Robust Identification Method for Transmission Line Parameters That Considers PMU Phase Angle Error

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ABSTRACT Accurate transmission line parameters are the basis of power system calculations. The measured phasor measurement unit (PMU) phase angle data at both ends of a line may contain large errors caused by synchronization problems, which can seriously affect the accuracy of parameter identification. This paper proposes a robust PMU-based method for calculating transmission line parameters from PMU data at both ends of a line in such a way that a synchronization error between the ends does not degrade the results. Specifically, a \(\pi\)-equivalent model for the transmission line is established, and a least square objective function for positive parameter identification is derived. Furthermore, to reduce the impact of noise and biased data, median estimation is used to obtain the final result. Finally, a simulation shows the effectiveness and robustness of the proposed method, and its practicality is demonstrated in a case study using measured PMU data.

INDEX TERMS Parameter identification, phase angle error, transmission line, positive sequence parameter, median estimation.

I. INTRODUCTION Accurate transmission line parameters are essential for power flow calculations, fault analysis, relay settings and other power system calculations. At present, the main methods of line parameter identification include theoretical calculations, offline power measurements and live measurements. Live measurements of line parameters have received significant attention because of convenience and economy. Live measurement methods can be sorted into three categories according to the data source: (1) parameter identification based on fault record data [1]–[3]; (2) parameter identification based on SCADA (Supervisory Control and Data Acquisition) measurement or joint SCADA and PMU measurements [4]–[8]; and (3) parameter identification based on PMU measurements [9]–[25].

PMUs that are geographically dispersed in a power system can provide synchronized voltage and current phasor measurements and power flow measurements. PMUs provide high precision and uploading frequency data [26], which are useful for line parameter identification. In addition, with the increasing number of PMUs installed, lines that have PMUs installed at both ends can be decoupled from the system for independent parameter identification. Consequently, there is widespread interest in the direct use of PMU data to obtain line parameters.

In practice, PMU data may contain noise and errors, such as from phasor estimation algorithms, transducers, and hardware [27]–[29]. To reduce the effects of noise and errors, different methods have been used to improve the estimation accuracy. Ref. [15] employs a three-phase static state estimation before parameter calculation. Ref. [16] proposes an optimal estimator for line parameter identification based on nonlinear optimal estimation theory to minimize the...
impacts of the measurement errors. Ref. [17] presents four line parameter identification methods, among which multiple measurement methods using linear regression show superior resistance to random noise and bias errors. Ref. [18] proposes a method for line impedance parameter estimation and identifies the correct constants for phasor measurements. Refs. [19], [20] use an adaptive IGG (Institute of Geodesy & Geophysics, Chinese Academy of Sciences) criterion to eliminate the influence of large deviation data. Ref. [21] incorporates the Huber function into a recursive least squares (RLS) method to improve its robustness to bad data. Ref. [22] improves the traditional least squares algorithm by using an extended Kalman filter. Ref. [23] proposes an orthogonal distance regression approach to solve the zero-sequence parameter estimation problem. Ref. [24] introduces biased measurement errors into the algorithm as additional unknowns.

Under normal PMU operating conditions, these methods can realize the estimation of line parameters even if there is measurement noise and minor deviation data. However, it is worth noting that PMU measurements are not perfectly synchronized in practice because of synchronization issues, such as synchronization system failure, GPS signal loss and GPS interference [30], [31], which may result in a large phase angle mismatch between PMU measurements. Moreover, large phase angle mismatches have been observed in real PMU measurements [32]–[35]. For example, phase angle shifts and jumps are observed in [32], [34], and a long-term phase angle difference (PAD) deviation is observed in [35]. Moreover, because of the importance of data quality in PMU-based applications, PMU data are susceptible to time synchronization attacks (TSAs) [36]–[39], which would introduce errors in phase angle data, and even false data injection attacks (FDIAs) [40], [41].

To address the phase angle mismatch, Ref. [42] derives approximate expressions for the influence of PAD errors in PMU-based line parameter calculations. In particular, if the PAD error approximately equals the real voltage PAD across the line, the relative error of the identified reactance can approach 100%. Moreover, although most of the existing PMU-based methods are robust to gross errors, measurement noise and fewer bad data, they do not work well under long-term large PAD errors, phase angle shifts or jumps. In addition, some researchers have suggested avoiding the direct use of PMU phase angle information in the calculation [43].

Therefore, a line parameter identification method using the PMU data from both ends of a transmission line has been proposed in this paper, as a PMU PAD error caused by a synchronization error will not degrade the results. Specifically, the positive sequence parameters are calculated based on a \( \pi \)-equivalent model, and a least square objective function with nonlinear equations for positive parameter identification is derived. To avoid the influence of PAD errors on parameter identification, the measured PAD is not used in the identification model. In addition, to mitigate the influence of noise and biased data, the median of a number of estimations is used to obtain the final result. Simulated and measured data are used to demonstrate the effectiveness, adaptability and robustness of the proposed method and its corresponding advantages over other methods proposed in the literature.

The rest of the paper is organized as follows. The PMU PAD error is analyzed, and an actual example of PAD errors observed in China is presented in Section II. A parameter identification model independent of PMU PAD is derived in Section III. Then, a robust median estimation method and a flowchart of the proposed method are presented in Section IV. Case studies with simulated data and measured PMU data are presented in Sections V and VI, respectively. Finally, the conclusions are provided in Section VII.

II. ANALYSIS OF PAD ERROR AND MEASURED PMU DATA

The positive-sequence \( \pi \)-equivalent model of a transmission line is shown in Fig. 1, where \( Z = R + jX = 1/(g+jb) \) represents the equivalent impedance of the line and \( Y_C = jy_c \) represents the equivalent susceptance. \( \dot{U}_M, \dot{I}_M, \dot{U}_N, \) and \( \dot{I}_N \) represent the positive sequence voltage and current phasors at both sides of the line, respectively. \( P_M, Q_M, P_N, \) and \( Q_N \) represent the active and reactive power at both sides of the line, respectively.

A. ANALYSIS OF PMU PAD ERROR

Let \( \Delta \theta_U = \arg(\dot{U}_M/\dot{U}_N) \) and \( \Delta \theta_I = \arg(\dot{I}_M/\dot{I}_N) \) represent the voltage and current PADs between the two ends of the line. The line parameter identification based on the PMU data at both ends of the line is related to the PAD between both ends of the line rather than the absolute value of the single-end phase angle data. As mentioned above, the PAD error can affect the parameter identification results. The source of the PMU PAD error can be divided into two aspects:

1) The time synchronization of the PMUs at either or both ends of the line is incorrect. This situation may be caused by a timing system failure including GPS problems, such as loss of signal or interference. The power measured by the individual PMU is accurate because the PAD between the local voltage and current phasors is accurate.

2) There is a phase angle error in a PMU device.
FIGURE 2. Measured voltage and current of both ends of the line in PMUs.

FIGURE 3. Measured active and reactive power of both ends of the line in PMUs.

FIGURE 4. Comparison of the measured voltage PAD and active power.

The source of error can be attributed to the transducer accuracy, phasor estimation algorithms, and hardware errors. The source of error can also be due to PMUs from different vendors having different phasor algorithms and filter designs.

B. QUALITY OF PAD IN MEASURED PMU DATA AND PROBLEM STATEMENT

For a 220 kV, 11.34 km transmission line (with the parameters $R = 0.453 \, \Omega, X = 3.435 \, \Omega, Y_C = 4.04 \times 10^{-5} \, S$), the PMU data measured at both ends include the voltage and current phasors and the active and reactive power, which are shown in Figs. 2 and 3. The measured voltage PAD ($\Delta \theta_U$) obtained directly from the PMU phase angle measurements and the active power of bus $m$ are shown in Fig. 4.

In Fig. 2, the voltage and the current amplitude of both buses are basically constant, and phase angles slide smoothly. In Fig. 3, the active and reactive power measurements at both ends of the line satisfy the normal line power loss relationship and are correct.

On the other hand, the active power flow in a transmission line can be estimated (ignoring the parallel susceptance of the line) by:

$$P_M \approx g(U_M^2 - U_M U_N) - U_M U_N b \sin \Delta \theta_U$$  \hspace{1cm} (1)

where $g = R/(R^2 + X^2)$, $b = -X/(R^2 + X^2)$.

For a high-voltage transmission line, the resistance is much smaller than the reactance ($R \ll X$), so $b \gg g$ and $b \approx -1/X$, $g \approx 0$. In many cases, the PAD across the line is generally small (e.g., less than $7^\circ$) (s.t. $\sin \Delta \theta_U \approx \Delta \theta_U$, $\cos \Delta \theta_U \approx 1$). Thus, the power flow can be expressed as follows.

$$P_M \approx -U_M U_N b \sin \Delta \theta_U \approx U_M U_N \frac{\Delta \theta_U}{X}$$  \hspace{1cm} (2)

Thus, the measured active power $P$ is approximately in direct proportion to the voltage PAD $\Delta \theta_U$, and $\Delta \theta_U$ should be in the same direction as the power flow, as shown in equation (2). However, in Fig. 4, although the voltage angle difference and the active power are basically constant, they move in opposite directions, which does not agree with (2). (The power flow is positive, but the negative angle indicates that the flow should be negative) This observation indicates a bias error with the voltage angle difference. In addition, when the viewpoint of the power measurement is correct, the bias error is likely to be caused by the time synchronization problem; thus, there may be the same constant bias error in the current angle difference.

Furthermore, using the method in [19], the parameter identification results with the measured PMU data are shown in Table 1.

| Identified Parameter | Parameters in the control room | Identification result | Relative error |
|---------------------|--------------------------------|-----------------------|---------------|
| $R(\Omega)$         | 0.453                          | 1.6467                | 263.52%       |
| $X(\Omega)$         | 3.435                          | -1.3293               | -429.82%      |
| $Y_c(S)$            | 4.14×10^{-5}                   | 3.79×10^{-5}          | -8.47%        |

Table 1 shows that the identification errors using the measured PMU data are relatively large, and the reactance identification value is even negative. The above examples show that the PAD errors existing in PMU data can seriously affect the parameter identification, giving poor results.
$I_M, U_N, I_N, P_M, Q_M, P_N, Q_N$, calculate the transmission line parameters.

### III. PARAMETER IDENTIFICATION MODEL INDEPENDENT OF PAD

For the transmission line mentioned in Section II, to avoid the influence of PAD error, the PMU phase angle data are abandoned; only the voltage and current amplitude and the active and reactive power data are used to calculate the transmission line parameters.

The bus N is assumed to be the reference bus, and then the voltage phase angle of bus N is set to 0. The voltage phase angle of bus M is assumed to be $\alpha$, which is equal to the voltage PAD between buses M and N. The voltage phasors can be expressed as follows.

\[
\begin{align*}
\hat{U}_N &= U_N \angle 0 = U_{NR} & (3-a) \\
\hat{U}_M &= U_M \angle \alpha = U_{MR} + jU_{MI} = U_M \cos(\alpha) + jU_M \sin(\alpha) & (3-b)
\end{align*}
\]

where $U_M$ and $U_N$ are the voltage amplitudes of buses M and N, respectively, $U_{MR}$ and $U_{MI}$ are the real and imaginary terms of the voltage at bus M, $U_{NR}$ is the real term of the voltage at bus N, and its imaginary term is 0.

The PAD $\theta_N$ between the voltage and current phasors of bus N can be calculated through the active and reactive power measured by the PMU, similar to bus M.

\[
\begin{align*}
\theta_N &= \arctan\left(\frac{U_N I_N \sin(\theta_N)}{U_{IN} \cos(\theta_N)}\right) = \arctan\left(\frac{Q_N}{P_N}\right) & (4-a) \\
\theta_M &= \arctan\left(\frac{U_M I_M \sin(\theta_M)}{U_{IM} \cos(\theta_M)}\right) = \arctan\left(\frac{Q_M}{P_M}\right) & (4-b)
\end{align*}
\]

Moreover, the current phasors of bus M and N can be obtained and written in real and imaginary terms.

\[
\begin{align*}
\hat{I}_N &= I_N \angle (-\theta_N) = I_{NR} + jI_{NI} = I_N \cos(\theta_N) + jI_N \sin(-\theta_N) & (5-a) \\
\hat{I}_M &= I_M \angle (\alpha - \theta_M) = I_{MR} + jI_{MI} = I_M \cos(\alpha - \theta_M) + jI_M \sin(\alpha - \theta_M) & (5-b)
\end{align*}
\]

According to Kirchhoff’s law, the voltage and current measured by the PMU should satisfy the following equations under ideal conditions.

\[
\begin{align*}
\hat{I}_N &= (\hat{U}_N - \hat{U}_M) \times (g + jb) + j\frac{y_c}{2} \hat{U}_N & (6-a) \\
\hat{I}_M &= (\hat{U}_M - \hat{U}_N) \times (g + jb) + j\frac{y_c}{2} \hat{U}_M & (6-b)
\end{align*}
\]

Combining (3), (5) and (6) and separating the real and imaginary parts, four equations containing line parameters are obtained. The active and reactive power can also be calculated by the voltage and current phasors in (3) and (6), as shown in (7). Then, another four equations can be obtained.

\[
\begin{align*}
P_N &= \text{Re}(\hat{U}_N \hat{I}_N^*) & (7-a) \\
Q_N &= \text{Im}(\hat{U}_N \hat{I}_N^*) & (7-b) \\
P_M &= \text{Re}(\hat{U}_M \hat{I}_M^*) & (7-c) \\
Q_M &= \text{Im}(\hat{U}_M \hat{I}_M^*) & (7-d)
\end{align*}
\]

Furthermore, the active and reactive power loss can be calculated by (8).

\[
\begin{align*}
P_M + P_N &= [(I_{NI} - \frac{y_c}{2} \times U_{NR})^2 + (I_{NR})^2] \times R & (8-a) \\
P_M + P_N &= [(I_{MI} - \frac{y_c}{2} \times U_{MR})^2 + (I_{MR})^2] \times R & (8-b) \\
Q_N + Q_M + \frac{y_c}{2} U_M^2 + \frac{y_c}{2} U_M^2 &= (I_{NI} - \frac{y_c}{2} \times U_{NR})^2 + (I_{NR})^2 \times X & (8-c) \\
Q_N + Q_M + \frac{y_c}{2} U_N^2 + \frac{y_c}{2} U_N^2 &= (I_{MI} - \frac{y_c}{2} \times U_{MR})^2 + (I_{MR})^2 \times X & (8-d)
\end{align*}
\]

To improve the accuracy of solving the equation, the trigonometric function with unknowns $\alpha$ involved in the equations is represented by two unknowns $A$ and $B$, as shown in (9).

\[
\begin{align*}
\cos(\alpha) &= A & (9-a) \\
\sin(\alpha) &= B & (9-b)
\end{align*}
\]

Then, equation (10) can be obtained.

\[
A^2 + B^2 = 1 & (10)
\]

Thus, 13 equations in equations (6), (7), (8), (9), and (10) are obtained, including five unknowns: $g$, $b$, $y_c$, $A$, and $B$. Ideally, the above equations can be used to find the unknowns. However, the measured data include measurement noise due to voltage and current scaling error, quantization error and so on, so they do not always give the best solution. To find the optimal solution, these equations are reformulated into the following deviation functions ($f(i)$), as shown in (11). In detail, (10) corresponds to (11-a); (6) to (11-b)-(11-e); (7) to (11-f)-(11-i); (8) to (11-j)-(11-m).

\[
\begin{align*}
f(1) &= A^2 + B^2 - 1 & (11-a) \\
f(2) &= (UM \times A - U_{NR}) \times g - U_M \times B \times b + I_{NI} & (11-b) \\
f(3) &= (UM \times A - U_{NR}) \times b + U_M \times B \times g - \frac{y_c}{2} \times U_{NR} + I_{NI} & (11-c) \\
f(4) &= (UM \times A - U_{NR}) \times g - U_M \times B \times b - \frac{y_c}{2} \times U_M \times B - I_M \times (\cos(\theta_M) \times A + B \times \sin(\theta_M)) & (11-d) \\
f(5) &= (UM \times A - U_{NR}) \times b + U_M \times B \times g + \frac{y_c}{2} \times U_M \times A - I_M \times (B \times \cos(\theta_M) - A \times \sin(\theta_M)) & (11-e) \\
f(6) &= ((UM \times A - U_{NR}) \times g - U_M \times B \times b) \times U_{NR} + P_N & (11-f) \\
f(7) &= ((UM \times A - U_{NR}) \times b + U_M \times B \times g - \frac{y_c}{2} \times U_{NR} \times U_{NR} - Q_N & (11-g)
\end{align*}
\]
where $F$ is the objective function, $x$ are the parameters to be identified, and $[x_i^\text{min}, x_i^\text{max}]$ is the boundary of $x_i$.

When the objective function is at a minimum, $x^* = [g^k b^k \gamma^k A^k B^k]$ is the optimal result. Then, the identified line parameters can be obtained at snapshot $k$.

$$R^k = g^k \sqrt{[g(k)]^2 + [b(k)]^2}$$  \hspace{1cm} (13-a)

$$X_k = -b^k \sqrt{[g(k)]^2 + [b(k)]^2}$$  \hspace{1cm} (13-b)

Through the above model, the voltage PAD between buses $M$ and $N$ is one of the quantities to be determined. Thus, the impact of the PAD error caused by the time synchronization error is eliminated.

Note: In the line parameter identification that uses the PMU data of both sides of the line, both sides of the PMU data should be from the same time, that is, both PMUs record the same system condition. In the proposed method, it is recommended to use steady-state PMU data that do not contain system disturbances, including shunt capacitor and shunt reactor switching. Therefore, the voltage and current amplitudes and the active and reactive power are approximately unchanged within the synchronization time frame so that both sides of the PMU data with phase angle removed can be regarded as the data recording the same system condition. If there is a system disturbance, the voltage and current amplitude and the active and reactive power may change abruptly within the synchronization time frame. With a sufficiently large time synchronization error $\Delta t_s$, one PMU may record the predisturbance condition, and the other PMU may record the postdisturbance condition, which can be illustrated by Fig. 5. Therefore, the PMU data cannot be regarded as the data in the same system condition, and the identification results may be degraded.

IV. SOLUTION WITH MEDIAN ESTIMATION

A. SOLUTION TO THE SINGLE SNAPSHOT

The above nonlinear least squares problem is solved using the function `fminsearch` in MATLAB [44]. This function can find the minimum of the unconstrained multivariable function using the derivative-free method. The setup of the algorithm is as follows:

An initial value $x^{(0)}$ needs to be set. In this paper, the initial line parameters are set to the empirical parameter of the line. The initials A and B are set based on (2). The search boundary is set to be between plus or minus 20% of the initial value. The termination tolerance on the function value is set to 1e-4.

B. MEDIAN ESTIMATION

In general, with PMU measurements at $n$ different snapshots, $n$ sets of nonlinear equations ($f_i(1), \cdots, f_i(13), \cdots f_i(1)$) can be obtained. Thus, the problem of parameter identification in light of noisy PMU data can be expressed with the following traditional objective functions:

$$\min \quad TF = \sum_{k=1}^{n} F_k = \sum_{k=1}^{n} \sum_{i=1}^{13} (f_i(k))^2$$  \hspace{1cm} (14)

The method using (14) can be defined as the “traditional method.” If the measurement data have a large deviation
The result of the traditional method will be greatly affected. Therefore, the median estimation is used to mitigate the effects of noise and large deviations.

In this paper, different results can be obtained with each snapshot PMU data based on (12) and (13). Then, a reliable identification result can be obtained with the above median estimation.

\[ R_{\text{final}} = M(R) \]
\[ X_{\text{final}} = M(X) \]
\[ Y_{\text{C,final}} = M(Y_C) \]  

(15)

where \( R_{\text{final}} \), \( X_{\text{final}} \), and \( Y_{\text{C,final}} \) represent the collections of identified line parameters. \( R \), \( X \), and \( Y_C \) represent the sets of identification results with \( n \) snapshot data. \( M(\cdot) \) represents the median value.

Based on the above mathematical model and median estimation, a robust method for identifying the positive sequence parameters of the transmission line considering the PMU phase angle error is constructed.

### C. FLOWCHART OF THE PARAMETER IDENTIFICATION

In detail, the procedure to calculate the line parameters is shown as follows, with the flowchart shown in Fig. 6.

1. **Step 1:** Obtain the PMU data on both ends of the transmission line.
2. **Step 2:** Analyze the PMU data to see whether there is a PAD error. (A preliminary analysis of the data can be performed using (2).) If it is determined that an error exists, go to Step 5; otherwise, go to next step.
3. **Step 3:** Calculate the parameters using the normal method (e.g., methods in [17], [19]).
4. **Step 4:** If the identified results are within the normal range, stop; otherwise, go to Step 5.
5. **Step 5:** Calculate the parameters using the proposed model independent of PAD.
6. **Step 6:** Use the median to obtain the final identification result.

Note: the normal range of the line parameters in Step 4 can be set as 80%-120% of offline parameters used in the control room [45] or empirical parameters.

### D. COMMENTS ON THE PROPOSED METHOD

The advantages of the method are as follows:

1. The phase angle data do not be used to avoid the influence of PAD error.
2. The PMU data are used. Compared with SCADA data, PMU data have the characteristics of high upload frequency, which can avoid the situation in which the SCADA data are not synchronized (generally 2-3 s or even 5-10 s) and the measured power flow condition of each end of the line may be different.

The median value is robust with the following benefits:

1. The value is not affected by extreme values (individual bad data), i.e., when there is a large deviation of individual measurements, the result of the traditional method may seriously deviate from the actual value, but the proposed algorithm will not.
2. The value can effectively reduce the influence of gross errors in most measurements. In general, the value can avoid the influence of large gross errors in measurements no more than 50% of the total snapshots.
3. The speed of the proposed method is faster than that of the traditional method using only an objective function (14). As in the proposed method, each set of values is calculated independently, and then the median estimation is used; thus, the total computational burden is small.

### V. CASE STUDIES WITH SIMULATED DATA

In this section, a 500 kV system is built, and two examples are provided to verify the effectiveness and robustness of the proposed method.

#### A. MODEL SETTING AND DATA ACQUISITION

A 500 kV, 300 km single-circuit transmission line is modeled in PSCAD. The line parameter setting values are shown in Table 2. The load is a constant power model, and 6 s PMU data (sampling period is 10 ms) at both ends of the line are obtained. The PMU data include the positive sequence voltage, the current amplitude and phase angle and the active and reactive power. In this paper, 500 sets of data in the steady state (without phase angle data) are used.

#### B. EFFECTIVENESS AND ROBUST PERFORMANCE VERIFICATION

In this subsection, the noise immunity and robustness of the median estimation algorithm are verified by adding zero-mean Gaussian distribution noise to the simulated PMU.
amplitude data to emulate real system conditions. The comparison of the normal method using phase angle data and the proposed method under 1% TVE is performed to justify the accuracy of the proposed method.

(1) Example 1: Different intensities (0.1% and 0.2%) of noise are added to verify the noise immunity of the method. A Gaussian distribution noise with zero mean and a standard deviation of 0.1% (0.2%) is added to the N-side and both sides of the three-phase voltage amplitude. The results with and without noise are shown in Table 2.

Table 2 shows that when there is no error in the PMU data, the identification results are very close to the set values, which verifies the effectiveness of the proposed method. When noise is added to the N-side or both sides of the voltage amplitude, the identified parameters gradually deviate from the set value. As the noise level increases, the identified parameters show greater deviation from the actual value, but overall, the reactance and susceptance can be accurately identified. It is worth noting that the resistance is more susceptible to voltage noise, which agrees with the relevant theories in [42].

(2) Example 2: Bad data are added to verify the robust performance of the method. This example simulates the extreme case of data loss from the PMU. Specifically, 0.2% intensity noise is added to both sides of the voltage amplitude, and 20% of the N-side voltage amplitude is set to 0. The identification results are shown in Table 3.

Table 3 shows that when there are some bad data on both sides of the voltage amplitude, compared with the traditional least squares algorithm, the identification value of the proposed method is more similar to the set value, the relative error is small, and the identification result is more accurate.

(3) Example 3: Comparison of the normal method using phase angle data (the adaptive IGG [19]) and the proposed method under 1% total vector error (TVE).

Both methods are tested under N-side voltage measurement with 1% TVE error which is all resulting from phase angle or amplitude (IEEE C37.118.1 synchrophasor standard: maximum TVE of synchrophasor is 1%). The results are shown in Table 4.

In Table 4, when 1% TVE error is all resulting from phase angle, the proposed method can identify the line parameters accurately as it is independent of phase angle error. While the error of phase angle will affect the results of adaptive IGG method, especially the reactance $X$, which is consist with the relevant theories of [42]. When 1% TVE error is all resulting from amplitude, the identified resistance $R$ with adaptive IGG method is affected greatly, since it is extremely sensitive to voltage amplitude error [42]. By contrast, the identified resistance $R$ with the proposed method is much better. The identified reactance $X$ is slightly worse than the IGG adaptive method. In general, the proposed method has a better performance than the adaptive IGG method under voltage measurement with 1% TVE.

In summary, the above examples show the effectiveness of the proposed robust method in identifying the positive sequence parameters of the transmission line. In the case with noise, error or bad data, the algorithm can provide relatively accurate identification results. This result demonstrates the ability to resist small measurement noise, error and bad data.

VI. CASE STUDY WITH MEASURED PMU DATA

A. RESULT OF HYPERPLANE CLUSTERING

The measured PMU data for the 11.34 km long 220 kV transmission line mentioned in Section II has been used. The PMU uploading frequency is 25 Hz. One minute of data is used. The identified reactance of different snapshots is shown in Fig. 7. Then, the median value is taken as the final result. The comparison of the adaptive IGG [19] and the proposed method is shown in Table 5.

Table 5 shows that the resistance and reactance of the adaptive IGG method using the PMU data directly are poor,
in which the reactance is negative. The identified parameters of the proposed method are close to the accepted value and relatively good. The relative deviation of susceptance is 9.75%, indicating that there may be errors in the susceptance of the control room. Through the comparison with the adaptive IGG method, it is shown that the proposed method can effectively identify the line parameters independent of the PMU PAD error.

VII. CONCLUSIONS

A robust line parameter identification method independent of the PMU phase angle difference (PAD) error is presented. This method does not use PMU phase angle measurement to avoid the influence of PMU PAD errors caused by synchronization problems in the line parameter identification and can take advantage of the high upload frequency of PMU data. A median estimation is used to resist the influence of noise and large deviation due to large errors, which improves the identification accuracy. It is recommended to use steady-state PMU data that do not contain system disturbances to eliminate the impact of time synchronization error in magnitude data on the proposed method.

The simulation results show that when noise with/without bad data is added to the measurement, the method can reduce the influence of noise and bad data and obtain better identification results. A case study of measured data shows that this method can better avoid the problem of inaccurate identification results due to PMU PAD errors, yielding a better result.

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