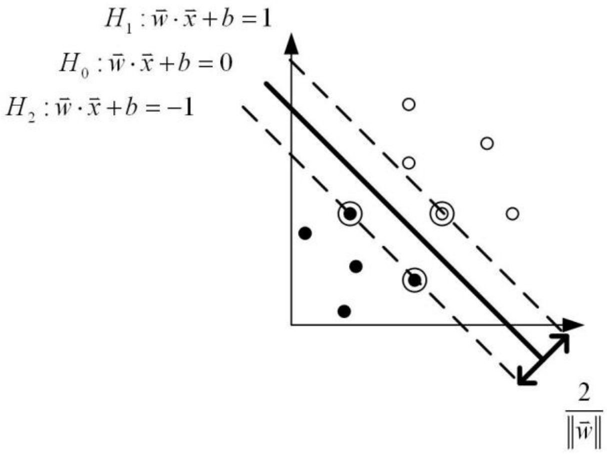

Figure 1. Optimal hyperplane and maximum margin.

As practical problems are often not to be linearly separable, the linear SVM has been extended to a nonlinear function by mapping the training data to an expanded feature space using a nonlinear transformation. An N dimensional linear separator $\vec{w}$ and a bias b then constructed for the set of transformed vectors

$$\Phi(x_i)=\Phi_1(x_i),\Phi_2(x_i),...,\Phi_N(x_i),\ i=1,...,l \qquad (4)$$

Classification of an unknown vector x is done by first transforming the vector to the separating space ($\vec{x}_i \to \Phi(x)$) and then taking the sign of the function. The computation of the decision boundary of an SVM for the nonseparable case consists in solving the following optimization problem:

$$\begin{aligned} &\min\ V=\frac{1}{2}\|\vec{w}\|^2+C\sum_{i=1}^{N}\lambda_i \\ &\text{subject to } y_i\cdot\left\{\vec{w}\cdot\Phi(x_i)+b\right\}\geq 1-\lambda_i \\ &\qquad \lambda_i\geq 0,\ \ i=1,\dots,N \end{aligned} \qquad (5)$$

Instead of solving (5) directly, it is much easier to solve the dual problem (6), in terms of the Lagrange multipliers α_i

$$\begin{aligned} &\text{minimize } W(\alpha) \\ &=-\sum_{i=1}^{N}\alpha_i+\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}y_i y_j\alpha_i\alpha_j\Phi(\vec{x}_i)\cdot\Phi(\vec{x}_j) \\ &=-\sum_{i=1}^{N}\alpha_i+\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}y_i y_j\alpha_i\alpha_j K(\vec{x}_i,\vec{x}_j) \end{aligned} \qquad (6)$$

subject to:

$$\sum_{i=1}^{N}y_i\alpha_i=0 \text{ and } 0\leq\alpha_i\leq C,\ \ i=1,\dots,N$$

which is quadratic optimization problem. From the solution, α_i, $i=1,\dots,N$ of (6), the decision rule $f(x)$ can be computed as

$$\begin{aligned} f(x)&=\vec{w}\cdot\Phi(x)+b=\sum_{i=1}^{N}\alpha_i y_i\Phi(\vec{x}_i)\cdot\Phi(\vec{x}_j)+b \\ &=\sum_{i=1}^{N}\alpha_i y_i K(\vec{x}_i,\vec{x}_j)+b \end{aligned} \qquad (7)$$

where the number of units $K(\vec{x}_i,\vec{x}_j)$ is kernel function to determine by the number of support vectors.

The training points with $\alpha_i>0$ are the support vectors, and (7) depends entirely on support vectors. The threshould b can be calculated using (1) and (2), which is valid for any support vector

$$b=y_{SV}-\sum_{i=1}^{N}\alpha_i y_i K(\vec{x}_i,\vec{x}_j) \qquad (8)$$

III. Power System Dynamic

A. Extended Equal Area Criterion

Transient stability is the ability of a power system to retain synchronism subject to disturbances [9]. In the extended equal area criterion, the multi-machine system is decomposed into a “candidate critical machine” and the remaining machines, aggregated to an equivalent one. The former is a machine (or cluster of machines) likely to be responsible for the systems separation, should the circuit breaker operations be used to island the part of the system which leads to loss of synchronism. Using the above aggregation with the well-known equal area criterion, a simple analytic direct methodology is devised that has a number of advantages [10].

In order to model the equivalent machine denoted by aggregated to one machine and its motion, we use the standard Centre of Angles (COA) δ_{COA} concept, while considering only the machines of the all remaining machines with machine s excluded. In this case we set:

$$\delta_{COA}=\frac{\sum_{i=1}^{n}H_i\delta_i}{\sum_{i=1}^{n}H_i} \qquad (9)$$

where H_i is inertia coefficient of the i_{th} machine, and δ_i is rotor angle of the i_{th} machine.

B. Assessment Indices Calculation

Transient instability of a power system is directly related to the angular separation between generators, Therefore, the generator rotor angles have been used for deriving indicators of transient instability [9]. The synchronous generator rotor angle δ_i is calculated in the simulation, and the maximum angle deviation of any one machines and at any time is recorded, denoted by $\delta_{i,\max}$. This value is later utilized to determine the system stability after faults. The transient stability assessment

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result is obtained by observing difference in rotor angle between δ_{COA} and $\delta_{i,\max}$:

$$\eta = |\delta_{i\max} - \delta_{COA}| < 180° \tag{10}$$

where when the transient stability index $\eta < 180°$, the system is considered as stable [11], [12].

Due to once the fault occurs the protection relay is triggered to isolate the fault point but the system may be still unstable, therefore to avoid system blackout, the suitable load is to be tripped to make the system return to another stable operating point after the fault has been isolated. The rule of suitable loads tripping is presented as

$$\text{No trip} \rightarrow \text{Trip samll load} \rightarrow \text{Trip large load} \tag{11}$$

Employing the generator rotor angle δ and loads tripping data for each training, the training samples can be established for the input of each training case.

IV. CASE STUDY

A. Study System

In this paper, the two-area power system is used as the sample power system to assess the system stability assessment. The model of a power system used in this paper is shown in Fig. 2 [9]. The system contains 12 buses and two areas. The system is consist of two areas where each area supplied by two generators, each having a rating of 900 MVA. The generator is connected to electrical power system grid through a transformer. The load on the system is assumed as constant impedance.

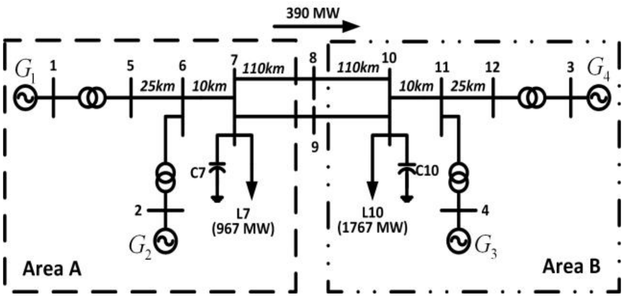

Figure 2. Single-line diagram of two-area power system.

B. Test Results

This paper use different loading conditions to increase the number of training samples to promote the accuracy rate of SVM. In simulation, the two-area power system is considered, the load is changed randomly in a range of 5% and -10%, and then 747 samples are generated, as shown in Table I. All the considered faults are three-phase short circuit at each bus, and cleared after 4 cycles. The feature selections as training samples include generator rotor angle δ and suitable loads tripping. The training samples are used to train the SVM. The training samples are then tested with different samples for accuracy evaluation.

TABLE I. SYSTEM LOAD VARIATION

	Origin system load	load +5%	load +4%	load +3%	load +2%	load +1%
L7 (MW)	967	1015.6	1005.7	996.0	986.3	976.7
L10 (MW)	1767	1855.6	1837.7	1820.0	1802.3	1784.7
	load -1%	Load -2%	load -3%	load -4%	Load -5%	load -6%
L7 (MW)	957.3	947.7	938.0	928.3	918.7	909.0
L10 (MW)	1749.3	1731.7	1714.0	1696.3	1678.7	1661.0
	load -7%	load -8%	Load -9%	load -10%		
L7 (MW)	899.3	889.6	880.0	870.3		
L10 (MW)	1643.3	1625.6	1608.0	1590.3		

We use the training and test samples to examine the effectiveness of the SVM to power system dynamic analysis. Table II presents the evaluation indices of SVM. Fig. 3 is the accuracy rate of SVM. Fig. 4 is the computation time of SVM. It can be observed that the precision of SVM increased as the data set is scaled up. Moreover, as the number of samples increase to 747, the precision reach 70.86%.

TABLE II. EVALUATION INDICES OF SVM

Number of samples	100	200	300
Accuracy rate of SVM	0.2131	0.4496	0.5265
Computation time (sec)	0.1345	0.236	0.3727
Number of samples	500	600	747
Accuracy rate of SVM	0.6243	0.6644	0.7086
Computation time (sec)	0.6110	0.7727	1.1615

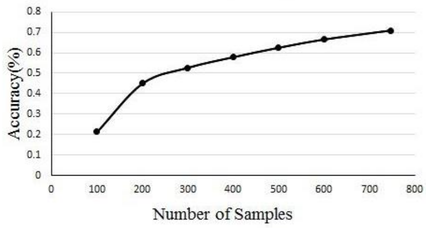

Figure 3. Accuracy rate of SVM.

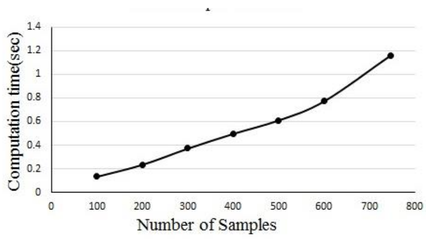

Figure 4. Computation time of SVM.

V. Conclusion

This paper has presented power system dynamic analysis based on Support Vector Machine (SVM) to decide which one of the loads should be tripped after a fault occurs and then is isolated to make the system stable. In order to protect the system against blackout, the suitable load to be tripped to make the system return to another stable operating point after the fault has been isolated. The power system dynamic analysis consists of three steps: First, the features include generator rotor angles and suitable loads tripping are selected to represent the system status. Then, the SVM model is trained using the selected features. Finally, the accuracy of the proposed SVM is examined. The simulation results reveal that the precision of SVM increased as number of training samples are scaled up, and the accuracy rate of the SVM can reach 70.86%. The SVM is computationally efficient to train extracted data features, making the SVM feasible for assessing system dynamic tasks in power system.

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