THE THEVENIN EQUIVALENT PARAMETER ROBUST ESTIMATION CONSIDERING THE MEASUREMENT OF BAD DATA

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ABSTRACT

This paper presents a Huber-M estimation of Thevenin equivalent calculation method using variable forgetting factor and projection statistics for the accuracy of Thevenin equivalent parameter identification in time-varying outliers. The method employ the Huber function based on projection statistics to suppress the influence of outliers on parameter identification to improve the robustness of the algorithm by using local measurement data. It also can trace the change of system quickly by using a variable forgetting factor. In order to improve the stability and generalization performance of the model, the paper adopt regularization technique algorithm to solve the problem of ill-conditioned matrix inversion. The simulation results of IEEE 30 node systems verify the effectiveness and accuracy of the proposed method.

Keywords: Thevenin equivalent, parameter identification, forgetting factor generalized regularization, bad data

1. INTRODUCTION

The Thevenin equivalent theory, one of the main algorithms for evaluate the security and stability of the grid has been widely used due to its clear concept and simple principle [1]. Meanwhile, with the rapid development of wide-area measurement systems and it wide application in power systems, the online stability analysis and control based on measurement data and Thevenin equivalent voltage has gained widespread attention [2]-[3]. This paper proposes a Huber-M estimation method based on the variable forgetting factor and projection statistics to estimate the Thevenin equivalent parameters. The algorithm suppresses the influence of measurement noise, bad data and bad leverage measurement on system parameter estimation accuracy by using Huber-M estimation based on projection statistics in power system. In order to enhance the adaptive tracking ability in time-varying outliers, this paper designs a variable forgetting factor method, which makes the forgetting factor adaptively adjust according to the changes of the environment. In addition, this paper solves the ill-conditioned problem of matrix inversion by using regularization techniques. By comparing with the existing methods, the simulation results verify that the proposed method is feasible and effective.

2. THEORY AND METHOD

2.1 Traditional Thevenin equivalent method description

The Thevenin Equivalence Theorem states that a system outside the research load node can be replaced by a series model of the equivalent impedance *Z* and the equivalent power source *E* in any liner circus for power system analysis. Fig.1 shows the load factor of Thevenin equivalent circuit.

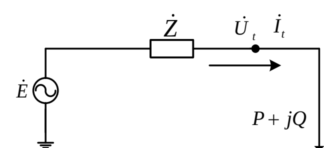

Fig 1 Thevenin equivalent circuits

According to the basic circuit theory:

$$\dot{E} = \dot{U}_t + \dot{Z}\dot{I}_t \tag{1}$$

Where, $\dot{U}_t$ is load node voltage, $\dot{I}_t$ is the sum of the currents flowing through the load, where $\dot{U}_t = U_{tr} + jU_{ti}$, $\dot{I}_t = I_{rt} + jI_{it}$; $\dot{E}$ 、 $\dot{Z}$ are the equivalent potentials of the Thevenin equivalent model and the equivalent reactance, respectively. The formula (1) can be used to get the Thevenin equivalent of the node.

$$Z = \frac{U_{t_2} - U_{t_1}}{I_{t_1} - I_{t_2}} \tag{2}$$

Where, t_1, t_2 represent the measured values of the voltage and current values at the load bus bars at two

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close times. The above formula is a least squares solution process which use to calculate the Thevenin equivalent parameter by using the two-time flow data.

2.2 Huber-M estimation of the Thevenin equivalent parameter identification method based on variable forgetting factor and projection statistics

In order to improve the function of the Thevenin equivalent parameter identification method and the real-time tracking ability, this paper introduces the variable forgetting factor method and the robust M estimation technique based on projection statistics (PS) algorithm, to proposes new robust adaptive algorithm with regularization and forgetting. The cost function of the algorithm is expressed as:

$$J(\dot{X}_k)=\sum_{i=1}^{k} w_i^2\lambda^{k-1}\rho(rs_i)+\frac{1}{2}\sigma\left\|\dot{X}_k\right\|^2 \tag{3}$$

Where, λ is a forgetting factor. In this paper, a variable forgetting factor method is used to overcomes the shortcomings of the fixed forgetting factor with character of slow convergence in fast change system and make the forgetting factor adaptively adjust according to the changes of the system during the online estimation process. $0.5\sigma\|\dot{x}_k\|^2$ is the regularization term, σ is the generalized regularization parameter.

$rs_i=\dot{r}_i/sw_i$ is the standardized residual, $\dot{r}_i=\dot{y}_i-\dot{h}_i\dot{X}_i$ is the residual. $s=1.4826b_m median_i|r_i|$ is the robust scale estimate, $median_i|r_i|$ represents the median of the absolute residual r_i. b_m is a correction factor that get the unbiasedness for a finite sample which is size k under Gaussian distribution, and 1.4826 is to consistency of the method [4]. w_i is the coefficient that characterizes the measured value of the lever measurement determined by the projection statistical PS algorithm [5], b_i usually set to 1.5 to produce good statistics under different distributions without increasing the deviation caused by the outliers.

$\rho()$ is M-estimate function, where chooses Huber nonlinear function:

$$\rho(rs_i)=\begin{cases}\frac{1}{2}rs_i^{\,2} & |rs_i|\le c\\ c\left|rs_i^{\,2}\right|-\frac{c^2}{2} & |rs_i|>c\end{cases} \tag{4}$$

The C value is between 1.5 and 3, which is 1.5.

Minimize the cost function (3), let the cost function $J(\dot{X}_k)$ pair differentiate and make the result to 0, get

$$\dot{R}_k\dot{X}_k=\dot{S}_k \tag{5}$$

Where

$$\dot{R}_k=\lambda\dot{R}_{k-1}+\sigma(1-\lambda)I+\frac{\varphi(rs_i)}{s^2}\dot{h}_k\dot{h}_k^T \tag{6}$$

$$\dot{S}_k=\lambda\dot{S}_{k-1}+\frac{\varphi(rs_i)}{s^2}\dot{h}_k\dot{y}_k \tag{7}$$

Where, $u(rs_i)=\partial\rho(rs_i)/\partial rs_i$, $\varphi(rs_i)=u(rs_i)/rs_i$.

To construct the simple form, we define

$$\dot{R}_k^*=\lambda\dot{R}_{k-1}+\sigma(1-\lambda)\dot{I} \tag{8}$$

Equation (6) can be transformed as:

$$\dot{R}_k=\dot{R}_k^*+\frac{\varphi(rs_i)}{s^2}\dot{h}_k\dot{h}_k^T \tag{9}$$

Equations (8) and (9) can be written using the Sherman-Morrison-Woodbury formula [6] as

$$\begin{aligned}(\dot{R}_k^*)^{-1}&=(\lambda\dot{R}_{k-1}+\sigma(1-\lambda)\dot{I})^{-1}\\&=\frac{1}{\lambda}\dot{R}_{k-1}^{-1}-\frac{\sigma(1-\lambda)}{\lambda^2}\dot{R}_{k-1}^{-1}(\dot{I}+\frac{\sigma(1-\lambda)}{\lambda}\dot{R}_{k-1}^{-1})^{-1}\dot{R}_{k-1}^{-1}\end{aligned} \tag{10}$$

$$\begin{aligned}&\dot{R}_k^{-1}=(\dot{R}_k^*+\frac{\varphi(rs_i)}{s^2}\dot{h}_k\dot{h}_k^T)^{-1}=(\dot{R}_k^*)^{-1}-\\&\frac{1}{s^2}\varphi(rs_k)(\dot{R}_k^*)^{-1}\dot{h}_k(\dot{I}+\frac{1}{s^2}\varphi(rs_k)h_k^T(\dot{R}_k^*)^{-1}\dot{h}_k)^{-1}\dot{h}_k^T(\dot{R}_k^*)^{-1}\end{aligned} \tag{11}$$

To facilitate notation, define $(\dot{R}_k^*)^{-1}=\dot{P}_k^*$, $\dot{P}_k=\dot{R}_k^{-1}$, (10) and (11) can be re-formatted as

$$\dot{P}_k^*=\frac{1}{\lambda}\dot{P}_{k-1}-\frac{\sigma(1-\lambda)}{\lambda^2}\dot{P}_{k-1}(\dot{I}+\frac{\sigma(1-\lambda)}{\lambda}\dot{P}_{k-1})^{-1}\dot{P}_{k-1} \tag{12}$$

$$\dot{P}_k=\dot{P}_k^*-\frac{1}{s^2}\varphi(rs_k)\dot{P}_k^*\dot{h}_k(I+\frac{1}{s^2}\varphi(rs_k)\dot{h}_k^TP_k^*\dot{h}_k)^{-1}\dot{h}_k^T\dot{P}_k^* \tag{13}$$

According to (5), (6) and (7), then $\dot{X}_k$ is obtained as

$$\begin{aligned}\dot{X}_k&=\dot{X}_{k-1}-\delta(1-\lambda)\dot{P}_k\dot{X}_{k-1}\\&+\frac{1}{s^2}\varphi(rs_k)\dot{P}_k\dot{h}_k^T(\dot{y}_k-\dot{h}_k\dot{X}_{k-1})\end{aligned} \tag{14}$$

Where, $\dot{X}_k$ is parameter matrix to be sought. $(\dot{y}_k-\dot{h}_k\dot{X}_{k-1})$ is the a priori error, rs_k is the posterior error.

2.3 Variable forgetting factor

The forgetting factor λ is used to eliminate the effect of old data at a fixed rate in the classical recursive least squares algorithm. Paper [7] proposed that the forgetting factor λ is most suitable between 0.95 and 0.99. In order to improve the ability to track the change of real-time and eliminate the influence of historical failure data. This paper proposed an error-based variable forgetting factor method. Since the value is in the range [0,1], the forgetting factor can be defined as follows:

$$\lambda=\left[\frac{1}{1+\mathrm{L}(k)}\right]_{\lambda_{\max}}^{\lambda_{\min}} \tag{15}$$

$$L(k)=\mu_1e(k)+\mu_2e(k)^2 \tag{16}$$

Where, e(k) is the estimation error at k. μ_1, μ_2 is the error-sensitive control coefficient which used to control the rate of forgetting factor. The coefficient μ_1 can quickly pass the error to the forgetting factor, so that the forgetting factor changes rapidly; μ_2 control the rate of the forgetting factor and maintain the stable of numerical stability, μ_1 is relatively small and μ_2 is relatively large for systems with large convergence errors, the opposite applies. $\lambda_{\min}$ 、 $\lambda_{\max}$ is the upper and lower limits of the forgetting factor, $\lambda_{\max}$ generally take a value less than 1 or take 1. $\lambda_{\min}$ is related to the specific problem, but the value $\lambda_{\min}$ should not be too small to avoid numerical instability.

3. *SIMULATION VERIFICATION*

The IEEE 30-node system is used as a sample to prove the accuracy and effectiveness of the proposed algorithm. The method of verification as follows: the system running state data is taken from the power flow calculation result sampled by the wide-area measurement system, the accuracy of the algorithm is analyzed by comparing the voltage value calculated by the standard model power flow after the load fluctuation with the voltage value obtained by using the calculated node Thevenin equivalent model.The parameter settings are as follows: $\mu_1=2.4$, $\mu_2=18$, $\lambda_{\min}=0.8$, $\lambda_{\max}=1$.

In this paper, load node 16 is observation node, and the load of all nodes in the IEEE 30-node system is slowly increasing (4% load ramp growth) to simulate the real-time fluctuation of user load and obtain the voltage and current values of node 16. The voltage and current are superimposed with a Gaussian distribution with a desired value of 0 and a standard deviation of 0.01 as the voltage and current measurement values in order to simulate the noise in the measurement data of the wide-area measurement system. At the same time, considering the impact of outliers, bad leverage measurement and forgetting factor on the accuracy of the Thevenin equivalent parameter, this paper sets the following two different scenarios.

(1) The outlier is the result of increasing the voltage and current values of the 30th and 60th seconds to 2.5 times. The fixed forgetting factor $\lambda=0.985$ is used in the Huber-M estimation algorithm.

(2) The bad leverage value is the current value of the 30th second increased to 2.5 times and the voltage value is constant. The variable forgetting factor proposed in this paper is used in the Huber-M estimation algorithm.

Calculate the Thevenin equivalent parameters through the data of continuous power flow calculation by classical least squares method (RLS), Huber-M estimation method (Huber M) and the method of proposed in this paper (GM-PS). After obtaining the Thevenin equivalent parameter, for greater accuracy of the Thevenin equivalent parameters, adding a set of random perturbations (not higher than 35 %) to node 16 while the load on the other nodes remains the same in the original system. Obtain the voltage amplitude of node 16 through the original 30-node system power flow calculation and the two-node system power flow calculation after the Thevenin equivalent. Here, the node voltage value calculated by the original 30-node system power flow is selected as the true value (True).

Scene 1: An outlier in the measured data.

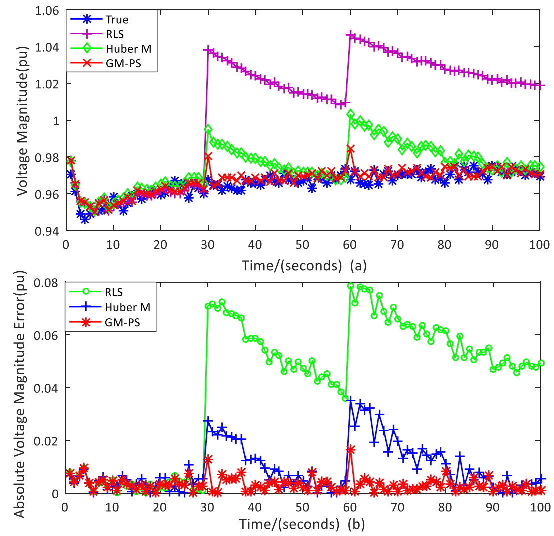

Fig 2 Voltage magnitude and absolute voltage magnitude error at node 16

Fig.2(a) is a voltage amplitude diagram of the node 16 obtained from the original IEEE 30-node system and three types of the Thevenin equivalent two-node system. It can be seen from Fig. 3(a) that the method in this paper is more accurate and less biased than the other two methods. When an outlier occurs in the equivalent data, the method can quickly eliminate the effects of outliers and quickly track system changes.

Fig.2(b) shows the absolute error curve sum of the three equivalent methods. It can be seen from the figure that the equivalent error of the classical least squares estimation method increases sharply when an outlier occurs in the system measurement. The Huber-M estimation and proposed method eliminate the impact of historical fault data, so the equivalent error can be quickly reduced and stabilized. However, the downward trend of Huber-M estimation error is slower than that of the proposed method. When the system tends to be stable, Huber-M estimates the error more.

Scenario 2: Poor lever measurement in measurement data

The following figure shows three equivalent methods and power flow calculation results. It can be seen from Fig.3(a) that compared with the power flow calculation result the deviation of the calculation result in this method is smaller than the least squares method and Huber-M estimation method when the bad lever measurement value appears in the 30th second. It can be apparent from Fig.3(b) that relative to the least squares method, the forgotten factor provided in this paper combined with the Huber-M estimation method has higher steady state identification accuracy and lower error.

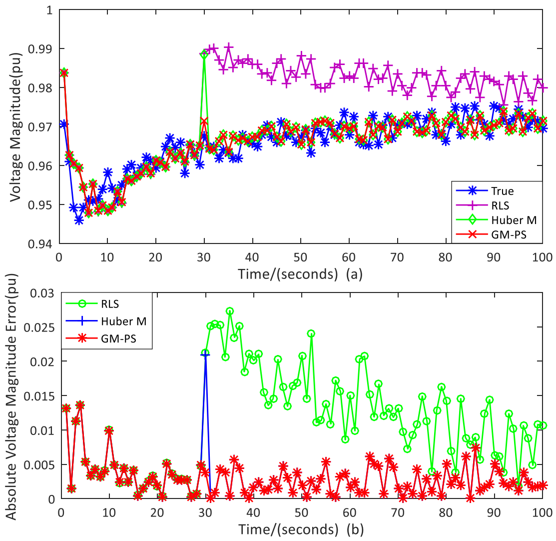

Fig 3 Voltage magnitude and absolute voltage magnitude error at node 16

Fig. 4 reflects the change of the forgetting factor in the parameter identification process. It can be seen from the forgetting factor stays around 0.98 when the system is in stable; The parameter estimation error appears sharply when there have outlier or bad leverage measurement, and the forgetting factor is rapidly reduced, the system changes are quickly tracked.

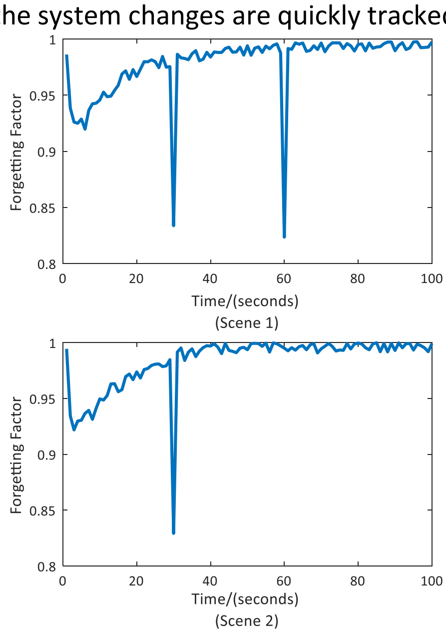

Fig 4 Value of the forgetting factor

The above simulation results show that the proposed method has better adaptive tracking ability and robustness than the least squares algorithm and Huber-M estimation algorithm. And it is more effective for Identification of Thevenin's Equivalent Parameter in the outlier and bad leverage measurement environment.

4. CONCLUSION

This paper proposes a Thevenin equivalent parameter identification method based on the variable forgetting factor and projection statistics through analyzes the parameter drift problem, gross difference consideration and measuring bad leverage. To eliminate the influence of the bad lever measurement in the power system, the Huber-M estimation technique based on the projection statistical algorithm is adopted using the dynamic tracking ability and adaptability of the enhance algorithm of variable forgetting factor. The algorithm has broad application prospects in areas such as online analysis and monitoring of power systems because it can quickly and accurately calculate the system's Thevenin equivalent parameters Only need to measure local data.

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