On-Line PMU-Based Transmission Line Parameter Identification

Xuanyu Zhao, Huafeng Zhou, Di Shi, Huashi Zhao, Chaoyang Jing, Chris Jones

***Abstract*—China Southern Power Grid Company (CSG) recently developed and implemented an online PMU-based transmission line (TL) parameter identification system (TPIS). Traditionally, TL parameters are calculated based on transmission tower geometries, conductor dimension, estimates of line length, conductor sags, etc. These parameters only approximate the effect of conductor sag and ignore the dependence of impedance parameters on temperature variation. Recent development in PMU technology has made it possible to calculate TL parameters accurately. The challenges are that such an application requires highly accurate PMU data while the accuracy of PMU measurements under different working/system conditions can be uncertain. With a large number of PMUs widely installed in its system, CSG plans to improve and update the EMS database using the newly developed TPIS. TPIS provides an innovative yet practical problem formulation and solution for TL parameter identification. In addition, it proposes a new metric that can be used to determine the credibility of the calculated parameters, which is missing in the literature. This paper discusses the methodologies, challenges, as well as implementation issues noticed during the development of TPIS.**

***Index Terms*—Impedance parameters, phasor measurement unit (PMU), transmission line.**

I. INTRODUCTION

IN the past, transmission line (TL) parameters have been calculated based on factors such as tower geometry, conductor dimensions, actual line length estimates, and conductor sag. These parameters only approximate the effect of the sag of the conductors and ignore the dependence of the impedance parameters on temperature. With the development of PMU technology, synchronized phasors offer the possibility for accurate calculation of transmission line parameters. China Southern Power Grid Company (CSG) recently developed and implemented an online PMU-based TL parameter identification system (TPIS).

More accurate TL impedance parameters will help in the following ways: 1) improve accuracy in relay settings where accurate relay settings can lead to faster fault isolation and decrease the likelihood of undesired relay tripping, 2) improve post-event fault location and thus lead to a quicker restoration of the systems, 3) improve transmission-line modeling in power flow calculations, 4) determine when an unreported transmission line extension has occurred, and 5) dynamically load TL, which maximizes the line usage while ensuring system reliability/stability.

CSG has the world's first 800 kV DC transmission project while operating one of the world's most complex systems. The project comprises a hybrid operation of AC and DC along the east-west corridor covering long distances and significant capacity. Challenges for the CSG grid include integration of renewable energy along with grid stability and operations control. CSG has put tremendous efforts to maintain grid reliability and create a smart grid that incorporates increased renewable integration, lower costs for customers, and an open infrastructure that takes advantage of evolving tools and grid devices. With a large number of PMUs widely installed in its system, CSG plans to validate, improve, and update the network parameters in its EMS database using the newly developed TPIS.

Many methods have been proposed in the literature to determine TL impedance parameters using synchrophasor measurements. Authors in [1] propose four methods using a number of equations (linear/nonlinear) and discuss their performance when there is error/noise in the PMU measurements. Reference [2] proposes to use the full TL model for parameter identification if the line is not fully transposed and the system is unbalanced. Reference [3] proposes a method by treating TL as a two-port network and solve for its ABCD parameters first using two sets of measurements taken under different loading conditions. In [4] TL distributed impedance parameters is solved directly by solving two linear equations. Reference [5] introduces a method that is based on least square error (LSE) approach. An extended Kalman Filter based approach is proposed in [6]. The combination of SCADA measurements and PMU measurements at different time intervals are proposed to estimate parameters of TL in [7]. This approach neglects the fact that TL impedance varies under different loading conditions at different time intervals. As pointed out in [1], PMU-based TL parameter identification is very demanding in terms of the quality and accuracy of the measurements. In other words, even small errors in the phasor measurements can lead to huge errors in the estimated impedance parameters. Recently, much attention has been given to PMU data quality issues with considerable efforts being spent on developing methods for PMU calibration [8]–[11].

Ideally, PMUs are expected to generate highly accurate measurements. PMU data are time tagged with accuracy of better than 1 microsecond and magnitude accuracy, i.e., better than 0.1%. As required by the IEEE standard [12], for example, the total vector error (TVE) between a measured phasor and its theoretical value should be well within 1%

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under steady state operating conditions. However, this potential performance is not always achieved in actual field installations due to unbiased random measurement noise and biased errors from the instrumentation channels [13], [14]. Fig. 1 shows the magnitude and phase angle plots of real PMU measurements. As shown in the two plots, 5400 samples (3 minutes) of synchronized phasor data are contaminated with spikes and complex noise behaviors. Even though PMUs are expected to be highly accurate, they are not in the practical environment.

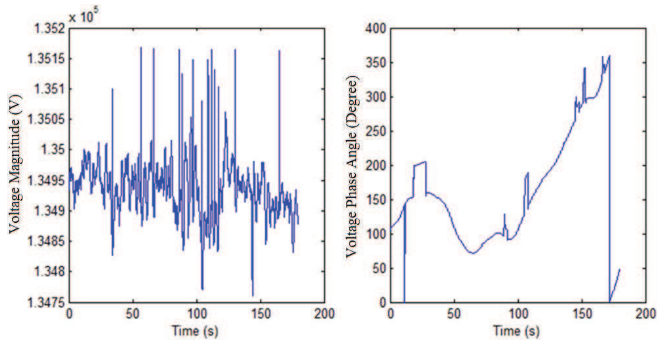


Fig. 1. Recorded magnitude and phase angle of a voltage phasor from a PMU.

Generally speaking, the biggest challenge in this field still lies in the fact that TL parameter identification requires highly accurate PMU data while the accuracy of PMU measurements under different working/system conditions can be uncertain. For example, existing TL parameter identification methods neglect to include physical constraints into the parameter identification process. During the development of TPIS, CSG has identified that including physical constraints can be very helpful. Based on this, in this paper we propose a novel yet practical problem formulation and solution for transmission line parameter identification. In addition, we propose a new metric that can be used to determine the credibility of the calculated parameters online, which is missing in the literature. Finally, this paper discusses the methodologies, challenges, as well as some implementation issues noticed during TPIS development.

II. Transmission Line Parameter Identification Methodology

A. Measurement Equations

A general PI model for TL is shown in Fig. 2, where $V^{\mathrm{S}}, I^{\mathrm{S}}, V^{\mathrm{R}}$ and I^{R} represent the voltage and current phasor measurements at both ends of the line while Z and Y are the series impedance and shunt admittance.

In order to obtain a linear relationship between the phasor measurements and the unknowns, a two-port ABCD parameter is used. The ABCD parameters are identified and the following equations obtained:

$$V^{\mathrm{S}} = AV^{\mathrm{R}} - BI^{\mathrm{R}}, \tag{1}$$
$$I^{\mathrm{S}} = CV^{\mathrm{R}} - DI^{\mathrm{R}}, \tag{2}$$

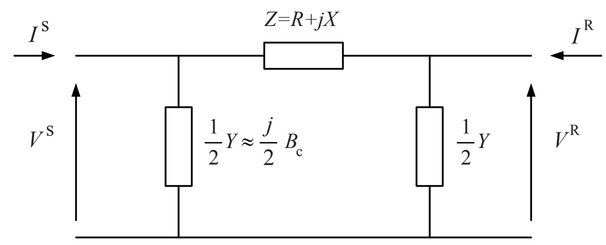


Fig. 2. Transmission line PI model.

denote $(\cdot)_{\mathrm{r}}$ and $(\cdot)_{\mathrm{i}}$ as the real part and imaginary part of the corresponding variable. Equations (1) and (2) can be expanded into four real equations as shown below:

$$V_{\mathrm{r}}^{\mathrm{S}} = A_{\mathrm{r}}V_{\mathrm{r}}^{\mathrm{R}} - A_{\mathrm{i}}V_{\mathrm{i}}^{\mathrm{R}} - B_{\mathrm{r}}I_{\mathrm{r}}^{\mathrm{R}} + B_{\mathrm{i}}I_{\mathrm{i}}^{\mathrm{R}} \tag{3}$$
$$V_{\mathrm{i}}^{\mathrm{S}} = A_{\mathrm{r}}V_{\mathrm{i}}^{\mathrm{R}} + A_{\mathrm{i}}V_{\mathrm{r}}^{\mathrm{R}} - B_{\mathrm{r}}I_{\mathrm{i}}^{\mathrm{R}} - B_{\mathrm{i}}I_{\mathrm{r}}^{\mathrm{R}} \tag{4}$$
$$I_{\mathrm{r}}^{\mathrm{S}} = C_{\mathrm{r}}V_{\mathrm{r}}^{\mathrm{R}} - C_{\mathrm{i}}V_{\mathrm{i}}^{\mathrm{R}} - D_{\mathrm{r}}I_{\mathrm{r}}^{\mathrm{R}} + D_{\mathrm{i}}I_{\mathrm{i}}^{\mathrm{R}} \tag{5}$$
$$I_{\mathrm{i}}^{\mathrm{S}} = C_{\mathrm{r}}V_{\mathrm{i}}^{\mathrm{R}} + C_{\mathrm{i}}V_{\mathrm{r}}^{\mathrm{R}} - D_{\mathrm{r}}I_{\mathrm{i}}^{\mathrm{R}} - D_{\mathrm{i}}I_{\mathrm{r}}^{\mathrm{R}}. \tag{6}$$

Assuming N sets of measurements have been obtained, collectively the $4 \cdot N$ equations can be written into matrix format to obtain:

$$\begin{bmatrix} \vdots \\ \left(V_{\mathrm{r}}^{\mathrm{S}}\right)^n \\ \left(V_{\mathrm{i}}^{\mathrm{S}}\right)^n \\ \left(I_{\mathrm{r}}^{\mathrm{S}}\right)^n \\ \left(I_{\mathrm{i}}^{\mathrm{S}}\right)^n \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots & & & \vdots & & & & \vdots \\ \left(V_{\mathrm{r}}^{\mathrm{R}}\right)^n & -\left(V_{\mathrm{i}}^{\mathrm{R}}\right)^n & -\left(I_{\mathrm{r}}^{\mathrm{R}}\right)^n & \left(I_{\mathrm{i}}^{\mathrm{R}}\right)^n & 0 & 0 & 0 & 0 \\ \left(V_{\mathrm{i}}^{\mathrm{R}}\right)^n & \left(V_{\mathrm{r}}^{\mathrm{R}}\right)^n & -\left(I_{\mathrm{i}}^{\mathrm{R}}\right)^n & -\left(I_{\mathrm{r}}^{\mathrm{R}}\right)^n & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \left(V_{\mathrm{r}}^{\mathrm{R}}\right)^n & -\left(V_{\mathrm{i}}^{\mathrm{R}}\right)^n & -\left(I_{\mathrm{r}}^{\mathrm{R}}\right)^n & \left(I_{\mathrm{i}}^{\mathrm{R}}\right)^n \\ 0 & 0 & 0 & 0 & \left(V_{\mathrm{i}}^{\mathrm{R}}\right)^n & \left(V_{\mathrm{r}}^{\mathrm{R}}\right)^n & -\left(I_{\mathrm{i}}^{\mathrm{R}}\right)^n & -\left(I_{\mathrm{r}}^{\mathrm{R}}\right)^n \\ \vdots & & & \vdots & & & & \vdots \end{bmatrix} \cdot \begin{bmatrix} A_{\mathrm{r}} \\ A_{\mathrm{i}} \\ B_{\mathrm{r}} \\ B_{\mathrm{i}} \\ C_{\mathrm{r}} \\ C_{\mathrm{i}} \\ D_{\mathrm{r}} \\ D_{\mathrm{i}} \end{bmatrix}, \tag{7}$$

where $(\cdot)^n$ refers to the corresponding quantity in the n^{th} set of measurements.

Considering noise in the measurement, (7) can be simply written as:

$$\boldsymbol{z} = \boldsymbol{H\beta} + \boldsymbol{\varepsilon}, \tag{8}$$

where $\boldsymbol{z}$ and $\boldsymbol{H}$ are the measurement vector and matrix, respectively; $\boldsymbol{\beta}$ is the unknown vector composed of ABCD parameters; $\boldsymbol{\varepsilon}$ is measurement error vector, which is assumed to be normally distributed.

The impedance parameters of TL and ABCD parameters are related by the following relationship:

$$A = D = 1 + \frac{1}{2}YZ = 1 + \frac{\mathrm{j}}{2}B_{\mathrm{c}}(R + \mathrm{jX}), \tag{9}$$

$$B = Z = R + \mathrm{jX}, \tag{10}$$

$$C = Y\left(1+\frac{1}{4}YZ\right) = \mathrm{jB_c}\left[1+\frac{\mathrm{j}}{4}\mathrm{B_c}(\mathrm{R}+\mathrm{jX})\right]. \quad (11)$$

B. Problem Formulation

It has been demonstrated in [1] and [2] that TL parameter identification is very sensitive to the noise/error in the PMU measurements. For example, as shown in [1], a 1% error in the voltage measurement can lead to over 20% error in the calculated series resistance and reactance. In the development of TPIS, even negative series resistance has been observed many times.

One thing we found out was that if physical constraints can be considered in the parameter identification process, the accuracy of parameter estimation can be greatly improved. First, from (9), one equality constraint can be identified:

$$A_{\mathrm{r}} = D_{\mathrm{r}}\,, \quad (12)$$

$$A_{\mathrm{i}} = D_{\mathrm{i}}\,, \quad (13)$$

or

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & -1 \end{bmatrix} \cdot \boldsymbol{\beta} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \quad (14)$$

Write the equation above simply as:

$$\boldsymbol{A}_{\mathbf{eq}} = \boldsymbol{\beta}. \quad (15)$$

Second, although hand-calculated parameters only approximate the sag effect and neglect the temperature variation, it is believed that the true line parameters still stay within a certain error band of the hand-calculated ones under different system operating conditions. The line parameters stored in the EMS database can be used as additional inequality constraints for the impedance parameters. Assuming R^{EMS}, X^{EMS}, and $B_{\mathrm{c}}^{\mathrm{EMS}}$ are the parameters of the TL stored in the EMS database, the following constraints can be set up:

$$0 \le (1-\alpha_{\mathrm{R}})R^{\mathrm{EMS}} \le R \le (1+\alpha_{\mathrm{R}})R^{\mathrm{EMS}} \quad (16)$$

$$0 \le (1-\alpha_{\mathrm{X}})X^{\mathrm{EMS}} \le X \le (1+\alpha_{\mathrm{X}})X^{\mathrm{EMS}} \quad (17)$$

$$0 \le (1-\alpha_{\mathrm{Bc}})B_{\mathrm{c}}^{\mathrm{EMS}} \le B_{\mathrm{c}} \le (1+\alpha_{\mathrm{Bc}})B_{\mathrm{c}}^{\mathrm{EMS}} \quad (18)$$

$$R<X, \quad (19)$$

where α_{R}, α_{X}, and α_{Bc} are constants that define the error bands of the TL parameters.

Equations (9)–(11) can be broken up into real equations as shown below:

$$A_{\mathrm{r}} = D_{\mathrm{r}} = 1-\frac{1}{2}B_{\mathrm{c}}X, \quad (20)$$

$$A_{\mathrm{i}} = D_{\mathrm{i}} = \frac{1}{2}B_{\mathrm{c}}R, \quad (21)$$

$$B_{\mathrm{r}} = R, \quad (22)$$

$$B_{\mathrm{i}} = X, \quad (23)$$

$$C_{\mathrm{r}} = -\frac{1}{4}B_{\mathrm{c}}^2R, \quad (24)$$

$$C_{\mathrm{i}} = B_{\mathrm{c}}-\frac{1}{4}B_{\mathrm{c}}^2X. \quad (25)$$

Combining(16)–(25), it is easy to get both the lower and upper boundaries for the ABCD parameters such that:

$$\boldsymbol{lb} \le \boldsymbol{\beta} \le \boldsymbol{ub}, \quad (26)$$

where $\boldsymbol{lb}$ and $\boldsymbol{ub}$ are vectors representing the lower and upper boundaries identified. In addition, another inequality constraint can be obtained based on (19):

$$\boldsymbol{A\beta}<0 \Leftrightarrow \begin{bmatrix} 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 \end{bmatrix} \cdot \boldsymbol{\beta}<0\,. \quad (27)$$

Therefore, the TL parameter identification problem is formulated as a least-squares, curve-fitting problem subject to both equality and inequality constraints, as shown below:

$$\min_{\beta} \frac{1}{2}\|H\boldsymbol{\beta}-\boldsymbol{z}\|_2^2, \qquad \text{s.t.} \begin{cases} \boldsymbol{A\beta}<0, \\ \boldsymbol{A}_{\mathrm{eq}}\boldsymbol{\beta}=0, \\ \boldsymbol{lb} \le \boldsymbol{\beta} \le \boldsymbol{ub}, \end{cases} \quad (28)$$

where $\|\bullet\|_2^2$ denotes the square of the L^2-norm of the corresponding vector.

C. Bad Data Detection

The classical method described in [15] and [16] is used for bad data detection after solving the constrained least-squares. Bad data identification is achieved by checking the normalized residuals of each measurement, which proceeds as follows:

Step 1: Solve the curve-fitting problem described in (28) and obtain the residual for each measurement point:

$$\boldsymbol{r}^i = \boldsymbol{z}^i - \boldsymbol{H}^i\boldsymbol{\beta}, \quad i=1,2,...,N. \quad (29)$$

Step 2: Compute the normalized residual as:

$$(\boldsymbol{r}^i)^{\mathrm{norm}} = \frac{\boldsymbol{r}_i}{\sqrt{\Omega_{ii}}}, \quad i=1,2,...,N, \quad (30)$$

where $\boldsymbol{\Omega_{ii}}$ is the diagonal element of the matrix $\boldsymbol{\Omega}$,

$$\boldsymbol{\Omega} = \boldsymbol{H}(\boldsymbol{H}^{\mathrm{T}}\boldsymbol{H})^{-1}\boldsymbol{H}^{\mathrm{T}}. \quad (31)$$

Step 3: Find the largest normalized residual $r_{\max}^{\mathrm{norm}}$ and check whether it is larger than a prescribed identification threshold c, for example 3.0:

$$r_{\max}^{\mathrm{norm}}>c. \quad (32)$$

Step 4: If (32) does not hold, then no bad data will be suspected; otherwise, the data sample corresponding to the largest normalized residual is the bad data and should be removed from the data set.

Step 5: If bad data is detected and removed from the data set, the algorithm flow must return to Step 1) and the process above must be repeated. Otherwise, this process ends and solutions are found.

D. Practical Implementation

In practice, it is possible that the EMS's line impedance values are significantly wrong. We have considered this possibility in the implementation of the TPIS. If the EMS's line impedance values are significantly wrong, two possible consequences may occur. The first one is that the optimization algorithm fails to converge and does not yield a solution. The second one is that the optimization algorithm gives a solution at the boundary condition. Due to the significantly wrong constraints, in both cases the residuals obtained from (29) will be very large. And if all the residuals are big, TPIS will give a warning indicating that either there are bias errors in the PMU measurements or that the EMS impedance values are significantly wrong. When this happens, we suggest first to relax the constraints and convert the parameter identification problem into a general least-squares problem, solve it, and then check the credibility of the calculated impedances.

Although EMS values may be significantly wrong, for most cases our experiences show that the error bands are usually well within 20%. Therefore, in this work, we use 20% as the error band.

III. Online Implementation and Credibility Metric

Generally, it is very difficult to determine the credibility of the calculated TL parameters mainly because in reality their corresponding true values are unknown, and there is no way to make comparisons (due to the lack of reference values). Most of the validation in existing research is based on simulations in which the true values are assumed a priori to be known values and used throughout the simulation. Having a metric that can quantify the credibility of the calculated parameters in a real-time environment is of critical importance in practice for applications like such and so.

In TPIS, for every five seconds, one set of impedance parameters is generated for the TL under consideration. PMU data collected during the five seconds are used to conduct bootstrapping. Bootstrapping is one type of resampling technique that can be used to estimate the properties of an estimator by sampling from an approximating distribution. By resampling with replacement, we assume that each sample of PMU measurements is independent and identically distributed. We solve the problem described by (26) for each set of sampled PMU data to get one set of TL impedance parameters. Conduct the sampling many times to get a series of estimated parameters so that we can calculate the variances of the calculated TL impedance parameters. The ratio of the variance of the parameters to the corresponding value stored in EMS database is used as the credibility metric for the parameter identification. That is, the parameter obtained is credible if the corresponding metric is smaller than a pre-determined threshold:

$$\sigma(x) \leq \xi_x \quad x = R, X, \text{or}\, B_c \tag{33}$$

where $\sigma(x)$ stands for the variance of variable parameter x.

During the implementation, two parameters are identified to be critical, as discussed below:

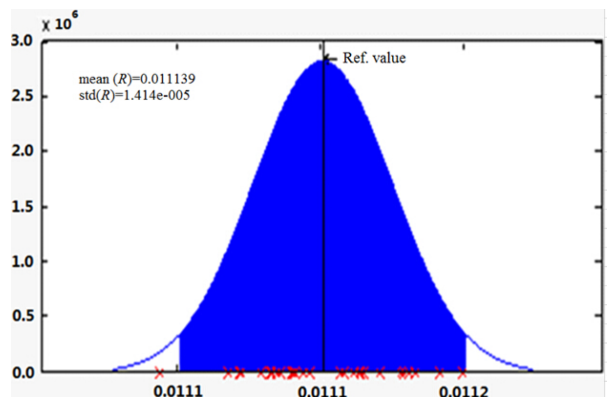
1) Number of bootstrapping samples: This number defines how many times the program will acquire bootstrap samples from the set of available data points. It is strongly recommended that this number be larger than 30. As the number of bootstrap samples increases, the variances associated with the parameters decrease; however, execution time increases as the number of bootstrap samples increases and selecting arbitrarily large numbers may not be desirable. A tradeoff is needed.

2) Number of data points in each bootstrap sample: This number determines how many data points are selected with each bootstrap sample. Increasing this number may lead to greater variance in the estimated parameters but will also increase the computation time. A tradeoff is needed.

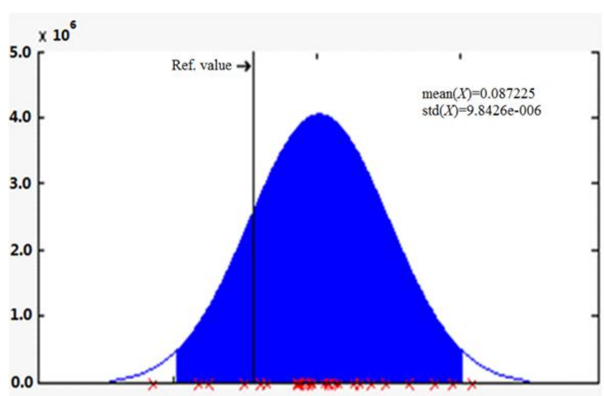
Fig. 3 serves as an example to show the output of the TPIS during one 5-second interval. (Reference value in the figure refers to the parameter identified in the EMS database.)

Fig. 4 shows the flowchart for the online implementation of TPIS.

The implementation framework of TPIS is shown in Fig.5 Bootstrapping plays an important role in the proposed method. The duration of the resampling interval period can have a major impact on results. In practical applications, the bootstrapping interval period is chosen to be 2 min.



(a)



(b)

Fig. 3. Visualization of the credibility metric for the calculated impedance parameters. (a) Statistics for the calculated series resistance. (b) Statistics for the calculated series reactance.

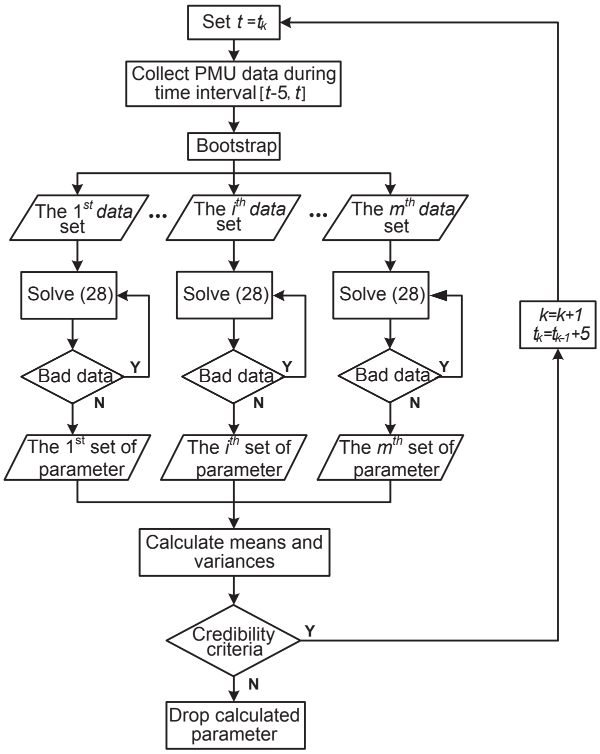


Fig. 4. Online implementation of TPIS.

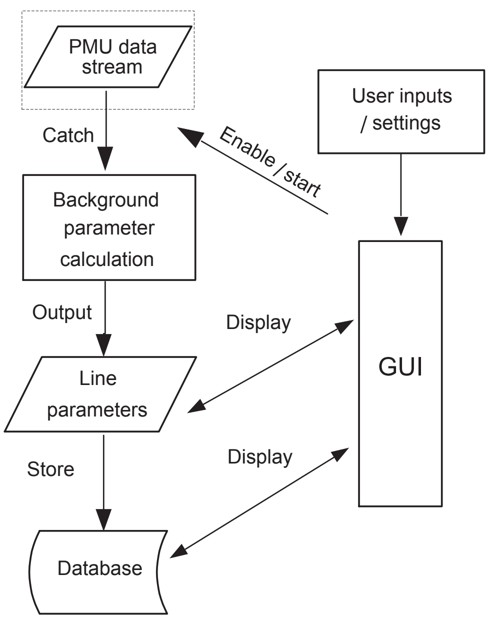


Fig. 5. Application framework of TPIS.

IV. Numerical Example

This section presents an application example of TPIS. The TPIS has been implemented to a 525 kV transmission line at CSG. This line is called Fengyi–Laibin, and it connects two substations, Fengyi and Laibin, in Southern China. During a one-hour period, we conducted experiments and calculated parameters for the line, as shown below in Fig. 6, Fig.7, and Fig. 8.

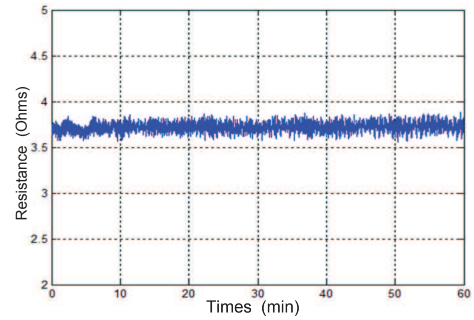


Fig. 6. Calculated series resistance for Fengyi–Laibin.

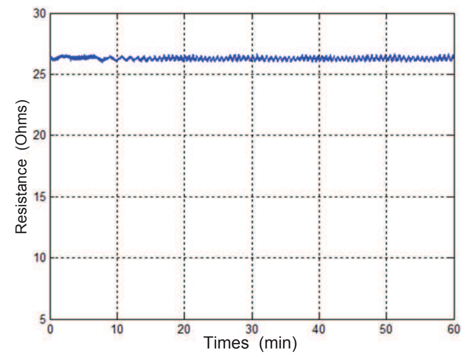


Fig. 7. Calculated series reactance for Fengyi–Laibin.

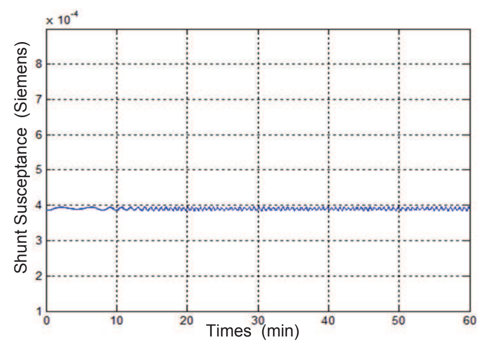


Fig. 8. Calculated shunt susceptance for Fengyi–Laibin.

TABLE I
COMPARISON BETWEEN CALCULATION AND EMS DATABASE

Parameter	EMS Database	Calculated	Difference (%)	Standard Deviation
Series Impedance $\|Z\|$ (Ohms)	23.8	25.8	7.8	0.12
Shunt Susceptance B_c (S)	3.6E-04	3.9E-04	7.7	1E-06

As can be seen from the plots, the impedance parameters do not vary much during the experiment period. In addition, as shown in Table I, the calculated series impedance differs from the EMS database by about 7.8% while the shunt susceptance differs from the database by 7.7%. These differences could be due to the inaccurate estimate of the line length as well as the specific loading conditions at the moment when this experiment was conducted.

V. Conclusion

PMU has the potential to improve the accuracy of transmission line parameters in the EMS database. More accurate parameter means better power system modeling, faster and more accurate fault location as well as more economic system operation. China Southern Power Grid has developed an online transmission line parameter identification system based on phasor measurement units (PMU). The following challenges were noticed and lessons were learnt during this development: 1) it was identified that although PMU are generally more accurate devices, measurement errors may come from the instrumentation channel due to various causes; 2) it has been identified that if the physical constraints associated with the transmission line are included in the computation, accuracy of the calculated parameters can be greatly improved. 3) it is critical to identify the credibility of the calculated transmission line impedance parameters for system operators in order to make the calculation useful; 4) through bootstrapping, multiple sets of PMU measurements can be obtained so as to identify the credibility of the calculated parameters online based on the proposed metric, which is based on the standard deviation of the calculated parameters; 5) a novel method is proposed to calculate the positive-sequence transmission line impedance parameters, and this approach can be extended to calculate the other sequence impedance parameters as well.

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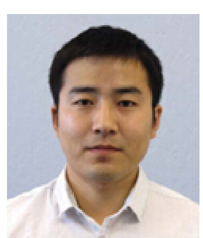

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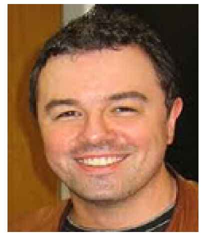

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