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PMU-Based Transmission Line Parameter Identification at China Southern Power Grid

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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 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.

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1. INTRODUCTION

Transmission line (TL) parameters in the past have been calculated by engineers based on the tower geometries, conductor dimensions, estimates of actual line length, conductor sag, and some other factors. These parameters only approximate the effect of the sag of the conductors and ignored the dependence of the impedance parameters on temperature. With the development of the PMU technology, synchronized phasors offer the possibility to make transmission line parameters calculated accurately. 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. More accurate relay settings will 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. 5) Dynamically load TL, which maximizes the line usage while ensures system reliability/stability.

CSG operates one of the world's most complex systems. CSG has the world's first ±800 DC transmission project. Hybrid operation of AC and DC, west-east corridor with long-distance and huge-capacity, complicated network structure with renewable energy integration, striking problem on grid stability, and great challenge on operation control all are the features of the CSG's grid. Towards the development of smart grid and with increasing renewable integration, CSG has put tremendous efforts to maintain grid reliability, minimize costs for customers, and to create an open infrastructure that can take 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] proposed four methods using number of equations (linear/nonlinear) and discussed their performance when there is error/noise in the PMU measurements. Paper [2] proposed to use the full TL model for parameter identification if the line is not fully transposed and system is unbalanced. Paper [3] proposed 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. An extended Kalman Filter based approach was proposed in [4]. As pointed out by [1], PMU-based TL parameter identification is very demanding on 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, people started to pay attention to the PMU data quality issues and lots of efforts have been spent in developing methods for PMU calibration [5]-[7]. 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.

It is recognized that existing methods neglect to include physical constraints into the parameter identification process. During the development of TPIS, we realized including physical constraints can be very helpful based on which we proposed a novel yet practical problem formulation and solution for such problems. In addition, we propose 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 some implementation issues noticed during the development of TPIS.

2. TL PARAMETER IDENTIFICATION METHODOLOGY

2.1. Measurement Equations

A general PI model for TL is shown in Figure. 1, where V^S, I^S V^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.

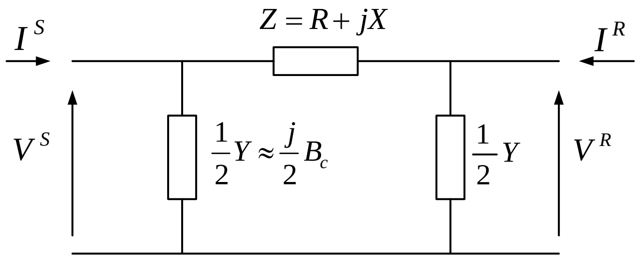


Figure. 1 Transmission line PI model

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

$$V^S = A \cdot V^R - B \cdot I^R \quad (1)$$

$$I^S = C \cdot V^R - D \cdot I^R \quad (1)$$

Denote $(\bullet)_r$ and $(\bullet)_i$ as the real part and imaginary part of the corresponding variable. Equation **Error! Reference source not found.**-(1) can be expanded into four real equations as shown below:

$$V_r^S = A_r \cdot V_r^R - A_i \cdot V_i^R - B_r \cdot I_r^R + B_i \cdot I_i^R \quad (2)$$

$$V_i^S = A_r \cdot V_i^R + A_i \cdot V_r^R - B_r \cdot I_i^R - B_i \cdot I_r^R \quad (3)$$

$$I_r^S = C_r \cdot V_r^R - C_i \cdot V_i^R - D_r \cdot I_r^R + D_i \cdot I_i^R \tag{4}$$

$$I_i^S = C_r \cdot V_i^R + C_i \cdot V_r^R - D_r \cdot I_i^R - D_i \cdot I_r^R \tag{5}$$

Assuming *N* sets of measurements have been obtained, we can collectively write the *4•N* equations into matrix format to obtain:

$$\begin{bmatrix} \vdots \\ (V_r^S)^n \\ (V_i^S)^n \\ (I_r^S)^n \\ (I_i^S)^n \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots & & & \vdots & & & & \vdots \\ (V_r^R)^n & -(V_i^R)^n & -(I_r^R)^n & (I_i^R)^n & 0 & 0 & 0 & 0 \\ (V_i^R)^n & (V_r^R)^n & -(I_i^R)^n & -(I_r^R)^n & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & (V_r^R)^n & -(V_i^R)^n & -(I_r^R)^n & (I_i^R)^n \\ 0 & 0 & 0 & 0 & (V_i^R)^n & (V_r^R)^n & -(I_i^R)^n & -(I_r^R)^n \\ \vdots & & & \vdots & & & & \vdots \end{bmatrix} \cdot \begin{bmatrix} A_r \\ A_i \\ B_r \\ B_i \\ C_r \\ C_i \\ D_r \\ D_i \end{bmatrix} \tag{6}$$

where $(\bullet)^n$ refers to the corresponding quantity in the *n*th set of measurements.

Considering noise in the measurement, equation (6) can be simply written as:

$$z = H \cdot \beta + \varepsilon \tag{7}$$

where *z* and *H* are the measurement vector and matrix, respectively; β is the unknown vector composed of ABCD parameters; ε is measurement error which is assumed to be normally distributed.

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

$$A = D = 1 + \frac{1}{2} \cdot Y \cdot Z = 1 + \frac{j}{2} \cdot B_c \cdot (R + jX) \tag{8}$$

$$B = Z = R + jX \tag{9}$$

$$C = Y \cdot \left(1 + \frac{1}{4} \cdot Y \cdot Z\right) = jB_c \cdot \left[1 + \frac{j}{4} \cdot B_c \cdot (R + jX)\right] \tag{10}$$

2.2 Problem Formulation

It has been demonstrated in [1] and [2] that TL parameter identification is very sensitivity to the noise/error in the PMU measurements. For example, as shown in [1], a 1% error in the voltage measurements can lead to over 20% error in the calculated series resistance and reactance. In this project, 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 equation (8), one equality constraint can be identified:

$$A_r = D_r \tag{11}$$

$$A_i = D_i \tag{12}$$

or

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & -1 \end{bmatrix} \cdot \beta = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{13}$$

Write the equation above simply as:

$$A_{eq} \cdot \beta = 0 \tag{14}$$

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 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_c^{EMS} are the parameters of the TL stored in the EMS database, the following constraints can be set up:

$$0 \le (1-\alpha_R) R^{EMS} \le R \le (1+\alpha_R) \cdot R^{EMS} \tag{15}$$

$$0 \le (1-\alpha_X) \cdot X^{EMS} \le X \le (1+\alpha_X) \cdot X^{EMS} \tag{16}$$

$$0 \le (1-\alpha_{Bc}) \cdot B_c^{EMS} \le B_c \le (1+\alpha_{Bc}) \cdot B_c^{EMS} \tag{17}$$

$$R < X \tag{18}$$

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

Equations (8)-(10) can be broken up into real equations as shown below:

$$A_r = D_r = 1 - \frac{1}{2} \cdot B_c \cdot X \tag{20}$$

$$A_i = D_i = \frac{1}{2} \cdot B_c \cdot R \tag{21}$$

$$B_r = R \tag{19}$$

$$B_i = X \tag{20}$$

$$C_r = -\frac{1}{4} \cdot B_c^2 \cdot R \tag{21}$$

$$C_i = B_c - \frac{1}{4} \cdot B_c^2 \cdot X \tag{22}$$

Combing equations (15)-(22), it is easy to get both the lower and upper boundaries for the ABCD parameters such that:

$$lb \le \beta \le ub \tag{23}$$

where *lb* and *ub* are vector representing the lower and upper boundaries identified. In addition, another inequality constraint can be obtained based on equation (18):

$$A\cdot\beta<0 \iff \begin{bmatrix}0 & 0 & 1 & -1 & 0 & 0 & 0 & 0\end{bmatrix}\cdot\beta<0 \tag{24}$$

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:

$$\min_{\beta}\ \frac{1}{2}\cdot\left\|H\cdot\beta-z\right\|_2^2$$
$$s.t.\ \begin{cases}A\cdot\beta<0\\ A_{eq}\cdot\beta=0\\ lb\le\beta\le ub\end{cases} \tag{25}$$

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

2.3. Bad Data Detection

The classical method described in [8]-[9] 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 (25) and obtain the residual for each measurement point:

$$r^i=z^i-H^i\cdot\beta,\qquad i=1,2,\ldots,N \tag{26}$$

Step 2) Compute the normalized residual as:

$$\left(r^i\right)^{norm}=\frac{r_i}{\sqrt{\Omega_{ii}}},\qquad i=1,2,\ldots,N \tag{27}$$

where Ω_{ii} is the diagonal element of the matrix Ω

$$\Omega=H(H^TH)^{-1}H^T \tag{28}$$

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

$$r_{\max}^{Norm}>c \tag{29}$$

Step 4) If equation (31) 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.

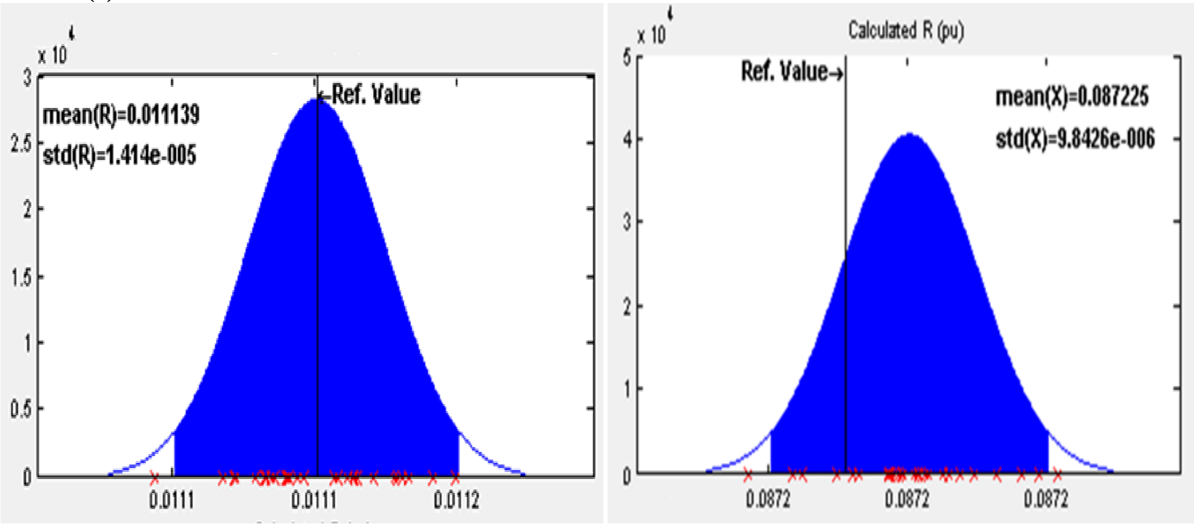
3. ONLINE IMPLEMENTATION AND CREDIBILITY METRIC

It is generally 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 comparison. Most of the validation in existing research is based simulation 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 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 re-sampling techniques 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 equation (25) for each set of sampled PMU data to get one set of TL impedance parameters. Conduct the sampling many times so that we can calculate the variances of the calculated parameters. Ratio of the variance of the parameters to the corresponding value stored in EMS data base 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:

$$\sigma(x) \le \xi_x \qquad x = R, X, or\, B_c \tag{30}$$

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



(a) Statistics for the calculated series resistance (b) Statistics for the calculated series reactance

Figure 2. Credibility metric for the calculated impedance parameters

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

- 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. Tradeoff is needed.
- 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. Tradeoff is needed.

Figure 2. 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.)

Figure 3. shows the flowchart for the online implementation of TPIS.

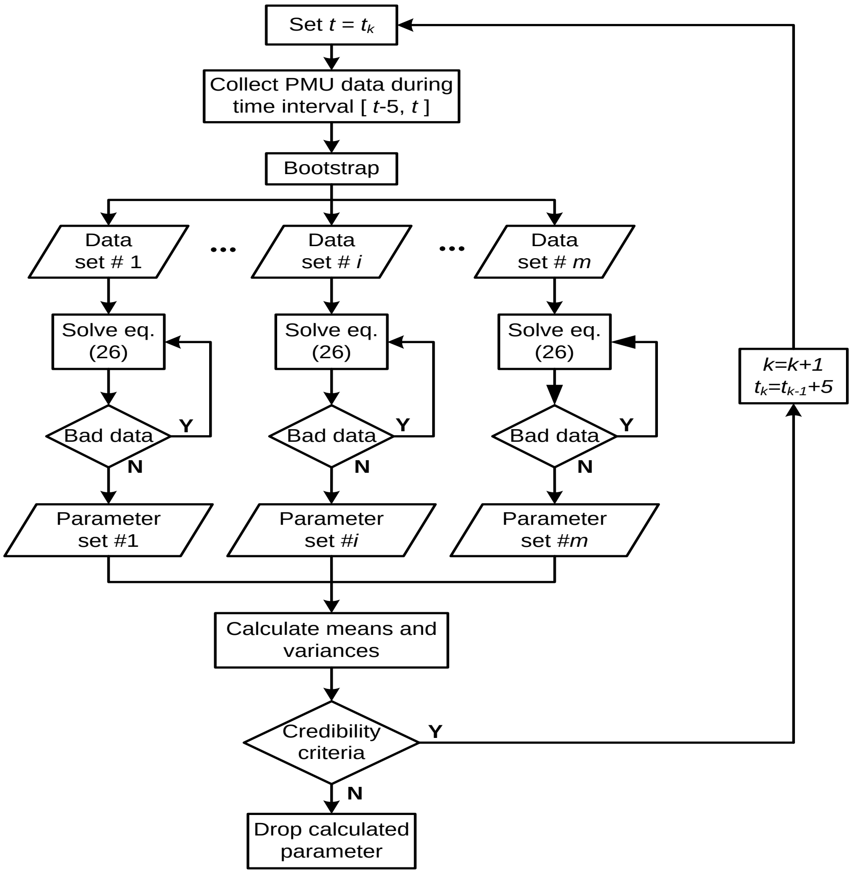


Figure 3. Online implementation of TPIS

4. NUMERICAL EXAMPLE

The TPIS has been implemented to a 525kV transmission line at CSG. This line is named as "Feng Yi-Lai Bin", which connects two substations Feng Yi and Lai Bin in Southern China. During a one-hour period, we conducted the experiments and the calculated parameters for the line are shown below in Figure 4-Figure 6.

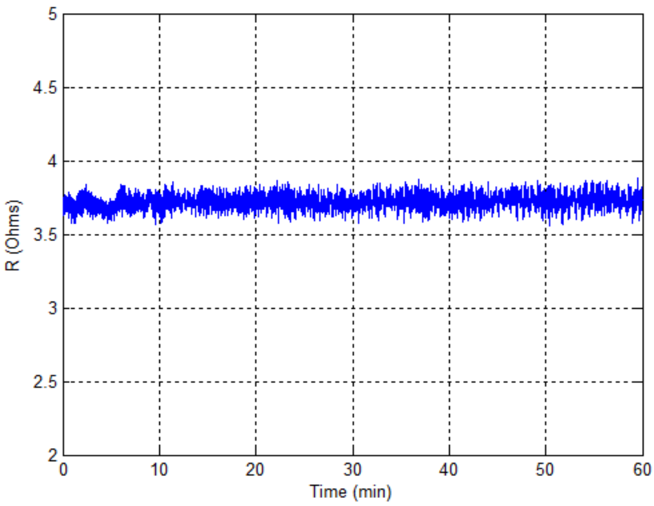


Figure 4. Calculated series resistance for Feng Yi-Lai Bin

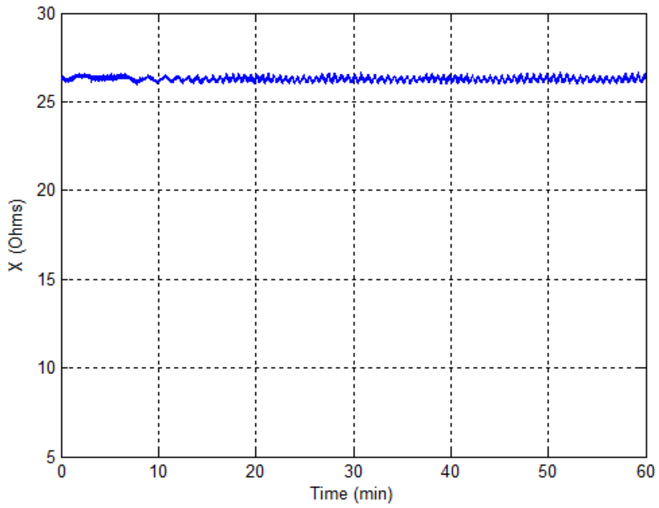


Figure 5. Calculated series reactance for Feng Yi-Lai Bin

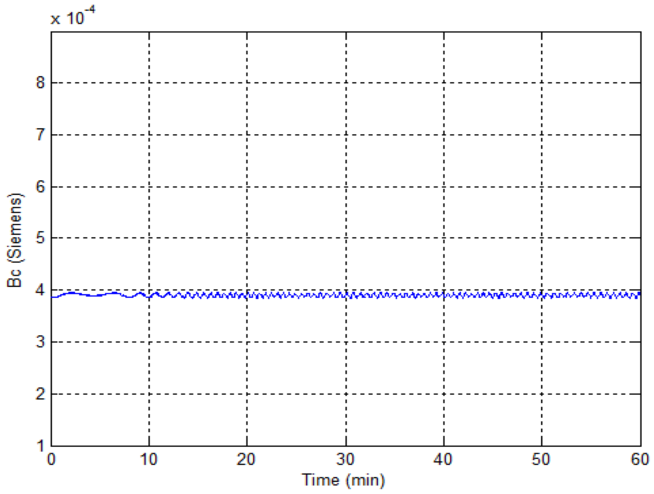


Figure 6. Calculated shunt susceptance for Feng Yi-Lai Bin

As can be seen from the plots, the impedance parameters do not vary much during the experiment period. In addition, as shown in Table 1, 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.

Table 1 Comparison between Calculation and EMS Database

Quantity	EMS Database	Calculated	Difference (%)
Series Impedance |Z| (Ohms)	23.8	25.8	7.8%
Shunt Susceptance Bc (S)	3.6E-04	3.9E-04	7.7%

5. 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. It was found that if the physical constraints associated with the transmission line were included, accuracy of the calculated parameters can be greatly improved. Through bootstrapping, multiple sets of PMU measurements can be obtained so as to identify the credibility of the calculated parameters based on the proposed metric. A novel method is presented to calculate the positive-sequence TL impedance parameters and this approach can be extended to calculate the other sequence impedance parameters as well.

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