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Transient Stability Analysis of Power System Using Improved Least Square Method and Energy Function

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***Abstract*—The wide application of WAMS (Wide Area Measurement System) provided a new thinking for transient stability analysis of power system. Based on real-time measurement information from WAMS, a method to quickly analysis power system transient stability that does not depend on network structure, model and parameters of power system is proposed in this paper. Firstly, the parameters of system are identified online by improved least squares method on basis of that the multi-machine power system is equivalently reduction to one machine infinity bus system. The equilibrium point and stability margin of equivalent system are rapidly computed, and then the stability of system is quickly judged. The simulation results show that the algorithm can accurately judge transient stability of system and has better anti-disturbance ability and robustness. The issue of dependence of transient stability analysis on system model and parameter is solved. The adverse influences of data lose and measurement errors in actual measurement of the WAMS on analysis results are avoided effectively.**

Keywords-power system; wide-area measurement system; parameter identification; energy function; transient stability analysis

I. INTRODUCTION

Last decade, an urgent requirement about the power system stability control has been proposed because of the large area blackout frequently occurred on the global. Power system transient stability control is the first line of defense of stable operation [1], with a particularly important research value, while transient stability analysis is its foundation. Therefore, it is important to look for a quick and accurate method for transient stability analysis. There are some traditional transient stability analysis methods such as mainly numerical integration and direct method [2], but it is difficult to coordinate its calculation accuracy and speed. Artificial intelligence method has the advantages of fast online calculation and easy to generate inspired rule of decision, which constituted a fine complementation with traditional analysis methods. Currently, the main artificial intelligence methods are support vector machine [3], neural network [4], machine learning method [5] etc. However, the calculated amount of artificial intelligence method is huge, so there are many difficulties in practical application.

WAMS has been widely used in modern power system for monitoring, operating and controlling [6], which functions and applications have improved. It not only can provide technical support to building strong and smart grid, but also provides a new idea in power system transient stability analysis, which mainly about trajectory prediction and estimation of power angle. There are curve extrapolation [7] and trajectory prediction method based on system model [8] for the moment. However, the adverse effect on analysis results was not considered in these approaches, which because of measurement data loss and measurement error of WAMS in practical application, and hindered its popularization of application in engineering. A method to quickly analysis power system transient stability that does not depend on network structure, model and parameters of power system is proposed in this paper. The basis of this method is that the multi-machine power system is equivalently reduction to One Machine Infinity Bus (OMIB) system. The parameters of system are identified online by Regularized Robust Recursive Least Squares (R3LS) [9] method. The equilibrium point and stability margin of equivalent system are rapidly computed, and then the stability of system is quickly judged. Thus, the accuracy of stability determination of system is improved greatly.

II. EQUIVALENT REDUCTION OF MULTI-MACHINE POWER SYSTEM AND PARAMETER IDENTIFICATION

A. Equivalent Reduction of Multi-machine Power System

The calculation speed of complex power system transient stability analysis can be improved effectively by using homology equivalence technology, which include identification and aggregation of homology cluster [10]. The homology cluster is identified by using composite criterion that consist of angle δ and rotate speed ω. The composite power angle is defined as

$$\delta_{com} = \delta + k\Delta\omega \tag{1}$$

Here, k is setting, and $\Delta\omega$ is the variation of rotate speed per sampling period. The critical cluster S and surplus cluster A could be separated at the biggest clearance of abutting composite power angle δ_{com} by descending sort the δ_{com} of every generator.

The power angles curve of complementation cluster are aggregated by using CCCOI-RM transform after separated. We can use two equivalent generators replace the complementation cluster, and reduction to two machine system. As discussed in [10] and [11], the two machine system can reduction to OMIB system further and the mathematical model is constructed as

$$M_{eq}\delta_{eq}'' = \alpha + \beta\cos\delta_{eq} + \gamma\sin\delta_{eq} \tag{2}$$

Here, $M_{eq} = M_S M_A \big/ \left(M_S + M_A\right)$ is equivalent inertial time constant, and $\delta_{eq} = \delta_S - \delta_A$ is equivalent power angle, and α、β、γ are parameters to be identified.

B. Model of Parameter Identification

In [10], the parameters to be identified of (2) were solved by Recursive Least Square (RLS) method with forgetting factor, but the calculation accuracy and anti-disturbance ability are not enough ideal. Thus, R3LS algorithm is used to solve it in this paper. But before, (2) needs reduce to Auto Regressive Moving Average (ARMA).

Define

$$\begin{gathered}\delta_{eq}''(mT) = \left[\delta_{eq}(m+1)T - 2\delta_{eq}(mT) + \delta_{eq}(m-1)T\right]\big/T^2 \\ m = 1, 2, \cdots, n-1\end{gathered} \tag{3}$$

Here, T is sampling period, and m is number of sampling times.

According to (3), (2) can be written as

$$\begin{aligned}&\delta_{eq}(k) - 2\delta_{eq}(k-1) + \delta_{eq}(k-2) = \left[\alpha T^2 + \right.\\ &\left.\beta T^2\cos\delta_{eq}(k-1) + \gamma T^2\sin\delta_{eq}(k-1)\right]\big/M_{eq}\end{aligned} \tag{4}$$

Consider the disturbance $\varepsilon(k)$ of system, (4) can be written as

$$\begin{aligned}&y(k) + a_1 y(k-1) + a_2 y(k-2) + \cdots + a_{na} y(k-na) = \\ &\quad b_1 u(k-1) + b_2 u(k-2) + \cdots + b_{nb} u(k-nb) + \\ &\quad c_1 v(k-1) + c_2 v(k-2) + \cdots + c_{nc} v(k-nc) + \\ &\quad d_1 w(k-1) + d_2 w(k-2) + \cdots + d_{nd} w(k-nd) + \\ &\quad \varepsilon(k) + e_1\varepsilon(k-1) + e_2\varepsilon(k-2) + \cdots + e_{ne}\varepsilon(k-ne)\end{aligned} \tag{5}$$

Define

$$\begin{aligned}&B_1 = \left[b_1, c_1, d_1\right], \cdots, B_{bn} = \left[b_{bn}, c_{cn}, d_{dn}\right]; \\ &U(k-1) = \left[u(k-1), v(k-1), w(k-1)\right]^T, \cdots, \\ &U(k-nb) = \left[u(k-nb), v(k-nc), w(k-nd)\right]^T\end{aligned}$$

Equation (5) reduction to ARMA as

$$\begin{aligned}&y(k) + a_1 y(k-1) + a_2 y(k-2) + \cdots + a_{na} y(k-na) = \\ &\quad B_1 U(k-1) + B_2 U(k-2) + \cdots + B_{nb} U(k-nb) + \\ &\quad \varepsilon(k) + e_1\varepsilon(k-1) + e_2\varepsilon(k-2) + \cdots + e_{ne}\varepsilon(k-ne)\end{aligned} \tag{6}$$

Here, k=n+1,n+2,...,t; n=max[na,nb,nc]; t is time stamp.

C. R3LS Algorithm

The vector $\theta = \left[a_1, a_2, \cdots a_{na}, B_1, B_2, \cdots B_{nb}, e_1, e_2, \cdots e_{ne}\right]^T$ is the parameter vector to be determined. To specify a prediction error criterion, a virtual linear prediction model is constructed as

$$\begin{aligned}&\hat{y}(k|\theta) = -a_1 y(k-1) - a_2 y(k-2) - \cdots - a_{na} y(k-na) + \\ &\quad B_1 U(k-1) + B_2 U(k-2) + \cdots + B_{nb} U(k-nb) + \\ &\quad e_1\varepsilon\left(k-1\middle|\hat{\theta}(k-1)\right) + \cdots + e_{ne}\varepsilon\left(k-ne\middle|\hat{\theta}(k-ne)\right) = \varphi^T(k)\theta\end{aligned} \tag{7}$$

Where

$$\begin{aligned}&\varphi(k) \triangleq \left[-y(k-1), \cdots, -y(k-na), U(k-1), \cdots, U(k-nb),\right. \\ &\left.\quad \varepsilon\left(k-1\middle|\hat{\theta}(k-1)\right), \cdots, \varepsilon\left(k-ne\middle|\hat{\theta}(k-ne)\right)\right]^T\end{aligned} \tag{8}$$

The prediction error at time k can be defined as

$$\varepsilon\left(k\middle|\hat{\theta}(k)\right) = y(k) - \hat{y}\left(k\middle|\hat{\theta}(k)\right) \tag{9}$$

Define

$$\varepsilon\left(k\middle|\theta(t)\right) = y(k) - \hat{y}\left(k\middle|\theta(t)\right) \tag{10}$$

And

$$\begin{aligned}J\left(\theta(t)\right) = &\frac{1}{2}\left(\theta(t) - \bar{\theta}\right)^T \prod(t)\left(\theta(t) - \bar{\theta}\right) + \\ &\sum_{k=n+1}^{t}\lambda^{t-k}\rho\left[\varepsilon\left(k\middle|\theta(t)\right)\right]\end{aligned} \tag{11}$$

Here, $\bar{\theta}$ is constant vector and the prior guess of parameter θ. The matrix $\prod(t)$ is a positive definite matrix. It describes the confidence level in this initial guess at time t. Its main function is that it resolves the under-determined problem associated with a normal LS estimation. For the regularized LS algorithm, the regularization term helps skew the estimate towards the initial guess. Note that if the initial guess is different from the true value, a bias is introduced into the estimation results. The constant λ is the forgetting factor. $\rho(\varepsilon)$ is a loss function that defines a measure for the errors. It is used to reduce the potential effect of no typical data, and that's the robustness property. In the normal case defined as

$$\rho(\varepsilon)=\begin{cases}\frac{1}{2}\varepsilon^2, & \text{if } |\varepsilon|\le 3\sigma \\ \frac{1}{2}(3\sigma)^2, & \text{if } |\varepsilon|>3\sigma\end{cases} \quad (12)$$

Here, the variable σ is the standard deviation of the ε.

Then, a regularized weighted LS estimation of the θ can be defined as

$$\hat{\theta}(t)=\arg\min\left[J(\theta(t))\right] \quad t\ge n+1 \quad (13)$$

III. TRANSIENT STABILITY ANALYSES

There are two equilibrium points s and u in the equivalent system (2) after fault. Equation (2) can be written as by being equal to zero

$$\alpha+\beta\cos\delta_{eq}+\gamma\sin\delta_{eq}=0 \quad (14)$$

Two radicals δ_{eqs} and δ_{equ} can be obtained with leading the parameters from using R3LS algorithm in the equation above. The equilibrium point s corresponds to δ_{eqs} is stable equilibrium point, and the equilibrium point u corresponds to δ_{equ} is instable equilibrium point. According to δ_{eqs} and δ_{equ}, the transient state energy and critical energy of system can be obtained.

The transient state energy of system at the fault clearance moment is

$$V_{cl}=V_{ke}+V_{pe}=\frac{1}{2}M_{eq}\omega_{eqcl}^2-\int_{\delta_{eqs}}^{\delta_{eqcl}}\left(\alpha+\beta\cos\delta_{eq}+\gamma\sin\delta_{eq}\right)d\delta_{eq} \quad (15)$$

Here, $V_{ke}=\frac{1}{2}M_{eq}\omega_{eqcl}^2$ is the kinetic energy and $V_{pe}=-\int_{\delta_{eqs}}^{\delta_{eqcl}}\left(\alpha+\beta\cos\delta_{eq}+\gamma\sin\delta_{eq}\right)d\delta_{eq}$ is the potential energy of system. ω_{eqcl} is the angular velocity and δ_{eqcl} is the power angle of the equivalent system at the fault clearance moment.

The critical energy of system is

$$V_{cr}=-\int_{\delta_{eqs}}^{\delta_{equ}}\left(\alpha+\beta\cos\delta_{eq}+\gamma\sin\delta_{eq}\right)d\delta_{eq} \quad (16)$$

The energy margin of system is

$$\Delta V=V_{cr}-V_{cl} \quad (17)$$

Equation (17) can be re-formatted as

$$\Delta V'=\left(V_{cr}-V_{cl}\right)/V_{cl} \quad (18)$$

According to the La Salle invariance principle and the second Lyapunov theorem, transient stability of system can be judged after obtaining the energy margin. We set a threshold value $\varepsilon(\varepsilon\ge 0)$ of transient stability determination. The different values can be set at the instance of accuracy, and in the normal case we set it 0.3. Judge transient stability as follow

a) If $\Delta V'>\varepsilon$, the power system transient is stable.

b) If $\Delta V'<-\varepsilon$, the power system transient is instable.

c) If $0<\Delta V'<\varepsilon$, the power system transient is critically stable.

d) If $-\varepsilon<\Delta V'<0$, the power system transient is critically instable.

IV. SIMULATION RESULTS AND ANALYSIS

An IEEE39 model is used in this paper to comparative analysis the transient stability results which using the method above, BPA simulation and the online RLS method with forgetting factor in [10]. In BPA simulation, generators use the classical model and load use the integrated dynamic load model. The online RLS method which contains forgetting factor and the R3LS algorithm are realized by MATLAB software. WAMS measurement data and fault Critical Clearance Time (CCT) are obtained by BPA simulation which the sampling period is 0.05s. Analysis results of the three methods are shown in TABLE Ⅰ. The '*'is the point of fault and all the faults are three-phase grounded short circuit.

TABELI. ANALYSIS RESULTS OF TRANSIENT STABILITY

Fault location	Fault CCT (s)	Fault clearance time (s)	R3LS		RLS		BPA result
			Energy margin	*Judgment*	*Energy margin*	*Judgment*	
25*-26	0.21	0.10	2.013	Stable	2.516	Stable	Stable
		0.15	0.632	Stable	0.839	Stable	Stable
		0.20	0.259	Critically stable	0.314	Stable	Critically stable
		0.21	0.104	Critically stable	0.147	Critically stable	Critically stable
		0.22	-0.194	Critically instable	0.078	Critically stable	Critically instable
		0.25	-0.872	Instable	-0.721	Instable	Instable
3*-4	0.26	0.15	2.537	Stable	2.782	Stable	Stable
		0.20	0.931	Stable	1.251	Stable	Stable
		0.25	0.271	Critically stable	0.418	Stable	Critically stable
		0.26	0.194	Critically stable	0.303	Stable	Critically stable
		0.27	-0.071	Critically instable	0.046	Critically stable	Critically instable
		0.30	-1.192	Instable	-1.027	Instable	Instable

The correctness of transient stability simulation results of above method is verified, because the results are consistent with BPA simulation. Nearby the critical stability point of the system, the results of RLS with forgetting factor sometimes are false. However, the method above can accurately determine system transient stability after clearing fault, because R3LS algorithm leads a positive definite matrix in the objective function, which makes the estimated value regularization and to be close to actual value. Thus, the accuracy of parameter identification is superior to ordinary least squares method.

In order to verify that the algorithm has strong robustness, Gaussian random white noise is added into WAMS data of BPA simulation in this paper. The simulation results are shown in TABLEⅡ. In order to simulate atypical measurement data because of short-term communication failure of WAMS, the data values of two sampling periods of node 16 are adjusted to zero. The simulation results are shown in TABLEⅢ.

TABELII. ANALYSIS RESULTS OF TRANSIENT STABILITY WITH ADDING NOISE TO MEASURED DATA

Fault location	Fault CCT (s)	Fault clearance time (s)	R3LS		RLS	
			Energy margin	***Judgment***	***Energy margin***	***Judgment***
25*-26	0.21	0.10	2.253	Stable	2.371	Stable
		0.15	0.571	Stable	0.492	Stable
		0.20	0.237	Critically stable	0.302	Stable
		0.21	0.092	Critically stable	0.114	Critically stable
		0.22	-0.184	Critically instable	0.091	Critically stable
		0.25	-0.931	Instable	-0.825	Instable

TABELIII. ANALYSIS RESULTS OF TRANSIENT STABILITY WITH ADJUSTING DATA OF TWO SAMPLE PERIODS AROUND FAULT OF NODE 16 TO ZERO

Fault location	Fault CCT (s)	Fault clearance time (s)	R3LS		RLS	
			Energy margin	***Judgment***	***Energy margin***	***Judgment***
25*-26	0.21	0.10	2.126	Stable	1.824	Stable
		0.15	0.681	Stable	0.789	Stable
		0.20	0.233	Critically stable	-0.047	Critically instable
		0.21	0.093	Critically stable	-0.083	Critically instable
		0.22	-0.169	Critically instable	-0.159	Critically instable
		0.25	-0.721	Instable	-0.624	Instable

In TABLEⅡ and Ⅲ, nearby the critical stability point of the system, the results of RLS with forgetting factor sometimes are false, too. But the judgment of R3LS is accurate. Because the loss function of measurement error is added to the objective function of R3LS algorithm, which can reduce the potential adverse effects of atypical measurement data. Simulation results show that this method has better robustness.

V. SUMMARY

A new method was constructed by using the WAMS measurement data, which could analysis power system transient stability accurately and quickly after clearing fault in this paper. It was shown that this method could accurately determine system transient stability by comparative analysis between BPA and MATLAB program simulation. Moreover, this method could still ensure the accuracy of judgment with WAMS measurement data containing noise or occurring short-term communication failure, and it has better robustness, which could avoid the adverse effect of data loss and measurement error effectively. The parameters of this method are obtained with the real-time measurement data or calculating directly, without prior knowledge of network structure and parameters. Thus, this method can adapt to the complex system model, reflect the actual operation of the system accurately, and can be used for real-time transient stability analysis.

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