Identification of Power Network Branch Parameters Based on State Space Transformation

HAIBO ZHANG[ID], **(Member, IEEE), ZHIWEI DIAO**[ID], **AND YUNFENG CUI**

State Key Laboratory of Alternate Electrical Power System With Renewable Energy Sources, North China Electric Power University, Beijing 102206, China

Corresponding author: Zhiwei Diao (paragon@ncepu.edu.cn)

ABSTRACT Deviations or errors in power system branch parameters will seriously affect the effectiveness of power system state estimation and subsequent advanced applications. In this paper, a local estimation algorithm for the suspicious parameters of power network branches is proposed based on the state space transformation. After the parameter detection process, a local estimation network is formed by setting the suspicious branch as the searching center. According to the measurement type, the measurement equations are established with branch parameters as state vector. Then, add the non-suspicious branch parameters in the region to the measurement equation as pseudo-measurements to improve the measurement redundancy. Finally, all suspicious parameters, including closely related ones, are identified simultaneously, and the estimated correction values are worked out by multi-section statistical analysis. The identification method is illustrated in the PMU and SCADA measurement systems. Considering that the voltage measurement in the SCADA system cannot be directly applied, a fixed-point iteration scheme is proposed. The identification process of the suspicious branch parameters is decomposed into two nested loop iterations. The validity of the algorithm is verified on the IEEE 118-bus and 300-bus systems and the influence of measurement error on the identification result is also discussed.

INDEX TERMS Parameter identification, state estimation, PMU measurement, SCADA measurement.

I. INTRODUCTION

The accuracy of power network branch parameters not only directly determines the effectiveness of EMS analysis and application software of power dispatching control center, but also seriously affects the accuracy, reliability and economy of power dispatching control [1]–[3]. The traditional method of network parameter identification is to add a few suspicious parameters as state variables to state estimation process [4]–[6]. However, the number of identifiable parameters that can be augmented is very limited and the accuracy is not high. In recent years, a lot of new parameter identification methods are emerging. Paper [7] summarizes the classification of methods for estimating error parameters, describes the main concepts behind each method, and points out the feasibility and limitations of each method. Paper [8] presents a hierarchical modeling method for parameter identification of large-scale networks, which divides the state space into

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two levels. A parameter identification method based on sensitivity is proposed in paper [9]. Paper [10] according to the sensitivity relationship between the branch power flow compensation component and the measurement residual, a branch parameter identification method is proposed. However, the method must set many threshold values according to the specific system. In paper [11], [12], Lagrange identification method is proposed. This method can get good identification result with one error parameter, but it is difficult to deal with multi-bad correlation measurement and parameter errors effectively. Paper [13] points out the shortcomings of using single measurement section and improves the method to multi-measurement section detection and identification. Paper [14] improves this method by using sparse technique, which greatly improves the calculation efficiency and can be applied to large networks. Paper [15] based on the normalized Lagrange multiplier, a fast parameter identification method similar to bad data identification is proposed, which overcomes the shortcomings of traditional augmented estimation method, such as complicated code and large amount of

calculation. Paper [16] presents a multi-input multi-output process method, which can use continuous or dispersed state space variables and impedance transfer function to obtain the estimation model and discusses the measurement noise. For the case of multiple bad data, paper [3] uses the distributed parameter model to construct nonlinear state estimation for localization, and the influence of shunt capacitance is fully considered. Paper [17] introduces a parameter identification method through fault recording data of protective devices. Through a screening model, the method has a good accuracy in identifying asymmetric line parameters. With the wide application of PMU measuring devices, its measuring accuracy is further improved, which provides a new way to detect and identify the branch parameters of power grid through PMU measurement. Paper [18] points out that it is impossible to detect the parameters of single edge cut set branch without PMU measurement or identify the parameters of double edge cut set branch. This article describes the method of finding the single edge and double edge cut set branches in large power systems. Paper [19] shows where PMU should be installed to ensure the detectability and identifiability of the parameters. Paper [20] and [21] proposed a method of state estimation by adding PMU measurements to SCADA based system. The former uses normalized Lagrange multipliers, and the latter uses normalized residual for detection.

For the process of suspicious parameter detection, this paper applies the method in paper [11] and focuses on the identification of erroneous parameters by using measurement data without gross errors. Aiming at the problem that the existing identification methods have low redundancy and are difficult to deal with multi-branch parameter errors, this paper follows the idea of state space transformation in paper [21] but uses the local area network parameter estimation instead of the single-branch estimation. By taking the branch parameters as the state vector, this method can be applied to identify multiple closely related suspicious parameters. The measurement equations are established according to different measurement types and the pseudo-measurement of the trusted parameters. In addition, considering that SCADA measurement system has no time scale, the sampling time of PMU measurement and SCADA measurement in the real system is difficult to achieve complete consistency. Therefore, the two measurement systems are discussed separately in this paper.

II. CALCULATION MODEL OF PMU MEASUREMENT SYSTEM
A. BRANCH CURRENT EQUATION
1) CURRENT MEASUREMENT EQUATION OF TRANSMISSION LINE BRANCH
The adopted pi equivalent model of transmission line is shown in Fig. 1. For easy operation, line parameters are represented by branch conductance g_{ij}, susceptance b_{ij} and the shunt susceptance to ground y_{ij}.

Considering that it is easier to realize linear state estimation by using Cartesian coordinates, the measurement equations
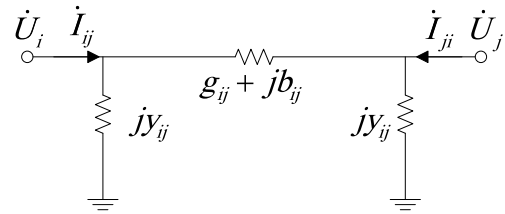

FIGURE 1. Pi model of transmission line.

in PMU system are established in their Cartesian form. Assuming the index of this branch is r. Set the branch parameters as state vector and regard the node voltage of the two boundary nodes as known quantity. The corresponding branch current measurement equation of the left side can be expressed as:

$$\begin{bmatrix} \text{Re}(\dot{I}_{ij}) \\ Im(\dot{I}_{ij}) \end{bmatrix} = \begin{bmatrix} (e_i - e_j) & -(f_i - f_j) & -f_i \\ (f_i - f_j) & (e_i - e_j) & e_i \end{bmatrix} \begin{bmatrix} g_{ij} \\ b_{ij} \\ y_{ij} \end{bmatrix} + v \quad (1)$$

where e_i, f_i and e_j, f_j are the real and imaginary parts of voltage phasor $\dot{U}_i$ and $\dot{U}_j$, $\text{Re}(\dot{I}_{ij})$ and $\text{Im}(\dot{I}_{ij})$ are the real and imaginary parts of the left side current phasor measurement, v is the measurement error vector.

The branch current equation of the right side has the same form like (1) and only i and j need to be exchanged. Simplify these branch current measurement equations as block matrix:

$$I_{Lr} = \begin{bmatrix} I_{Lr}^{(i,j)} \\ I_{Lr}^{(j,i)} \end{bmatrix} = \begin{bmatrix} H_{Lr}^{(i,j)} \\ H_{Lr}^{(j,i)} \end{bmatrix} x_{Lr} = H_{Lr} x_{Lr} \quad (2)$$

2) CURRENT MEASUREMENT EQUATION OF TRANSFORMER BRANCH
Assuming the index of this branch is s and the parameters are also represented by their admittance form, which is shown in Fig.2. Due to the excitation branch has little impact on the power network analysis, the excitation branch parameters $g_T + jb_T$ can be treated as a reliable parameter. The transformation ratio K is obtained from the measurement of the tap, which belongs to the measurement parameter so it's also regarded as a trusted parameter.
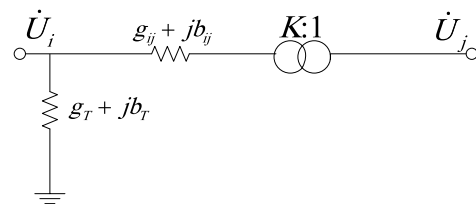

FIGURE 2. Calculation model of transformer.

The current equation of the transformer branch on the left side can be expressed in rectangular coordinates by setting g_{ij}, b_{ij} as state vector, and regarding the node voltage of the

two boundary nodes as known quantity:

$$\begin{bmatrix} \mathrm{Re}(\dot{I}_{ij}) - e_i g_T - f_i b_T \\ \mathrm{Im}(\dot{I}_{ij}) - f_i g_T + e_i b_T \end{bmatrix}$$
$$= \begin{bmatrix} (e_i - ke_j) & -(f_i - kf_j) \\ (f_i - kf_j) & (e_i - ke_j) \end{bmatrix} \begin{bmatrix} g_{ij} \\ b_{ij} \end{bmatrix} + v \quad (3)$$

The corresponding branch current equation of the right side is:

$$\begin{bmatrix} \mathrm{Re}(\dot{I}_{ji}) \\ \mathrm{Im}(\dot{I}_{ji}) \end{bmatrix} = \begin{bmatrix} -k(e_i - ke_j) & k(f_i - kf_j) \\ -k(f_i - kf_j) & -k(e_i - ke_j) \end{bmatrix} \begin{bmatrix} g_{ij} \\ b_{ij} \end{bmatrix} + v \quad (4)$$

Equation (3) and (4) can be simplified by block matrix:

$$I_{Ts} = \begin{bmatrix} I_{Ts}^{(i,j)} - I_{GTs} \\ I_{Ts}^{(j,i)} \end{bmatrix} = \begin{bmatrix} H_{Ts}^{(i,j)} \\ H_{Ts}^{(j,i)} \end{bmatrix} x_{Ts} = H_{Ts} x_{Ts} \quad (5)$$

For the three-winding transformer, the node voltage of the neutral point cannot be obtained directly from the measured data because PMU measurement devices cannot be installed at the neutral point. In addition, the low-voltage side of the three-winding transformer is generally not equipped with PMU measurement either. So, it may cause some regions cannot be observed when regarding branch parameters as the state vector and the parameters cannot be identified. In order to avoid the unobservable area affecting the application of the algorithm, the traditional voltage state estimation based on PMU measurement is processed before parameter detection and identification. After that, the voltage estimation value can be used for the node without PMU voltage measurement.

B. NODE INJECTION CURRENT EQUATION

In PMU measurement system, there are some zero-injection current nodes with very high precision. The characteristic of these nodes is that there is no generator or load directly connected to them. For the zero-injection node that all branches connected to it is installed with PMU measurement, the KCL equation of this node can be added to the measurement equation to improve the measurement redundancy.

For one of zero-injection node k, its zero-injection current equals to the sum of the current of the transmission lines and transformers which are connected to it, that is:

$$0 = \sum_{a \in \mathbf{A}} H_{La}^{(k,\cdot)} x_{La} + \sum_{b \in \mathbf{B}} H_{Tb}^{(k,\cdot)} x_{Tb} \quad (6)$$

where set $\mathbf{A}$ and $\mathbf{B}$ respectively represent line branch sets and transformer branch sets connected to node k.

C. PSEUDO MEASUREMENT OF BRANCH PARAMETER

After the detection process, the non-suspicious parameters of transmission lines and transformers can be used as pseudo measurement and can be added to measurement equations:

$$X_R = X_R^m + v \quad (7)$$

III. PARAMETER DETECTION PROCESS BY LAGRANGE MULTIPLIER METHOD

A. STEPS OF LAGRANGE MULTIPLIER PARAMETER DETECTION METHOD

The main idea of Lagrange multiplier detection method is to add parameter errors as zero equality constraints to the conventional state estimation model. Its main steps can be described as follows [11]:

1) Use the conventional WLS method to estimate the node voltage.
2) Calculate the Jacobian matrix with parameters as state vector and calculate the normalized Lagrange multiplier vector for the network parameters according to the corresponding formula and the state estimation results obtained in step 1).
3) If the maximum value of all normalized Lagrange multipliers $\lambda_{\max}^N$ is less than the given threshold, it is considered that there are no suspicious parameters in the network. Otherwise proceed to step 4).
4) Regarding the parameters corresponding to the largest normalized Lagrange multiplier as suspicious parameter, use the identification method to identify and modify it, and then return to step 1).

B. PROCESS FOR MULTIPLE SUSPICIOUS PARAMETERS

Considering that the conventional Lagrange multiplier method detects the parameters one by one, if there are multiple bad parameters in the same local area which are closely connected with electricity, the estimation and identification of one of the branches will be affected by the nearby error parameter branches, which will lead to the increase of the estimation error. Hence, the following strategy has been adopted:

1) According to the results of Lagrange multiplier detection method, the trusted parameter set T used in identification is processed dynamically.
2) After the process of parameter detection and identification one by one, the previously revised parameters are put into the suspicious parameter set S, the other parameters are put back into the set T. Then the parameters set S are identified again. If multiple parameters in set S appear in the same local area, these suspicious parameters are identified and corrected at the same time.

The process of parameter detection and identification can be described in detail by the flow chart shown in Fig.3.

IV. LOCAL NETWORK PARAMETER IDENTIFICATION PROCESS FOR PMU MEASUREMENT SYSTEM

A. FORMING LOCAL PART NETWORK

It is the measurement in the near area of the suspicious branch that determines the identification accuracy and the measurement in the remote area has little impact on the identification result. However, if the parameters are identified according to the whole network, the result will be probably affected by the bad data of the measurements in remote area, which will lead
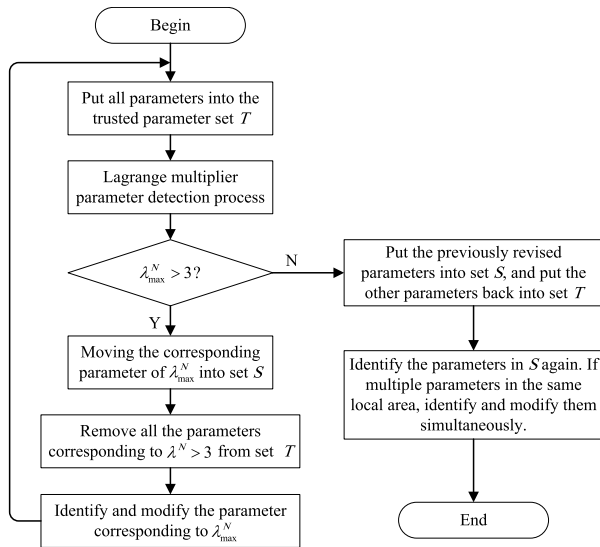
FIGURE 3. Flow chart of the parameter detection and identification process.

to the failure of identification. Hence, the local identification scheme is used in this paper.

After finding out the suspicious parameters through detection process, a local power network can be formed to do the identification process

If the two boundary nodes of the suspicious branch don't have zero injection constraint, this branch is taken as the local calculation area. Besides, take the branch containing the suspicious parameter as searching center, and search for other branches connected to the two boundary nodes. Then, select the branch with branch current measurement and regard the new searched nodes as boundary nodes. Finally, add the corresponding measurements to the measurement equation. It should be noticed that the zero injection constraints on the boundary nodes gained by the last search cannot be used.

Parameter identification in the local area has these following advantages: First, it can isolate other bad data outside the region to avoid its impact on parameter estimation. Second, the problem of non-observability caused by no current measurement at both ends of the suspicious branch can also be solved by using the zero-injection constraint. In addition, the computational efficiency will be improved because the computational area is relatively small and the measurement equation is linear.

After forming the calculation area, the non-suspicious branch parameters in this region are added to the measurement equation as pseudo equation to improve the measurement redundancy and identification accuracy.

B. STATE ESTIMATION WITH PARAMETERS AS STATE VECTOR

According to the types of measurements and branches, assuming that there are r transmission lines and s transformers in the local area, the measurement equations of the system

can be expressed as:

$$z = \begin{bmatrix} I_L \\ I_T \\ 0 \\ x_{RL} \\ x_{RT} \end{bmatrix} = \begin{bmatrix} H_L & \\ & H_T \\ H_{JL} & H_{JT} \\ \hline H_{RL} & \\ & H_{RT} \end{bmatrix} \begin{bmatrix} x_L \\ x_T \end{bmatrix} + v = H_p x_p + v \quad (8)$$

where $H_L = diag(H_{L1}, H_{L2} \cdots, H_{Lr}), H_T = diag(H_{T1}, H_{T2}, \cdots, H_{Ts}), x_L = (x_{L1}^T, x_{L2}^T, \cdots, x_{Lr}^T)^T, x_T = (x_{T1}^T, x_{T1}^T, \cdots, x_{Ts}^T)^T, H_{JL}$ and H_{JT} are block matrixes corresponding to zero-injection measurements, and can be formed according to (6). x_{RL} and x_{RT} represent the non-suspicious parameters of the transmission lines and transformers in the local area respectively. For each row of matrix H_{RL} and H_{RT}, only the columns corresponding to the non-suspicious parameters are 1, and the rest elements are 0.

Consider (8) as a normal measurement system:

$$z = H_p x_p + v \quad (9)$$

where z is the measurement vector, H_p is the Jacobian matrix of parameter, x_p is the parameter vector.

Since the measurement equations are linear, the WLS method can be used to estimate the branch parameters. The objective function is:

$$\min J(x) = (z - H_p x_p)^T R^{-1} (z - H_p x_p) \quad (10)$$

The linear state estimation solution of (10) is:

$$x_p = \Sigma^{-1} H_p^T R^{-1} z \quad (11)$$

where Σ is the gain matrix which refers to $H_p^T R^{-1} H_p$.

For multi-section data, the measurement information of each section is read one by one. First, establishing the measurement equations of the current section according to (8). Then, the suspicious parameter estimated value of this section is calculated by (11). Finally, the average value of the estimated values gained from each measurement section is taken as the final recommended estimated value of the suspicious parameter.

C. ALGORITHM FLOW CHART OF PMU MEASUREMENT SYSTEM

V. CALCULATION MODEL OF SCADA MEASUREMENT SYSTEM

A. BRANCH POWER EQUATION
1) POWER MEASUREMENT EQUATION OF TRANSMISSION LINE BRANCH

Referring to the ideas in PMU system, and considering that the polar coordinate system can reduce the modification of the existing program, the power flow equations of the transmission line shown in Fig. 1 can be expressed in their

polar form:

$$
\begin{bmatrix} P_{ij} \\ Q_{ij} \\ P_{ji} \\ Q_{ji} \end{bmatrix}
$$

$$
= \begin{bmatrix}
U_i^2 - U_i U_j \cos\theta_{ij} & -U_i U_j \sin\theta_{ij} & 0 \\
-U_i U_j \sin\theta_{ij} & -U_i^2 + U_i U_j \cos\theta_{ij} & -U_i^2 \\
U_j^2 - U_i U_j \cos\theta_{ij} & U_i U_j \sin\theta_{ij} & 0 \\
U_i U_j \sin\theta_{ij} & -U_j^2 + U_i U_j \cos\theta_{ij} & -U_j^2
\end{bmatrix}
$$

$$
\times \begin{bmatrix} g_{ij} \\ b_{ij} \\ y_{ij} \end{bmatrix} + v \tag{12}
$$

where P_{ij}, P_{ji}, Q_{ij} and Q_{ji} are active and reactive power of the branch respectively.

If the index of the transmission line branch is r, then (12) can be simplified by block matrix:

$$
S_{Lr} = \begin{bmatrix} S_{Lr}^{(i,j)} \\ S_{Lr}^{(j,i)} \end{bmatrix} = \begin{bmatrix} H_{Lr}^{(i,j)} \\ H_{Lr}^{(j,i)} \end{bmatrix} x_{Lr} = H_{Lr} x_{Lr} \tag{13}
$$

2) POWER MEASUREMENT EQUATION OF TRANSFORMER BRANCH

Similarly, for the transformer branch shown in Fig. 2, remove the power of the excitation branch:

$$
\begin{bmatrix} P_{ij} \\ Q_{ij} \\ P_{ji} \\ Q_{ji} \end{bmatrix}
$$

$$
= \begin{bmatrix}
U_i^2 - KU_i U_j \cos\theta_{ij} & -KU_i U_j \sin\theta_{ij} \\
-KU_i U_j \sin\theta_{ij} & -U_i^2 + KU_i U_j \cos\theta_{ij} \\
K^2 U_j^2 - KU_i U_j \cos\theta_{ij} & KU_i U_j \sin\theta_{ij} \\
KU_i U_j \sin\theta_{ij} & -K^2 U_j^2 + KU_i U_j \cos\theta_{ij}
\end{bmatrix}
$$

$$
\times \begin{bmatrix} g_{ij} \\ b_{ij} \end{bmatrix} + v \tag{14}
$$

If the index of the transformer branch is s, then (12) can be simplified by block matrix:

$$
S_{Ts} = \begin{bmatrix} S_{Ts}^{(i,j)} \\ S_{Ts}^{(j,i)} \end{bmatrix} = \begin{bmatrix} H_{Ts}^{(i,j)} \\ H_{Ts}^{(j,i)} \end{bmatrix} x_{Ts} = H_{Ts} x_{Ts} \tag{15}
$$

B. NODE INJECTION POWER EQUATION

When calculating the Jacobian matrix of parameters, it can be noticed that for each specific branch, the Jacobian elements are exactly the same as those in branch power measurement, and their values are not related to other branches. Assuming x_{kp} represents one of the branch parameter connected to node k and the index of this branch is n. The Jacobian element can be calculated by:

$$
\frac{\partial S_{Jk}}{\partial x_{kp}} = \frac{\partial S_{kp}}{\partial x_{kp}} \tag{16}
$$

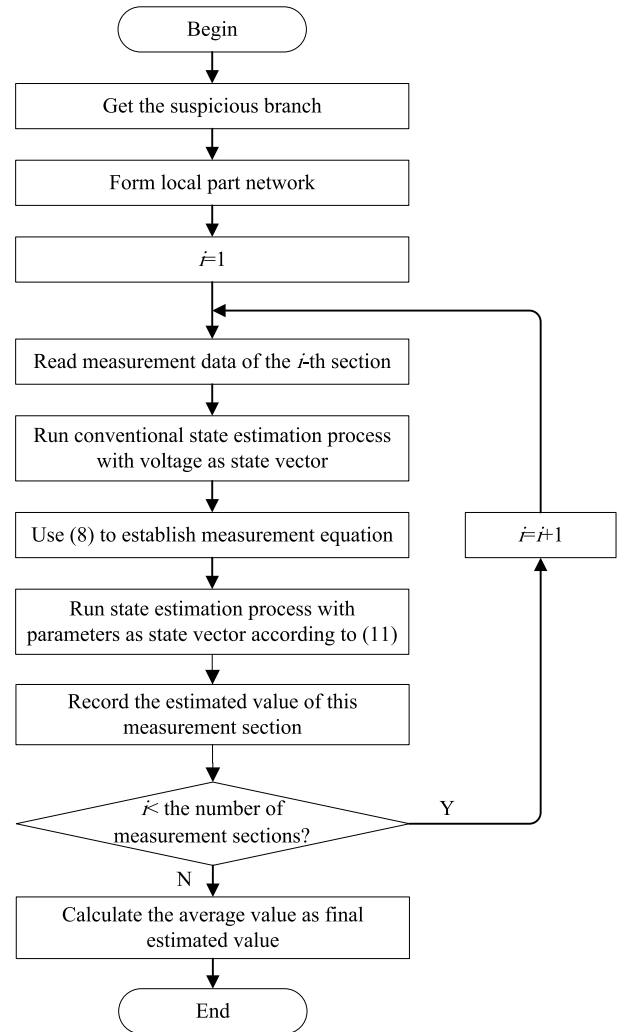**FIGURE 4.** Flow chart of PMU measurement system.

where S_{Jk} refers to the active or reactive injection power of node k, S_{kp} refers to $S_{Ln}^{(k,p)}$ or $S_{Tn}^{(k,p)}$ which depends on the type of the branch.

Therefore, the calculation of the injection measurement Jacobian elements is to search the branches connected to the node one by one. For each branch, use (12) or (14) to calculate the value according to the branch type and fill in the corresponding column of the Jacobian matrix. After this search, the other columns of this row are filled with 0.

VI. LOCAL NETWORK PARAMETER IDENTIFICATION PROCESS FOR SCADA MEASUREMENT SYSTEM

A. ESTABLISHING MEASUREMENT EQUATIONS IN LOCAL PART NETWORK

Different from the forming scheme in PMU system, a larger local network is needed to obtain more accurate node voltage values. For each new boundary nodes gained from the last search, search for other branches connected to them again.

During the searching process, the branch with branch power measurement is selected, and the branch with node

injection power measurement that can replace its branch power measurement is also selected. However, it is still necessary to remove the power injection measurement of the boundary nodes gained from the final search. Then, add the non-suspicious parameters to the measurement equations to obtain the form which is similar to (8):

$$
\begin{bmatrix} S_L \\ S_T \\ S_J \\ x_{RL} \\ x_{RT} \end{bmatrix} = \begin{bmatrix} H_L & \\ & H_T \\ H_{JL} & H_{JT} \\ H_{RL} & \\ & H_{RT} \end{bmatrix} \begin{bmatrix} x_L \\ x_T \end{bmatrix} + v \tag{17}
$$

For the measurement system of (17), its WLS state estimation iteration format is:

$$
\begin{aligned}
x_p^k = x_p^{k-1} &+ \Sigma_p^{-1}(u^k, x_p^{k-1}) \cdot H_p^T(u^k, x_p^{k-1}) \\
&\cdot R^{-1} \cdot \left[z - h\left(u^k, x_p^{k-1} \right) \right]
\end{aligned} \tag{18}
$$

where $\Sigma_p(u^k, x_p^{k-1})$ refers to $H_p^T(u^k, x_p^{k-1})R^{-1}H_p(u^k, x_p^{k-1})$

Unlike the PMU measurement system, the voltage phasor u in SCADA system cannot be measured directly, so the voltage phasor in (18) is an unknown quantity. In order to extended the identification method to SCADA system, a fixed-point iterative scheme is constructed.

First regard u as an implicit function of the branch parameter x_p:

$$
u^k = f(x_p^{k-1}) \tag{19}
$$

Regard (19) as a conventional state estimation with voltage as state vector, and solved it through iteration:

$$
\begin{aligned}
u^m = u^{m-1} &+ \Sigma_u^{-1}(u^{m-1}, x_p^{k-1}) \cdot H_u^T(u^{m-1}, x_p^{k-1}) \cdot R^{-1} \\
&\cdot [z - h(u^{m-1}, x_p^{k-1})]
\end{aligned} \tag{20}
$$

where $\mathbf{H_u}$ is the Jacobian matrix of voltage, $\Sigma_u(u^{m-1}, x_p^{k-1})$ refers to $H_u^T(u^{m-1}, x_p^{k-1})R^{-1}H_u(u^{m-1}, x_p^{k-1})$.

Regard the convergence result of (20) as u^k and put (19) into (18):

$$
\begin{aligned}
x_p^k = x_p^{k-1} &+ \Sigma_p^{-1}(f(x_p^{k-1}), x_p^{k-1}) \cdot H_p^T(f(x_p^{k-1}), x_p^{k-1}) \\
&\cdot R^{-1}[z - h(f(x_p^{k-1}), x_p^{k-1})]
\end{aligned} \tag{21}
$$

Thus, the fixed-point iteration scheme for x_p can be obtained by two nested iterations. During each round of iteration, the conventional state estimation with voltage as state vector is done first, which is the inner iteration. After convergence, the estimated values of voltage amplitude and phase angle of each node in the local area are obtained. With this result, the outer layer iteration is carried out, that is, the iterative solution of the parameters. Repeat such an iterative process until the difference between the two iterations is less than the precision demand. At this time, the value of the suspicious parameter in the result is taken as the estimated value of this measurement section.
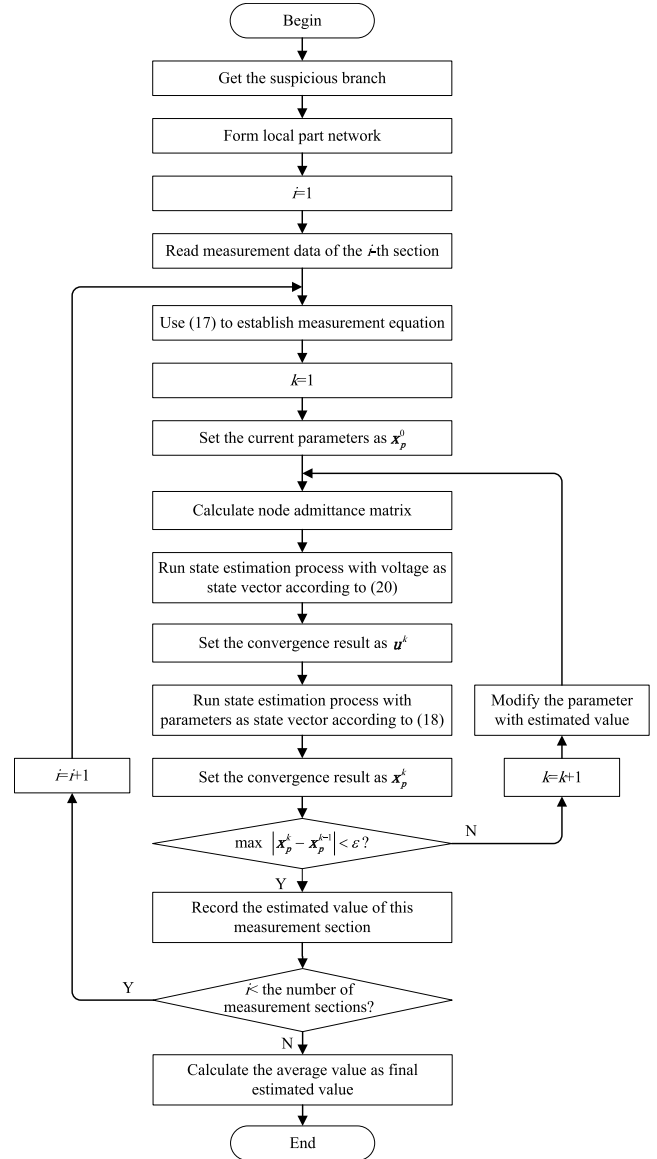

FIGURE 5. Flow chart of SCADA measurement system.

B. ALGORITHM FLOW CHART OF SCADA MEASUREMENT SYSTEM

VII. SIMULATION RESULTS

A. SIMULATION SYSTEM

Because the exact parameters of the actual system are not easy to obtain, IEEE 118-bus and 300-bus systems are selected for testing in this paper.

Considering the complex sources of measurement errors in practical systems, this paper regards measurement errors as random variables obeying normal distribution according to the theoretical assumptions of traditional WLS estimation method. Based on the power flow results, the different degrees Gaussian white noise with normal distribution is added to simulate the measurement error.

In addition, the subsequent examples assume that the measurements at all buses and branches are available except for special purposes.

TABLE 1. Detection and Identification result of IEEE 118-bus and 300-bus system.

Case No.	True Value (p.u.)	Set Value (p.u.)	λ_{max}^N	Estimated Value (p.u.)	Relative Error (%)	Identification Time (s)
1	0.0202	0.02424	12.31	0.020523	1.599	0.3
2	0.2480	0.29760	9.46	0.247710	0.117	0.4

TABLE 2. Comparison result of the reactance of transmission line.

Branch No.	True Value (p.u.)	Estimated Value of Proposed Method (p.u.)	Estimated Value of Comparison Method (p.u.)	Variance of Proposed Method	Relative Error of Proposed Method (%)	Relative Error of Comparison Method (%)	The Proposed Method Better?
3	0.0080	0.007834	0.008298	4.57×10^{-07}	1.824	3.987	Yes
7	0.0305	0.030490	0.030491	1.20×10^{-08}	0.034	0.030	No
9	0.0322	0.032201	0.032190	3.88×10^{-09}	0.003	0.031	Yes
37	0.0504	0.050498	0.050579	1.37×10^{-06}	0.194	0.354	Yes
38	0.0860	0.086020	0.086029	2.04×10^{-07}	0.023	0.034	Yes
52	0.1060	0.106952	0.106331	2.88×10^{-04}	0.899	0.312	No
96	0.0986	0.098645	0.098663	3.71×10^{-08}	0.046	0.064	Yes
97	0.0302	0.030349	0.030349	2.98×10^{-07}	0.493	0.493	Yes
112	0.1800	0.182165	0.181865	5.13×10^{-03}	1.203	1.036	No
126	0.0202	0.020523	0.020753	1.76×10^{-06}	1.599	2.737	Yes

B. PMU MEASUREMENT SYSTEM

1) SIMULATION RESULT ON IEEE 118-BUS AND 300-BUS SYSTEM

Based on the power flow data of IEEE 118-bus system, add 0.2% Gauss white noise as measurement error, and set the reactance of branch 126 to 0.02424, which is 120% of its original value. After detecting and identifying according to the flow chart shown in Fig. 3 and Fig. 4, the case 1 in Table 1 shows the calculation results and CPU time. And the local power network obtained is shown in Fig. 6.
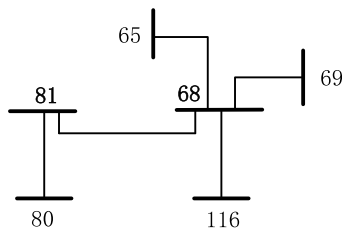

FIGURE 6. Formation of local part network.

Similarly, the reactance parameter of branch 53 in IEEE 300-bus system is set to 120% of the original value, and the case 2 in Table 1 shows the corresponding calculation results and CPU time.

For the running time shown in Table 1, since the parameter identification process is carried out in a local area, its CPU time is related to the size of the local area but not to the scale of the whole network.

2) COMPARISON WITH SINGLE BRANCH IDENTIFICATION SCHEME

For the identification part of [21], the similar idea is used, but it only takes the measurement of suspicious branch itself. It does not use zero-injection measurement, and no reliable parameter is added to the measurement equation either. The measurements of different sections are put together to process state estimation.

TABLE 3. Identification results of multiple suspicious parameters.

Test No.	Branch No.	True Value (p.u.)	Set Value (p.u.)	Estimated Value (p.u.)	Relative Error (%)
1	49	0.0268	0.0322	0.026389	1.533
	50	0.0094	0.0113	0.009342	0.617
2	53	0.1680	0.2016	0.168064	0.038
	56	0.0487	0.0584	0.049316	1.265

TABLE 4. Comparison result of the reactance of transmission line with bad data.

Branch No.	True Value (p.u.)	Estimated Value of Proposed Method (p.u.)	Estimated Value of Comparison Method (p.u.)	Relative Error of Proposed Method (%)	Relative Error of Comparison Method (%)	The Proposed Method Better?
7	0.0305	0.030586	0.030963	0.28	1.52	Yes
52	0.1060	0.107237	0.107965	1.17	1.85	Yes
112	0.1800	0.182600	0.184691	1.44	2.61	Yes

Select some branches in IEEE 118-bus system, which has zero-injection measurement. Set their reactance parameters to 120% of the original values respectively. Under the same measurement noise level, the identification results are listed in Table 2 using the method in [21] and the method proposed in this paper.

The test results show that the proposed method is superior to the single-branch identification method in most cases. In addition, the test results of different power flow levels indicate that the estimation accuracy of the two methods are almost unaffected by the power flow level.

3) IDENTIFICATION OF MULTIPLE SUSPICIOUS BRANCHES

Set the parameters of two electrical connected branches in IEEE 118-bus system to 120% of their original value at the same time. After the identification process shown in Fig. 4, the results obtained are shown in Table 3.

From the identification results, it can be noticed that the identification method proposed in this paper is also effective for the multi-suspicious branch parameters.

4) SITUATION OF SUSPICIOUS BRANCH MEASUREMENTS COTAINING BAD DATA

Based on 2), a 30% error is set at the current measurement of the suspicious branch in the first measurement section. Then, use two methods to get the identification results shown in Table 4.

The identification results show that if the measurement of suspicious branch contains bad data, it will be a greater impact on the method of only using single branch measurement. However, if the local part network scheme is adopted, it will be some robustness against bad data.

5) SITUATION OF SUSPICIOUS BRANCH WITH ZERO INJECTION MEASUREMENT ONLY

When there is no current branch measurement at the suspicious branch, the identification method in [21] doesn't work. However, if the both ends of the branch are zero injection nodes, the branch parameter can be identified by forming a local area mentioned before.

Take branch 94 as an example. Add 0.2% Gaussian white noise to simulate the measurement error and remove the current measurements from its both ends. The identification results are shown in Table 5.

TABLE 5. Identification result of the reactance of branch 94.

Set value (p.u.)	True Value (p.u.)	Estimated Value (p.u.)	Relative Error (%)
0.0240	0.0200	0.019829	0.85

6) INFLUENCE OF MEASUREMENT CONFIGURATION ON IDENTIFICATION ACCURACY

Based on 1), remove the PMU measurements of node 81 shown in Fig. 6. and the identification result of branch 126 is listed in Table 6.

TABLE 6. Identification result of the reactance of branch 126.

Set value (p.u.)	True Value (p.u.)	Estimated Value (p.u.)	Relative Error (%)
0.0202	0.02424	0.021112	4.51

Compared with the identification results in Table 1, it can be seen that the estimation error increases slightly. This is due to the lack of voltage measurement at node 81. Firstly, the voltage amplitude and phase angle of node 81 need to be estimated, and then the parameter is estimated with the estimated voltage. However, the branch parameter information is used in estimating the voltage, so the error of the reactance parameter of branch 126 will cause a slight deviation of the estimated voltage.

7) INFLUENCE OF MEASUREMENT ERROR ON IDENTIFICATION ACCURACY

In order to study the influence of current measurement and voltage measurement errors on the identification algorithm, the control variable method is used for test.

Based on the standard power flow data, only different white Gaussian noise is added to the voltage measurement, and 10 random measurement section data are generated at the same noise level. All current measurements are based on the exact values calculated by the power flow results. Under different noise levels, the reactance of branch 7 are identified by using the single branch identification method in [21] and the local network scheme in this paper respectively. The

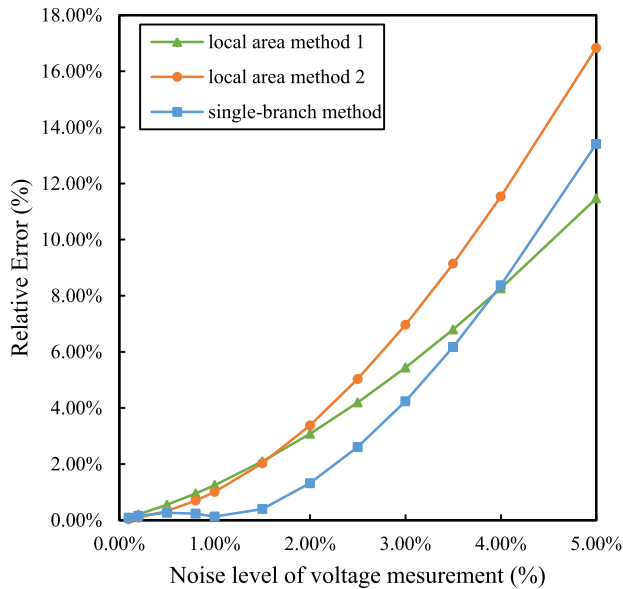variation of the relative error of the identification result is shown in Fig. 7.

FIGURE 7. Comparison of the influence of voltage measurement noise.

Noticed that paper [21] combines all measurement section data to process joint estimation. In this paper, the local area method is compared with two cases which uses section-by-section estimation and joint estimation respectively. In Fig. 7, the local area method 1 refers to the result of section-by-section estimation scheme, and the local area method 2 refers to the result of joint state estimation scheme.

The test results indicate that the estimation accuracy with parameters as state vector is greatly affected by the voltage measurement noise. When the error of voltage measurement is small, the identification accuracy of using local area measurement and using single-branch measurement is very close. With the increase of voltage measurement error, the identification error of the three methods increases rapidly and the robustness of single-branch method is better. In the estimation model with parameters as state vector, the voltage measurement noise is similar to the parameter error in the traditional estimation model with voltage as state vector. The more branches with larger parameter errors, the greater impact will be on the estimation results. Through this kind of comparison, it is not difficult to see that the single branch method is less affected by voltage noise because it uses fewer voltage measurements. In general, the parameter estimation method based on parameters as state variables is applied on the premise that the voltage measurement has high accuracy.

The test of robustness against current measurement noise is similar to that of voltage. Only different levels of current noise are added to the measurement, and all voltage measurements are based on power flow results. The variation of the relative error of the identification result by three methods is shown in Fig. 8.
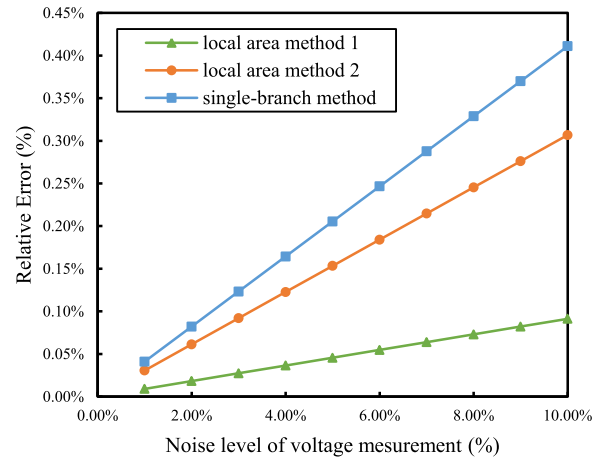

FIGURE 8. Comparison of the influence of current measurement noise.

The result shows that with the premise of very accurate voltage measurement, the accuracy of current measurement has little effect on the three methods, and the robustness of the local area method with zero injection measurement is better than that of the single-branch method. When the current measurement error is small, the identification accuracy of the three methods is also very close. With the gradual increase of the current measurement error, the identification error of the three methods increases slowly, and the robustness of the local area method using section by section scheme is obviously superior.

C. SCADA MEASUREMENT SYSTEM
1) SIMULATION RESULT ON IEEE 118-BUS SYSTEM
Similar to the PMU measurement system, add 0.2% Gauss white noise as measurement error based on standard power flow data, and set the reactance parameters of some branches to 120% of their original value respectively. The identification results are shown in Table 7.

TABLE 7. Identification result of the resistance of the branch.

Branch No.	True Value (p.u.)	Set Value (p.u.)	Estimated Value (p.u.)	Relative Error (%)
10	0.0209	0.0251	0.0208	0.282
13	0.0187	0.0224	0.0184	1.536
31	0.0156	0.0187	0.0155	0.507
63	0.0380	0.0456	0.0378	0.545
66	0.0715	0.0858	0.0724	1.240
89	0.0328	0.0394	0.0331	0.843
100	0.0482	0.0578	0.0479	0.575
119	0.0309	0.0371	0.0309	0.030
139	0.0238	0.0286	0.0237	0.475
164	0.0451	0.0541	0.0458	1.590

Similarly, set the reactance parameters of the transformer branches to 120% of their original value, and the identification results are shown in Table 8.

TABLE 8. Identification result of the reactance of the transformer branch.

Branch No.	True Value (p.u.)	Set Value (p.u.)	Estimated Value (p.u.)	Relative Error (%)
8	0.0267	0.0294	0.0272	1.690
36	0.0388	0.0427	0.0383	1.190
51	0.0375	0.0413	0.0368	1.950
93	0.0386	0.0425	0.0386	0.030
95	0.0268	0.0295	0.0264	1.640
102	0.0370	0.0407	0.0372	0.490
107	0.0370	0.0407	0.0370	0.030

2) IDENTIFICATION OF MULTIPLE SUSPICIOUS BRANCHES

Set the reactance of the two branches which are closely electrical connected with each other to 120% of their original value at the same time. After the identification process shown in Fig. 5, the results can be gained in Table 9.

TABLE 9. Identification results of multiple suspicious parameters in local power network.

| Test No.	Branch No.	True Value (p.u.)	Set Value (p.u.)	Estimated Value (p.u.)	Relative Error (%)
1	4	0.1080	0.1296	0.1083	0.249
	14	0.1600	0.1920	0.1586	0.899
2	11	0.0682	0.0818	0.0682	0.062
	14	0.1600	0.1920	0.1582	1.136
3	21	0.0437	0.0524	0.0437	0.046
	22	0.1801	0.2161	0.1792	0.475
4	75	0.2890	0.3468	0.2901	0.394
	76	0.2910	0.3492	0.2897	0.460
5	115	0.1410	0.1692	0.1383	1.946
	117	0.0406	0.0487	0.0414	2.034

It can be noticed that in SCADA system, either single suspicious branch or multi-suspicious branches can be identified successfully by the proposed method.

3) INFLUENCE OF MEASUREMENT ERROR ON IDENTIFICATION ACCURACY

Similarly, the control variable method is used to test the robustness of voltage amplitude measurement, branch power measurement and node injection measurement. The results show that in SCADA measurement system, when other kind of measurements are quite accurate, the single kind noise has little effect on the identification results.

Therefore, the robustness is tested by adding noise to all measurements. Taking the reactance parameter of branch 4 as an example, the Gauss white noise with different levels is added to all measurements simultaneously. And the variation of the relative error of the identification result is shown in Fig.9.
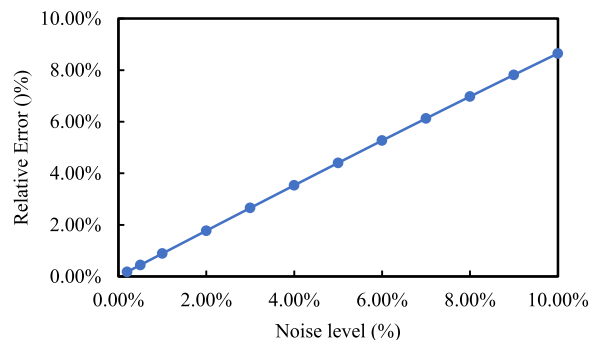
FIGURE 9. Influence of the measurement noise on identification results.

VIII. CONCLUSION

In this paper, a method of static parameter identification of power network based on state space transformation is proposed. The specific application steps of this method in PMU and SCADA measurement system are illustrated in details, and the effectiveness of this method is verified by IEEE standard system. However, this method requires high quantity and accuracy of PMU measurement devices, especially the voltage measurement error has a great impact on the identification results. The test results show that only when the voltage measurement error is controlled within 1%, the reliable identification results can be obtained.

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ZHIWEI DIAO was born in 1994. He is currently with the Department of Electronic and Electrical Engineering, North China Electric Power University, Beijing, China. His research interests include state estimation and power network parameter identification.

HAIBO ZHANG (M'16) was born in Heilongjiang, China, in 1975. He received the Ph.D. degree from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2005. He is currently a Professor with North China Electric Power University, Beijing. His research interests include energy management systems and power system simulation and control.

YUNFENG CUI was born in Shandong, China, in 1992. He received the master's degree from the Department of Electronic and Electrical Engineering, North China Electric Power University, Beijing, China, in 2017. He is currently with State Grid Beijing Electric Power Company.

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