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A New Robust Identification Method for Transmission Line Parameters Based on ADALINE and IGG Method

ANCHENG XUE[1], (Member, IEEE), HE KONG[1], YONGZHAO LAO[2], QUAN XU[3], YUEHUAN LIN[3], LI WANG[2], FEIYANG XU[1], (Graduate Student Member, IEEE), SHUANG LENG[1], ZHIYONG YUAN[3], AND GUOEN WEI[2]

[1]State Key Laboratory of Alternate Electrical Power System with Renewable Energy Source, North China Electric Power University, Beijing 102206, China
[2]Guangzhou Power Supply Bureau, Guangdong Power Grid Ltd., Guangzhou 510000, China
[3]Electric Power Research Institute, China Southern Power Grid Company Ltd., Guangzhou 510000, China

Corresponding author: Ancheng Xue (acxue@ncepu.edu.cn)

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ABSTRACT Accurate transmission line parameters are the basis of power system calculations. Aiming at obtaining accuracy online transmission line parameters in the case of large random noises even bad data in Phasor Measurement Unit (PMU) measurements, which occurs frequently in the practice, a new adaptive robust identification method combining adaptive linear neuron (ADALINE) and traditional robust IGG (Institute of Geodesy & Geophysics, Chinese Academy of Sciences) method is proposed. In detail, first, the identification model of transmission line parameters is presented based on the multi-period PMU measurements at both ends of the transmission line. Then, a parameter solving model based on ADALINE is established. Furthermore, to fully use measurement information, the adaptive robust ADALINE (ARA) are proposed, which applies the robust IGG weight function (Scheme I) to ADALINE to realize "three segments" robust identification. In addition, to improve the robustness, the expectation and variance of the equation residual sequence are estimated adaptively with the median principle to adjust the threshold for the IGG function to assure robustness (TAR), which is independent of the known information for the error of the measurement equipment. The cases based on PSCAD simulated data and measured data show the effectiveness and engineering practicality of the proposed method.

INDEX TERMS PMU, ADALINE, robust IGG, transmission line parameters identification, bad data, median estimation.

I. INTRODUCTION

Transmission line (TL) parameters are essential for power system analysis, operation and control. The accuracy of TL parameters will affect the credibility of various applications such as power flow calculation, state estimation, and power loss analysis [1]. Traditionally, the methods to obtain the TL parameters mainly include (1) offline power measurements, (2) live measurements.

However, the parameters obtained through offline power measurements will be different from the actual values more or less, as the TL parameters will change slowly under the influence of some factors such as geographic environment, temperature, and operating conditions [2].

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In the live measurement methods, the increasing number of phasor measurement units (PMU) affords an access to online identify the TL parameters. As the GridEye [3], the PMU can provide high-precision, high-upload frequency voltage and current phasors of the power grid [4], which are applied to state estimation [5], oscillation localization [6], stability evaluation [7], line outage detection [8], frequency response estimation [9] etc. Among them, the identification of TL parameters based on PMU data has also received widespread attention.

Currently, methods for TL parameter identification can be divided into two categories: 1) Methods based on 2 PMUs at both ends of the line. 2) Methods based on multiple PMUs in power grid.

In the methods of the first category, Ref. [10] identifies the erroneous transmission line parameters first, and then identifies the accurate line parameters using the least square algorithm based on PMU data at multiple snapshots. Ref. [11] employs a three-phase static state estimation to reduce the impact of noise and identifies the line parameters based on Kalman filter. Ref. [12] identifies the parameters in two circumstances, synchronous measurements and asynchronous measurements. Ref. [13] applies orthogonal distance regression approach for solving the zero-sequence parameter estimation problem.

In the methods of the second category, Ref. [14] proposes the PMU positive sequence measurement error model and estimates the actual transmission line parameters throughout the whole system. Ref. [15] proposes a numerical method to identify the topology and estimate line parameters without the information of voltage angles based on Newton-Raphson iteration and power flow equations.

Under normal PMU operating conditions, the above methods can realize the identification of line parameters even if there is measurement noise. However, due to gross error [16], worn-out equipments [17], timestamp shift [18], communication channel blockage [19], [20], GPS signal loss [21] and even cyberattacks [22], [23], the measurements of PMU could be abnormal and even missing, which have been observed commonly in practice. For example, Ref. [24] observes the impulsive deviation, zero value jump, continuous zero and Ref. [25] observed the angle step jump in measured data. In addition, Ref. [26] shows that small phase angle error may result in large reactance error in light load. Therefore, Ref. [22] defines multiple indexes to classify and detect the PMU data manipulation attacks; Ref. [23] assumes two different manipulation attacks and correct them based on DBSCAN; Ref. [27] detects the cyberattack effectively based on the generalized graph Laplacian (GGL) and flexible Bayes classifiers (BCs). Besides, for the TL parameter identification, the robustness can be enhanced through improving the algorithms. Ref. [28] applies an adaptive IGG (Institute of Geodesy & Geophysics, Chinese Academy of Sciences) criterion to robust least square method. And Ref. [29] proposes an adaptive data selection scheme to remove bad data. Refs. [30], [31] apply the median principles to improve the robustness of the methods.

In addition, over the last few decades, many researchers have studied the applications of artificial intelligence in power system, e.g., deep learning is applied in frequency disturbance event detection in Ref. [32]; regression tree is applied in voltage stability in Ref. [33]; reinforcement learning is used to emergency frequency control in Ref. [34]; adaptive linear neuron (ADALINE) is applied in parameter estimation [35]–[39]. Among methods for parameters estimation, ADALINE is widely used to identify the parameters as it applies the least mean square algorithm as the convergence criterion, which can achieve unbiased estimation of parameters. Specifically, Refs. [35]–[38] use the ADALINE to identify the generator parameters, and Ref. [39] uses the ADALINE to estimate the phase angle. However, the ADALINE is rarely applied to TL parameter identification.

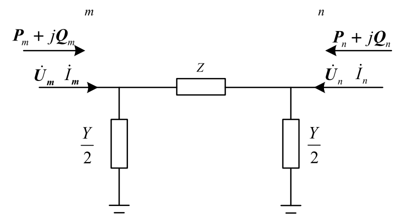

FIGURE 1. π-type equivalent circuit of transmission line.

On the other hand, as mentioned above, there may be bad data in PMU data, so it is worth to develop a new robust identification method, which combines the existing method and artificial intelligence, to resist the bad data under various conditions.

Recognizing the above problems, this paper proposes a robust TL identification method, named as adaptive robust ADALINE (ARA), based on ADALINE and adaptive robust IGG weight method. Specifically, based on the π-equivalent model of the TL, a parameter solution method based on ADALINE is proposed, and furthermore, combining the IGG weight function and adaptive estimation of threshold to assure robustness (TAR), the adaptive robust ADALINE is proposed. The main contributions of this article are as follows:

(1) An adaptive robust ADALINE method is proposed to identify the TL positive-sequence parameters.

(2) The IGG weight function and ADALINE are combined to realize the "three-segment" robust identification, which can make full use of the measurement information and can also well resist the adverse effects of bad data on the TL parameter identification.

(3) The median principle is applied to estimate the expectation and variance of the residual sequence to adaptively adjust the TAR of the weight function. Thus, the proposed method is independent of the known information of the measurement equipment's error, and is robust and practical.

The rest of the paper is organized as follows. Section II presents the identification model of TL positive-sequence parameters. Section III gives the parameter solution method based on ADALINE. Section IV proposes the adaptive robust ADALINE method, which combines the IGG robust method and ADALINE, and adjusts the TAR of IGG function adaptively based on the estimation of the expectation and variance of the residual sequence with median criterion. Section V illustrates the cases studies with simulated data to show the robustness of the proposed method. And section VI presents the case studies with measured PMU data to show the practicality of the proposed method. Finally, Section VII gives out the conclusions.

II. THE IDENTIFICATION MODEL OF TL POSITIVE-SEQUENCE PARAMETERS

The equivalent model of TL can be divided into a lumped parameter model and a distributed parameter model according to TL length. Both models can be represented by π-type equivalent circuit as shown in FIGURE 1.

In this paper, the TL positive sequence lumped parameter equivalent model with π-type equivalent circuit is used.

For TLs, the voltage phasors, current phasors, active power, and reactive power can be obtained from the PMUs installed at both ends of the line. Based on these PMU measurements, the linear mathematical model of TL can be established, as follows.

$$\begin{bmatrix} \dot{\boldsymbol{I}}_m \\ \dot{\boldsymbol{I}}_n \\ \boldsymbol{S}_m^* \\ \boldsymbol{S}_n^* \end{bmatrix} = \begin{bmatrix} \dot{\boldsymbol{U}}_m - \dot{\boldsymbol{U}}_n & \dot{\boldsymbol{U}}_m \\ \dot{\boldsymbol{U}}_n - \dot{\boldsymbol{U}}_m & \dot{\boldsymbol{U}}_n \\ U_m^2 - \boldsymbol{U}_m^* \dot{\boldsymbol{U}}_n & U_m^2 \\ U_n^2 - \boldsymbol{U}_n^* \dot{\boldsymbol{U}}_m & U_n^2 \end{bmatrix} \begin{bmatrix} 1/Z \\ Y/2 \end{bmatrix} \tag{1}$$

where $Z = R + jX = 1/(g+\mathrm{j}b)$ is the positive sequence equivalent impedance of the TL, Y=jB = j$2y_c$ is the positive sequence equivalent susceptance.

Furthermore, with real and imaginary parts, the Eq.(1) can be rewritten as follows.

where $\theta_{um} = \arg(\dot{U}_m)$, $\theta_{un} = \arg(\dot{\boldsymbol{U}}_n)$, $\theta_{umn} = -\theta_{umn} = \arg(\dot{\boldsymbol{U}}_m/\dot{\boldsymbol{U}}_n)$. I_{mR}, I_{mI}, I_{nR}, I_{nI} is the real and imaginary part of current phasor at bus m and bus n.

Mathematically, Eq. (2) can be written in the matrix form. Besides, considering the random measurement noise, Eq. (2) can be expressed as follows.

$$\boldsymbol{h}_t = \boldsymbol{G}_t \boldsymbol{x} + \boldsymbol{v}_t \tag{3}$$

where, $\boldsymbol{G}_t$, $\boldsymbol{h}_t$ are the PMU measurement matrix at time t, $\boldsymbol{v}_t$ is the residual vector at time t, $\boldsymbol{x}$ is the parameter vector to be identified.

In addition, since the PMU measurements have a high uploading frequency, multiple sets of data in a short time can be used, which could increase the redundancy of the equation and reduce the impact of random measurement noise. With T snapshots, the equation can be obtained.

$$\boldsymbol{h} = \boldsymbol{G}\boldsymbol{x} + \boldsymbol{v} \tag{4}$$

where, the coefficient of Eq.(4) is

$$\begin{aligned} \boldsymbol{G} &= [\boldsymbol{G}_1; \boldsymbol{G}_2; \cdots \boldsymbol{G}_T] \\ \boldsymbol{h} &= [\boldsymbol{h}_1; \boldsymbol{h}_2; \cdots \boldsymbol{h}_T] \\ \boldsymbol{v} &= [\boldsymbol{v}_1; \boldsymbol{v}_2; \cdots \boldsymbol{v}_T] \end{aligned} \tag{5}$$

III. ADALINE FOR TL PARAMETER IDENTIFICATION

Adaptive linear neuron (ADALINE) is a kind of neural network, whose structure is similar to the perceptron, but the activation function of the ADALINE is a linear function, i.e. $y = x$. Therefore, the output of ADALINE is continuous and can be taken to any value. The structure of the ADALINE is shown in FIGURE 2.

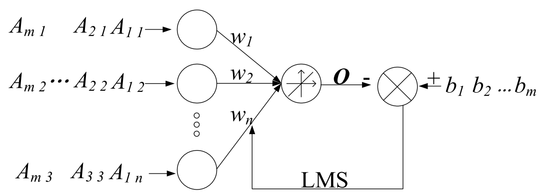

FIGURE 2. Illustration for the basic structure of ADALINE neural network.

In FIGURE 2, w_i is the weight of the i_{th} neuron, $\boldsymbol{A}$ is the input of the ADALINE, $\boldsymbol{O}$ is the output (predicted value) of the ADALINE, and $\boldsymbol{b}$ is the target output (target value) of ADALINE. n is the number of input neurons while m is the number of input data. where,

$$\boldsymbol{A} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix} \tag{6}$$

$$\boldsymbol{b} = [b_1, b_2, b_3 \cdots b_m]^T \tag{7}$$

$$\boldsymbol{W}^{(k)} = [w_1^{(k)}, w_2^{(k)}, w_3^{(k)} \cdots w_n^{(k)}]^T \tag{8}$$

According to the structure of the ADALINE, the predicted value at the k_{th} iteration is

$$\boldsymbol{O}^{(k)} = \boldsymbol{A}\boldsymbol{W}^{(k)} \tag{9}$$

ADALINE is trained with Least Mean Square algorithm (LMS), thus, its cost function is defined as follows.

$$E^{(k)} = \frac{1}{2}\sum_{i=1}^{m}(b_i - O_i^{(k)})^2 = \frac{1}{2}\sum_{i=1}^{m}(v_i^{(k)})^2 \tag{10}$$

The adjustment rules to the weight to minimize the cost function is stated as follows.

$$\boldsymbol{W}^{(k+1)} = \boldsymbol{W}^{(k)} + \eta \boldsymbol{A}^T(\boldsymbol{b} - \boldsymbol{O}^{(k)}) \tag{11}$$

$$0 < \eta < \frac{2}{\lambda_{\max}} \tag{12}$$

where η is the learning rate, $\lambda_{\max}$ is the maximum eigenvalue of input matrix $\boldsymbol{A}$.

In this paper, to identify the positive-sequence parameter of TLs, the ADALINE with three input neurons and one

$$\begin{bmatrix} I_{mR} \\ I_{mI} \\ I_{nR} \\ I_{nI} \\ P_m \\ Q_m \\ P_n \\ Q_n \end{bmatrix} = \begin{bmatrix} U_m\cos\theta_{um} - U_n\cos\theta_{un} & U_n\sin\theta_{un} - U_m\sin\theta_{um} & -U_m\sin\theta_{um} \\ U_m\sin\theta_{um} - U_n\sin\theta_{un} & U_m\cos\theta_{um} - U_n\cos\theta_{un} & U_m\cos\theta_{um} \\ U_n\cos\theta_{un} - U_m\cos\theta_{um} & U_m\sin\theta_{um} - U_n\sin\theta_{un} & -U_n\sin\theta_{un} \\ U_n\sin\theta_{un} - U_m\sin\theta_{um} & U_n\cos\theta_{un} - U_m\cos\theta_{um} & U_n\cos\theta_{un} \\ U_m^2 - U_mU_n\cos\theta_{umn} & -U_mU_n\sin\theta_{umn} & 0 \\ -U_mU_n\sin\theta_{umn} & U_mU_n\cos\theta_{umn} - U_m^2 & -U_m^2 \\ U_n^2 - U_nU_m\cos\theta_{unm} & -U_nU_m\sin\theta_{unm} & 0 \\ -U_nU_m\sin\theta_{unm} & U_nU_m\cos\theta_{unm} - U_n^2 & -U_n^2 \end{bmatrix} \begin{bmatrix} g \\ b \\ y_c \end{bmatrix} \tag{2}$$

output neuron is constructed according to Eq. (2). And $\boldsymbol{G}$ in Eq. (4) is the input data while $\boldsymbol{h}$ is the target data. i.e.,

$$\begin{aligned} \boldsymbol{A} &= \boldsymbol{G} \\ \boldsymbol{b} &= \boldsymbol{h} \end{aligned} \tag{13}$$

After training the ADALINE, the trained weight is the identification result, i.e. $\boldsymbol{W} = [w_1, w_2, w_3]^T = [g\ b\ y_c]^T$. In addition, in this paper, the convergence criterion of training ADALINE is that the iterations reach to 20000 or the cost function is less than or equal to 10^{-4}.

IV. ADAPTIVE ROBUST ADALINE (ARA)

In the case bad data exist in the measurements, the result obtained from ADALINE may be inaccurate [26]. Therefore, an adaptive robust ADALINE for TL parameter identification is proposed in this section. First, the theory of robust ADALINE is introduced. Then, the IGG (Institute of Geodesy & Geophysics, Chinese Academy of Sciences) robust method (Program I) [40] and adaptive estimation for the residual distribution are introduced. Finally, the overall process of parameter identification is given.

A. ROBUST ADALINE

The general idea of the robust ADALINE is to assign different weights to different training data to reduce the impact on bad data. Specifically, compared to traditional ADALINE, the change of the i_{th} training data are as follows:

Input data:

$$[A_{i1}\ A_{i2} \cdots A_{in}] \rightarrow R_i\,[A_{i1}\ A_{i2} \cdots\ A_{in}] \tag{14}$$

Target output data:

$$b_i \rightarrow R_i b_i \tag{15}$$

where R_i is the weight of the i_{th} training data

Then the cost function becomes:

$$E = \frac{1}{2}\sum_{i=1}^{m}(R_i b_i - R_i \boldsymbol{A}_i \boldsymbol{W})^2 = \frac{1}{2}\sum_{i=1}^{m}(R_i v_i)^2 \tag{16}$$

where $\boldsymbol{A}_i = [A_{i1} A_{i2} \cdots A_{in}]$.

Eqs. (14)-(16) show that weighting the i_{th} training data is equivalent to weighting the corresponding residual in the cost function, which can reduce the impact of abnormal data. e.g., when the weights are assigned to be equivalent, assuming $\boldsymbol{R} = [1, 1 \cdots 1]^T$, the robust ADALINE is converted into a traditional ADALINE. For the bad data, R_i can be set to 0, whose corresponding items in the cost function will also become 0, which reflects the robustness.

The above descriptions show that the robust ADALINE retains the advantages of ADALINE and has a robustness performance. The robustness of robust ADALINE is related to the weight selection. Further, the weights need to be determined according to the distribution of the residuals, so they need to be solved iteratively. In the following subsection, the IGG weight function is introduced to determine the weights of training data.

B. IGG ROBUST METHOD

The idea of the IGG (Institute of Geodesy & Geophysics, Chinese Academy of Sciences) method (Scheme I) is applying different weight functions and robust criteria for different measurement data, which aims to fully use the information of measurement data. The IGG method divides the measurement data into three categories: (1) the normal measurement; (2) the available measurement; (3) the harmful measurement. Correspondingly, the weight is divided into three categories: (1) the security zone; (2) the weight down zone (3) the elimination zone. Compared with a "two-segment" robust method (e.g. the Huber estimation in Ref. [41]) which only divides the measurement data into the normal measurement and the harmful measurement, the "three-segment" IGG robust method can make more effective use of measurement information.

The weight function of the IGG is

$$R_i(v_i) = \begin{cases} 1 & |v_i| \le s\sigma_0 \\ \frac{s\sigma_0}{|v_i|} & s\sigma_0 < |v_i| \le r\sigma_0 \\ 0 & |v_i| > r\sigma_0 \end{cases} \tag{17}$$

where v_i is the residual of the i_{th} measurement, R_i is the weight assigned to the i_{th} measurement, s, r is the coefficient of the threshold to assure robustness (TAR, i.e. $s\sigma_0$ and $r\sigma_0$ in Eq.(17)), and σ_0 is the standard deviation of the measurement error. s could take $1.0 \sim 1.5$, r could take $2.5 \sim 3.0$. And $s = 1.5$, $r = 3.0$ are used in this paper.

Eq. (17) shows that, the IGG can divide the measurements into three categories, and assign different robust criteria.

1) If the residual is not larger than $s\sigma_0$, then the least square method is used, and its weight value is set to 1;

2) If the residual is between $s\sigma_0$ and $r\sigma_0$, $R_i(v_i) = s\sigma_0/|v_i| < 1$. Then the weight is reduced, so the impact of the larger residual measurement on the parameter identification is reduced;

3) If the residual is larger than $r\sigma_0$, then the measurement is rejected, meanwhile, the corresponding weight value is set to 0, which reflect the robustness.

C. ADAPTIVE ESTIMATION OF RESIDUAL DISTRIBUTION

To ensure the robustness of ARA and the credibility of the identification results, the IGG weight function needs to divide the weight down zone and the elimination zone reasonably, i.e., the TAR needs to be selected reasonably. If the TAR is selected too large, the available measurements cannot be effectively suppressed or even all bad measurements cannot be effectively eliminated, which may reduce the algorithm's robustness; but if the TAR is selected too small, most of available measurements will be eliminated. Therefore, reasonable selection of the TAR can ensure the effectiveness of the algorithm and improve its adaptability.

The TAR of the weight function depends on the standard deviation of the measurement error, but in fact, the measurement equipment's error is not fixed, and not completely the same under different working conditions. So, the fixed TAR, based on the fixed standard deviation of the measurement error, may not meet the requirements of parameter identification. Therefore, in order to improve the adaptability of the algorithm, the standard deviation of residual should be estimated adaptively, according to the distribution of the residual sequence in the actual measurement.

As the residual sequence generally obeys the normal distribution. Thus, based on the normal distribution theory, the corresponding expectations and standard deviations are estimated as follows:

$$\mu \cong \frac{1}{N}\sum_{i=1}^{N} v_i \tag{18}$$

$$\sigma_0 \cong \sqrt{\frac{1}{N-1}\sum_{i}^{N}(v_i-\mu)^2} \tag{19}$$

However, for the measured data, the existence of bad data will cause some gross errors in the residual sequence. In this case, the main part of the residual sequence approximately obey the normal distribution, so, μ and σ_0 estimated by (18) and (19) will be disturbed by gross error and seriously deviate from the true value. Therefore, the distribution of the residual sequence can be effectively estimated only if the gross errors are eliminated.

To prevent the interference of the gross error on the estimation, the expectation and standard deviation of the residual sequence is estimated approximately based on the median principle [40], which is stated as follows.

$$\widehat{\mu} \cong \text{median}(\boldsymbol{v}) \tag{20}$$

$$\widehat{\sigma}_0 \cong \frac{\text{median}\,|\boldsymbol{v}-\text{median}(\boldsymbol{v})|}{0.6745} \tag{21}$$

where *median*($\boldsymbol{v}$) is the median of the residual sequence. When the number of samples is large enough, the expectation and standard deviation can be estimated effectively by Eqs. (20) and (21), without interference from bad data, as the median estimate has a strong robustness, which is still valid when the proportion of bad data is less than 50%.

Based on the effective estimation of the residual sequence distribution, the weight function of the IGG method can be changed to

$$R_i(\varepsilon_i) = \begin{cases} 1 & |\varepsilon_i| \le s \\ \frac{s}{|\varepsilon_i|} & s < |\varepsilon_i| \le r \\ 0 & |\varepsilon_i| > r \end{cases} \tag{22}$$

where ε_i is the regularization of v_i, i.e. $\varepsilon_i = \frac{v_i-\widehat{\mu}}{\widehat{\sigma}_0}$.

Theoretically, based on the median principle, the expectation and standard deviation of the residual sequence can be estimated effectively, and the TAR of the weight function can be adjusted adaptively, which can improve the adaptive ability to different measurement errors and improve the robustness of the algorithm and the credibility of the identification result. Combined with IGG method and median principle, the ADALINE can identify the TL parameters adaptively, which is called adaptive robust ADALINE (ARA).

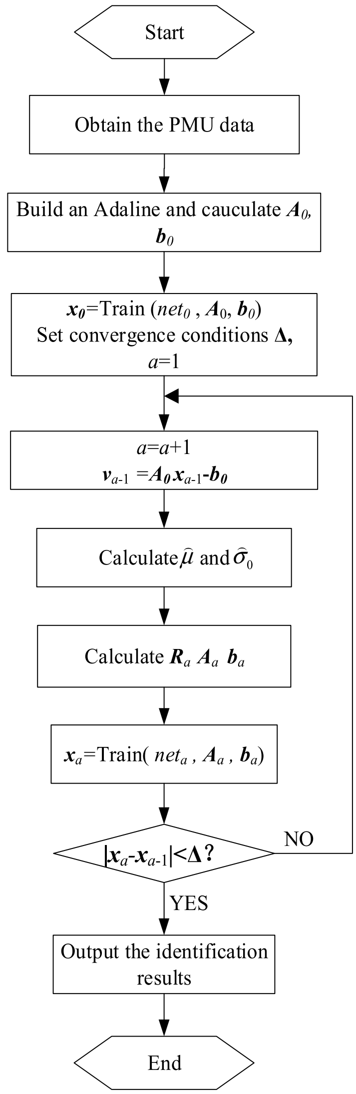

FIGURE 3. The flow chart of parameter identification.

Remark: With the median estimation, the proposed method is independent of the known information of the measurement equipment's error, thus, it is very practical.

D. TL PARAMETER IDENTIFICATION PROCESS

In general, the flowchart of the proposed parameter identification for the TL with ADALINE and IGG are shown in FIGURE 3.

In FIGURE 3, $\boldsymbol{x}_0$ =Train (net_0, $\boldsymbol{A}_0$, $\boldsymbol{b}_0$) means train the ADALINE net_0 with input data $\boldsymbol{A}_0$ and target output $\boldsymbol{b}_0$, and the weight of trained ADALINE is $\boldsymbol{x}0$.

Step 1: Obtain the PMU measurement data including voltage phasor, current phasor, active power and reactive power.

Step 2: Build the ADALINE with three input neurons and an output neuron; Calculate the $\boldsymbol{A}_0$,$\boldsymbol{b}_0$ by Eqs. (2) and (13).

Step 3: Train the ADALINE based on $\boldsymbol{A}_0$, $\boldsymbol{b}_0$ to obtain the identification results as the initial value and set the convergence conditions Δ, and set the number of iterations $a = 1$.

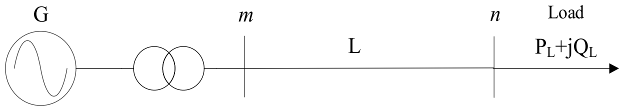

FIGURE 4. The 220 kV system diagram in PSCAD.

Step 4: $a = a+1$ and calculate the residual ν_{a-1} based on Eq. (4)

Step 5: Calculate the $\widehat{\mu}$ and $\widehat{\sigma}_0$ based on Eqs. (20) and (21).

Step 6: Calculate the $\boldsymbol{R}_a$, $\boldsymbol{A}_a$, and $\boldsymbol{b}_a$ by Eq.(22), Eq.(14) and Eq.(15), respectively.

Step 7: Train the ADALINE based on $\boldsymbol{A}_a$, $\boldsymbol{b}_a$ to obtain the identification results $\boldsymbol{x}_a$.

Step 8: If $|\boldsymbol{x}_a$-$\boldsymbol{x}_{a-1}| < \Delta$, output the identification results; else return to step 4.

V. CASE STUDIES WITH SIMULATED DATA

In this section, a 220 kV system is built, and two examples are provided to verify the effectiveness and robustness of the proposed method.

A. SIMULATION MODEL AND SETTINGS

A 220kV, 40km single-circuit transmission line is built in PSCAD, as shown in FIGURE 4, with the parameters: $R = 0.7126\Omega$, $X = 12.55\Omega$, $B = 1.4623 \times 10^{-4}$ S. The data uploading frequency is 25Hz.

In this paper, 500 snapshots of steady-state simulated PMU data are obtained with the load of 34+j8MVA. The simulated PMU data include the positive-sequence voltage phasors, current phasors, active power and reactive power at both ends of the line. The iteration convergence condition is set to $\Delta R = 0.0001$, $\Delta X = 0.001$, $\Delta B = 0.001 \times 10^{-4}$.

B. EFFECTIVENESS TEST

To verify the performance of the proposed method, the noises of different levels are added to the simulated data in this case. A normal distribution noises whose mean is 0 and standard deviation is σ_f of amplitude is added to the simulated PMU amplitude data. A normal distribution noise whose mean is 0 and standard deviation is σ_j is added to the simulated PMU angle data(The standard deviation σ means that the maximum of noise is 3σ [40]).

In the following simulation, the proposed method (ARA) in this paper is compared with the ARLS (adaptive robust least square method) proposed in Ref. [28] and the LS (least square method) proposed in Ref. [10]. The simulation results with different noise levels (the noise level is the maximum error) are shown in TABLE 1.

As shown in TABLE 1, if there is no noise, the three methods have same results. As the noise intensity increases, the relative errors of the results of the three methods gradually increases. Among them, the relative errors of the results of ARA and ARLS are close and better than LS.

This simulation case shows that, if there is no noise, the three methods are equivalent. But when the PMU data contain noise, the identification results of ARA and ARLS is better than LS as both methods adapt the IGG method to reduce the effect of noise.

TABLE 1. Relative errors under different intensity Gaussian noises using different methods.

Amplitude noise level	Angle noise level	Method	Error(%)		
			R	X	B
0	0	LS	-1.4371	0.0015	0.0019
		ARLS	-1.4371	0.0015	0.0019
		ARA	-1.4371	0.0015	0.0019
0.1%	0.1°	LS	-1.8450	0.0641	0.0227
		ARLS	-1.6786	0.0582	-0.0064
		ARA	-1.5030	0.0603	-0.0104
0.2%	0.2°	LS	1.9996	0.7964	0.0893
		ARLS	1.6646	0.5301	0.0807
		ARA	1.8652	0.7231	0.0841
0.3%	0.3°	LS	-7.0783	0.8220	0.2248
		ARLS	-5.4320	0.6921	0.1550
		ARA	-4.9320	0.7790	-0.1381

TABLE 2. Relative errors with abnormal data in voltage amplitude using different methods.

Method	Error(%)		
	R	X	B
LS	-79.4427	-79.9846	-79.9953
ARLS	-70.2563	-80.2251	-68.3978
ARA	2.3654	0.8032	0.1720

Overall, the three methods can identify the parameters accurately, since the data with noise added is evenly distributed around the true value and do not contain bad data. When there is no large deviation in measurements, the three methods are similar to least square method essentially, which have similar performance. Therefore, the three methods can identify the parameters accurately in this case.

C. ROBUSTNESS TEST

In this subsection, the robustness of the proposed method is tested.

In this simulation, the measurement data contain 0.2% level amplitude noise and 0.2° level phase angle noise, and furthermore, 20% of voltage amplitude data are added with bad data as follows.

$$U'_m = U_m \times (1 + \alpha) \tag{23}$$

where $\alpha = 0.2$ in this case study. With the above data, the results of different methods are shown in TABLE 2

TABLE 2 shows that, the relative errors of the result of ARLS and LS are larger than 60% while the relative error of the results of ARA is less than 3%, which shows that the proposed ARA has better robustness.

Furthermore, for the cases of different abnormal data percentages in voltage amplitude, the relative errors of the different methods can be obtained, as shown in FIGURE 5 ($E_R E_X E_B$ are the relative error of *R, X, B*).

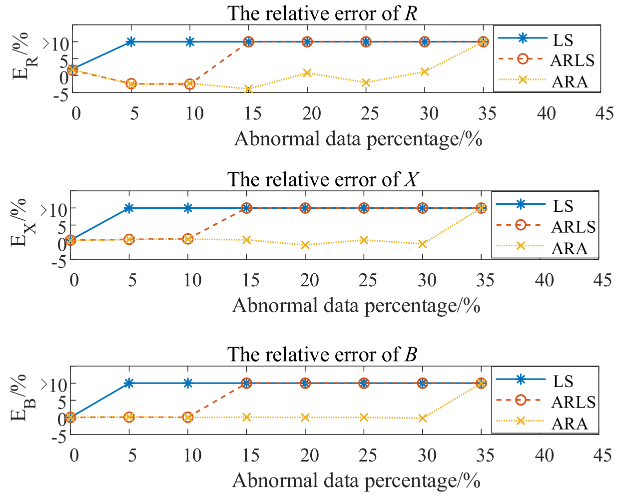

FIGURE 5. Relative errors of different abnormal data percentages in voltage amplitude using different methods.

FIGURE 5 shows that, LS can identify the TL parameters effectively only when there is no abnormal data. If 5% abnormal data exists, the error of LS identification results is larger than 10%, which is unreliable. And the identification result of ARLS is reliable when the abnormal data percentage is smaller than 10%, while the identification result of ARA is reliable when the abnormal data percentage is smaller than 30%.

This case shows that LS has poor robustness performance, while ARLS and ARA have certain robustness, and ARA is better than ARLS. Thus, the proposed ARA has better robustness and practicality.

VI. CASE STUDY WITH MEASURED DATA

The positive-sequence steady-state PMU measurements of a two-terminal 220kV TL in China are used to identify the

TABLE 3. Identified results based on measured PMU data using different methods.

Identified parameters	R/Ω	X/Ω	B/S
Parameters in control room	1.1420	8.6500	1.073e-04
LS	516.84	1059.7	7.551e-05
ARLS	1.1005	8.5898	1.013e-04
ARA	1.1045	8.6108	1.011e-04

positive sequence parameters. The TL is 28.548km long with R=1.1420Ω, X=8.6500Ω, $B = 1.073 \times 10^{-4} S$. The upload frequency of PMU data is 25Hz. In this paper, 58s data, (containing 1450 snapshots) are used. The overall PMU measurement quality is good, but some data contains deviation, as shown in FIGURE 6.

FIGURE 6 shows that, some impulsive bias may be contained in the voltage amplitude, the current amplitude, the active power and the reactive power around 7s and some step bias may be contained in the voltage angle and the current angle during 0∼7s at Bus m. Note that the curve of reactive power looks like a kind of "square wave". The reason is that the PMU measurements contain truncation errors, which is a common phenomenon in PMU data.

With the LS, ARLS, ARA method, the identification results can be obtained, as shown in TABLE 3.

TABLE 3 shows that, when the measured data contains deviations, the identification results of LS are inaccurate, while the identification results of ARLS and proposed ARA are close to the parameters in control room (obtained from offline power measure), which indicates that the proposed method is effective. Note that as the true value of TL parameters is unknown, thus, the identification result is considered as credible if it is close to the parameters in control room.

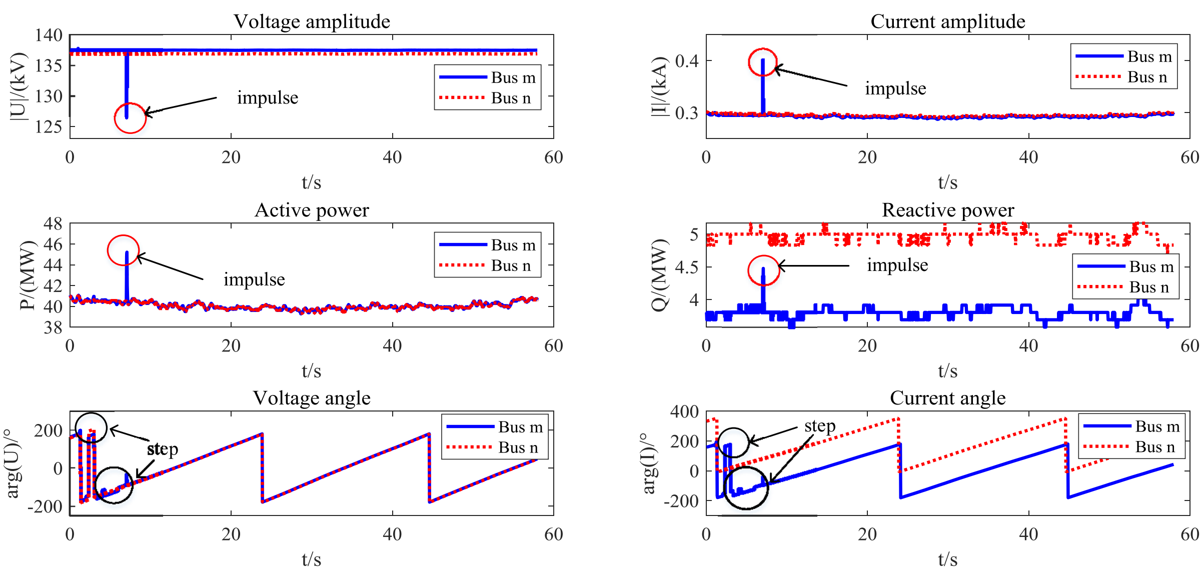

FIGURE 6. Measured PMU data for a 220kV TL in China.

In addition, the identification results of ARLS and ARA is close, the reason is that, in this case, the abnormal data accounts for a small proportion, i.e., only part of data is abnormal in 0-7s as shown in FIGURE 6. But according to the analysis in Section V.C, if the measured PMU data contain more abnormal data, the proposed ARA would have better robustness than the ARLS.

The case study with measured data shows that the proposed method can accurately identify the parameters when the measured data contain some abnormal data, and has good engineering practicability.

VII. CONCLUSION

An adaptive robust ADALINE, which combines the ADALINE (Adaptive linear neuron) and traditional IGG method, to identify the TL positive-sequence parameters, is proposed in this paper. With the IGG weight function, which can make full use of the measurement information, and ADALINE to realize the ''three-segment'' robust identification, the proposed method could well resist the adverse effects of bad data. Using the median principle to estimate the expectation and variance of residual sequence to adaptively adjust the TAR of the weight function, the proposed method is independent of the known information of the measurement equipment's error. Thus, the proposed method has strong robustness and practicality. The simulation results in the cases with/without bad data shows that, the proposed method can identify the TL parameters accurately and has better robustness than the existing methods. The case study with measured data shows that the method is practical even the measured data contain bad data.

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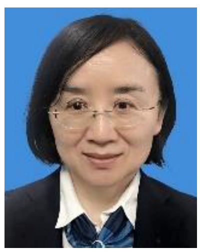
ANCHENG XUE (Member, IEEE) was born in Jiangsu, China, in 1979. He received the B.Sc. degree in applied mathematics and the Ph.D. degree in electrical engineering from Tsinghua University, Beijing, China, in 2001 and 2006, respectively. He held a postdoctoral position with the Institute of System Science, Chinese Academy of Sciences. He has been a Professor with North China Electric Power University, since March 2008. His research interest includes model- and data-driven power system stability analysis and control and protection, especially applications of the phasor measurement unit.

HE KONG was born in China, in 1996. He received the B.S. degree in electrical engineering from North China Electric Power University, where he is currently pursuing the master's degree. His research interest includes application of phasor measurement unit in power systems.

YONGZHAO LAO was born in Guangdong, China, in 1989. He received the B.Sc. degree from North China Electric Power University, in 2012, and the master's degree in electric power engineering from University College London, in 2013. He is currently a Junior Manager with the Power Control Center, Automation Department, Guangzhou Power Supply Bureau. His research interests include power system automation and smart substation technology.

QUAN XU was born in Anhui, China, in 1989. He received the B.Eng. degree in electrical engineering from Chang'an University, in 2011, and the master's degree in electrical engineering from Tsinghua University, in 2017. He is currently a Researcher with the Distribution Department, Electric Power Research Institute, China Southern Power Grid Company. His research interests include synchronous phasor measurement technology, wide area measurement, control protection technology, intelligent distribution networks, and intelligent sensor.

YUEHUAN LIN was born in Guangdong, China, in 1988. He received the B.Eng. degree and the master's degree in power system and automation from the South China University of Technology, in 2012 and 2015, respectively. He is currently a Researcher with the Distribution Department, Electric Power Research Institute, China Southern Power Grid Company. His research interests include distribution automation and sensor technology.



LI WANG was born in Xinjiang, China, in 1969. She received the B.Sc. degree in relay protection from North Electrical Power University, in 1993, and the master's degree from Zhejiang University, in 2019. She is currently the Deputy Director with the Power Dispatching and Controlling Center, Guangzhou Power Supply Bureau. Her research interests include wide-area protection, power system automation, and integrated energy system technology.

FEIYANG XU (Graduate Student Member, IEEE) was born in China, in 1995. He received the B.Sc. degree in electrical engineering from North China Electric Power University, where he is currently pursuing the Ph.D. degree. His research interests include application of phasor measurement unit in power systems and defense against phasor measurement unit data attack.

SHUANG LENG was born in China, in 1996. He received the B.S. degree in electrical engineering from North China Electric Power University, where he is currently pursuing the master's degree. His research interests include phasor measurement unit data quality and application of phasor measurement unit.

ZHIYONG YUAN was born in Jiangsu, China, in 1978. He received the Ph.D. degree in electrical engineering from Tsinghua University, in 2006. He is currently the Director of the Distribution Department, Electric Power Research Institute, China Southern Power Grid Company. His research interests include synchronous intelligent distribution networks and intelligent sensor.

GUOEN WEI was born in Guangdong, China, in 1973. He received the B.Sc. and master's degrees in relay protection from the South China University of Technology, in 1997 and 2003, respectively. He is currently a Supervisor with the Power Control Center, Automation Department, Guangzhou Power Supply Bureau. His research interests include power system automation and smart substation technology.