# **Parameters with PMU and Unsynchronized**<br> **SCADA Measurements in Distribution Grids**<br> *Inping Sun, Student Member, IEEE,* Qifang Chen, *Member, IEEE*, Mingchao Xia, *Senior Member,*<br> *IEEE*<br> *Abstract*—Line parameters pla icle has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.<br>
information: DOI: 10.17775CSEDPES.2020.06860, CSEE Journal of Power a been accepted for publication in a fiture issue of this journal, but has not been fully edited. Content may change prior to final publication.<br>
16. DOI: 10.1773/CSEEJPES.2020.0660, CSEE Journal of Power and Energy Systems<br> As been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.<br>
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Journal of Democratic Member, *IEEE*<br> **SCADA Measurements in Dis**

	current measurements, the line parameters are identified using		probab
	the total least squares (TLS) algorithm. Hardware simulations	$(\omega_{k}^{I_{ij}^2},\mu_{k}^{I_{ij}^2},\sigma_{k}^{I_{ij}^2})$	<b>GMM</b>
	demonstrate the effectiveness of the proposed method for distribution network line parameter detection and identification.	$(\omega_k^{\scriptscriptstyle P_i},\mu_k^{\scriptscriptstyle P_i},\sigma_k^{\scriptscriptstyle P_i})$	<b>GMM</b>
		$(\omega_k^{P_j}, \mu_k^{P_j}, \sigma_k^{P_j})$ GMM	
	<i>Index Terms—Line parameter detection and identification, the</i> time skew of PMU and SCADA measurements, distribution	$(\omega_{\scriptscriptstyle{k}}^{\scriptscriptstyle{\Delta P}},\mu_{\scriptscriptstyle{k}}^{\scriptscriptstyle{\Delta P}},\sigma_{\scriptscriptstyle{k}}^{\scriptscriptstyle{\Delta P}})$ GMM	
	systems, probability density function, sampling algorithm.	$t \in [1,tm]$	Time s
		$P(\Delta P_{t-1})$	<b>PDF</b>
	I. NOMENCLATURE		time in
Κ	The number of the Gaussian components in	$P(\Delta P_t, \Delta P_{t-1})$	Joint P
$\boldsymbol{R}$	the Gaussian mixture models (GMM). Resistance of the line.	$P(\Delta Q_{t-1})$	and $t-1$ <b>PDF</b>
X	Reactance of the line.		time in
$\Delta P$	Active power loss of the line.	$P(\Delta Q_t, \Delta Q_{t-1})$	Joint P
$\Delta Q$	Reactive power loss of the line.		$t$ and $t$
$\overline{A}$	Matrix of the current square measurements.	$P(I_t^2)$	<b>PDF</b>
$x_{RX}$	Matrix of the line impedance.		interva
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	This work was supported by the National Key Research and Development Program under Grant 2017YFB0902900 and Grant 2017YFB0902902.		Join
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Abstract-Line parameters play an important role in the control and management of distribution systems. Currently, phasor measurement unit (PMU) systems and supervisory control and data acquisition (SCADA) systems coexist in distribution systems. Unfortunately, SCADA and PMU measurements usually do not match each other, resulting in inaccurate detection and identification of line parameters based on measurements. To solve this problem, a data-driven method is proposed. SCADA measurements are taken as samples and PMU measurements as the population. A probability parameter identification index (PPII) is derived to detect the whole line parameter based on the probability density function (PDF) parameters of the measurements. For parameter identification, a power-loss PDF with the PMU time stamps and a power-loss chronological PDF are derived via kernel density estimation (KDE) and the conditional PDF. Then, the power-loss samples with the PMU time stamps and chronological correlations are generated by the two PDFs of the power loss via the Metropolis-Hastings (MH) algorithm. Finally, using the power-loss samples and PMU current measurements, the line parameters are identified using the total least squares (TLS) algorithm. Hardware simulations demonstrate the effectiveness of the proposed method for distribution network line parameter detection and identification. Index Terms-Line parameter detection and identification, the time skew of PMU and SCADA measurements, distribution	$y_{PQ}$ $\sigma_{\scriptscriptstyle T+1}$ $I_{ij}$ $P_i$ $Q_i$ $U_i$ $P_{j}$ $Q_i$ $ U_j $ $\mid \mu_k^j \mid'$ $\mu_k^j$ $(\omega_k, \mu_k, \sigma_k)$ $(\omega_{k}^{I_{\bar{y}}^{2}}, \mu_{k}^{I_{\bar{y}}^{2}}, \sigma_{k}^{I_{\bar{y}}^{2}})$ $(\omega_k^{P_i},\mu_k^{P_i},\sigma_k^{P_i})$ $(\omega_k^{P_j},\mu_k^{P_j},\sigma_k^{P_j})$	Matrix of the power loss. The smallest singular value. Current phasor of line between bus i and bus j. Active power flow of line from bus i to bus j. Reactive power flow of line from bus i to bus j. Voltage phasor at bus i. Active power flow of line from $busj$ to bus i. Reactive power flow of line from $busj$ to $bus$ Voltage amplitude at bus j. The mean of $ U_i '$ . The mean of $ U_i $ . The weight, mean, and standard deviation of the kth Gaussian component in the GMM probability density function (PDF). GMM PDF parameters of current square. GMM PDF parameters of active power flow $P_i$ . GMM PDF parameters of active power flow $P_i$ . $(\omega_k^{\Delta P}, \mu_k^{\Delta P}, \sigma_k^{\Delta P})$ GMM PDF parameters of active power loss.
systems, probability density function, sampling algorithm. I. NOMENCLATURE K The number of the Gaussian components in the Gaussian mixture models (GMM). Resistance of the line. R Reactance of the line. X $\Delta P$ Active power loss of the line. $\Delta Q$ Reactive power loss of the line. Matrix of the current square measurements. A Matrix of the line impedance. $x_{_{RX}}$ This work was supported by the National Key Research and Development Program under Grant 2017YFB0902900 and Grant 2017YFB0902902. J. P. Sun, Q. F. Chen, M. C. Xia (corresponding author, e-mail: $mchxia@bitu.edu.cn)$ are with the School of Electrical Engineering, Beijing Jiaotong University (BJTU), Beijing 100044, China.	$t \in [1,tm]$ $P(\Delta P_{t-1})$ $P(\Delta P_t, \Delta P_{t-1})$ $P(\Delta Q_{t-1})$ $P(\Delta Q_t, \Delta Q_{t-1})$ $P(I_t^2)$ $P(\Delta P_t, I_t^2)$ $P(\Delta Q_t, I_t^2)$ q(x X)	Time stamp. PDF value of $\Delta P_{t-1}$ at time stamp t-1 for the time interval $[1, tm]$ . Joint PDF value of $\Delta P_t$ and $\Delta P_{t-1}$ at time stamp t and $t-1$ for the time interval $[1, tm]$ . PDF value of $\Delta Q_{t-1}$ at time stamp t-1 for the time interval $[1, tm]$ . Joint PDF value of $\Delta Q_i$ and $\Delta Q_{i-1}$ at time stamp t and t-1 for the time interval $[1, tm]$ . PDF value of $I_n^2$ at time stamp t for the time interval $[1, tm]$ . Joint PDF value of $\Delta P_t$ and $I_u^2$ at time stamp t for the time interval $[1, tm]$ . Joint PDF value of $\Delta Q_t$ and $I_{ii}^2$ at time stamp <i>t</i> for the time interval $[1, tm]$ . The proposal PDF with mean $X$ and constant variance $\sigma_a$ .

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people have higher requirements for power distribution. Through careful monitoring, protection, and control of the measurements incorrectly in<br>
efficient, reliabl people have higher requirements for power distribution. Parameter identification, (Through careful monitoring, protection, and control of the measurements incorrectly identificient, reliable, and flexible operation [1]. In Through careful monitoring, protection, and control of the measurements incorrectly identifieven distribution systems can be ensured of transmission line parameters identifiering, relable, and flexible operation [1]. In d measurements. Fraction , reliable, and flexible operation [1]. In distribution an augmented state-parameter hyds, line parameter is one of the backbones of state estimation and blackout measurements to update the approximation, magneme grids, line parameter is one of the backbones of state estimation<br>
[2], fault location, reactive power optimization, and blackout measurements to update the<br>
management; therefore, a more accurate line parameter would the [2], fault location, reactive power optimization, and blackout measurements to update the approx approx power flow calculations and fault isolation. However, imeasurements at one end of imcorrect parameters may arise from management; therefore, a more accurate line parameter would<br>improve power flow calculations and fault isolation. However,<br>measurements at one end o<br>incorrect parameters may arise from poor line length estimation, measurem In smart distribution systems, with a higher penetration of the distributed generation (DG), demand response (DR) enabled loads, renewable energy, and power electronics equipment,

improve power flow calculations and fault isolation. However,<br>
incorrect parameters may arise from poor line length estimation,<br>
solow updating of the PMU and SCADA meas<br>
solve updating of the parameters and the detables, incorrect parameters may arise from poor line length estimation,<br>slow updating of network changes in the database, aging, or<br>environmental factors [3], [4]; therefore, the detection and voltage and current did no<br>identifi slow updating of network changes in the database, aging, or<br>environmental factors [3], [4]; therefore, the detection and voltage and current did not<br>demotische in parameters based on related changes; therefore, the time sk environmental factors [3], [4]; therefore, the detection and voltage and current did not<br>identification of incorrect line parameters based on related changes; therefore, the time sace<br>measurements is of great importance. F identification of incorrect line parameters based on related<br>
measurements is of great importance. Furthermore, the stands Considering the incorrect sequencements.<br>
measurements accuracy of the line parameters can be dire measurements is of great importance. Furthermore, the space and SCADA meads are also are also are directly affected by and SCADA meads are equipped with a in [17]. A method for measurement units (PMUs) are equipped with a accuracy of the line parameters can be directly affected by<br>
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equipped with a<br>
in [17]. A method for<br>
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PMU is installed at a bus, the cur Phasor measurement units (PMUs) are equipped with a<br>  $^{\text{m}}$  [17]. A method for estimal<br>
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allows was proposed using the<br>
and current phasors with exact time sta global positioning system (GPS) receiver and render voltage<br>and current phasors with exact time stamps [5], [6]. When a<br>lines was proposed<br>PMU is installed at a bus, the current phasors of the line<br>current and voltage sinc and current phasors with exact time stamps [5], [6]. When a<br>
PMU is installed at a bus, the current phasors of the line<br>
current and voltage sign measurements and the voltage phasor of this bus<br>
can be measured. The accura PMU is installed at a bus, the current phasors of the line current and voltage signals measure<br>connected to the other buses and the voltage phasor of this bused on abruptomized data we<br>can be measured. The accuracy of PMU connected to the other buses and the voltage phasor of this bus<br>can be measured. The accuracy of PMU measurements is high,<br>with a refresh rate of up to 50 (or even 100) times per second for<br>based on abrupt change detecti<br> can be measured. The accuracy of PMU measurements is high, synchronization using a 1 ime 1<br>with a refresh rate of up to 50 (or even 100) times per second for these don abrupt change detection<br>at are distant (7). In contra with a refresh rate of up to 50 (or even 100) times per second for<br>a 50-Hz system [7]. In contrast, modern supervisory control and<br>a coupling the carrelative (data causainements, a non-iterative<br>dime and transformer param a 50-Hz system [7]. In contrast, modern supervisory control and<br>
data acquisition (SCADA) measurements do not have exact line and transformer parameter<br>
time references and render voltage and current magnitude<br>
measuremen data acquisition (SCADA) measurements do not have exact<br>time references and render voltage and current magnitude<br>data [23]. Based on<br>measurements. SCADA systems typically consist of remote altimation<br>terminal unit compute time references and render voltage and current magnitude<br>
measurements. SCADA systems typically consist of remote<br>
terminal unit computers that can record real-time<br>
terminal unit computers that can record real-time<br>
term measurements. SCADA systems typically consist of remote large several measurements and deliver this data a corord real-time estimated states provided by a communication system [8]. Owing to the SCADA architecture, used co terminal unit computers that can record real-time using several measurement s<br>measurements and deliver this data to a control center with a<br>estimated states provided by a<br>its measurement value at present will not match th measurements and deliver this data to a control center with a<br>communication system [8]. Owing to the SCADA architecture,<br>moment when the value of the value of the particular moment when the value of measurement is taken, communication system [8]. Owing to the SCADA architecture, used conventional magnitude<br>its measurement value at present will not match the value of the PMU synchronized measurement<br>magnitude measurement is can be can be m its measurement value at present will not match the value of the<br>measurement when the SCADA measurement is taken, if the<br>measurements is excillates over time [9]. SCADA and IGG (Institute of Geode<br>measurements taken at ti moment when the SCADA measurement is taken, if the PMU measurements, and magnitude measurement is oscillates over time [9]. SCADA and IGG (Institute of measurements taken at time t are delayed for ati + bti + cti, Academy magnitude measurement is oscillates over time [9]. SCADA and IGG (Institute measurements taken at time t are delayed for ati + bti + cti, Academy of Science with the study of Science of data to be received by the control measurements taken at time *t* are delayed for ati + bti + cti, Academ<br>where ati is the period of the cyclic measurement gathering, bti<br>is the time for the set of data to be received by the control center, method<br>and cti here at is the period of the cyclic measurement gathering, bti<br>
methods [25]-[29], the least<br>
the time for the set of data to be received by the control center, method [30], a robust M-esti<br>
d cti is the dead time between is the time for the set of data to be received by the control center, method [30], a robust M-esti<br>and cti is the dead time between the arrival of measurements and their processing. For a given bus, the at is different fr and cti is the dead time between the arrival of measurements<br>and their processing. For a given bus, the ati is different from<br>intentificant measurement errors [24], PMU<br>one measurement to another with its value is between and their processing. For a given bus, the ati is different from<br>
one measurement to another with its value is between 0.1 s and<br>
0.9 s. Furthermore, bti varies from one bus to another and its<br>
1311, the uncertainty in PM one measurement to another with its value is between 0.1 s and<br>
0.9 s. Furthermore, bti varies from one bus to another and its<br>
1311, the uncertainty in PMU m<br>
value is between 0.1 s and 0.5 s [10]. At a given time *t*, o

0.9 s. Furthermore, bti varies from one bus to another and its [31], the uncertainty in PMU is value is between 0.1 s and 0.5 s [10]. At a given time  $t_0$ , one transformers errors [26/D]-[28], and sasigned to the time in value is between 0.1 s and 0.5 s [10]. At a given time t, one transformers errors [26]-[28], a SCADA measurement was taken at time ts|  $\lt t$  that can be in addition, many other m interval [t-T, t] where T is approximately SCADA measurement was taken at time  $tsl < t$  that can be  $\ln$  addition, many other measurement identification [33]-[11]. In samporameter identification [33]-[11]. In this study, the time skew of the SCADA measurements there

identification of hybrid measurements is appealing when<br>considering the fact that SCADA measurements do not match<br>with PMU measurements in distribution grids.<br>Incorporating PMU measurements can improve the line<br>parameter i identification of hybrid measurements is appealing when<br>considering the fact that SCADA measurements do not match<br>with PMU measurements in distribution grids.<br>Incorporating PMU measurements can improve the line<br>parameter i

identification of hybrid measurements is appealing when<br>considering the fact that SCADA measurements do not match<br>with PMU measurements in distribution grids.<br>Incorporating PMU measurements can improve the line<br>parameter i entification of hybrid measurements is appealing when<br>
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parameter identification, especially when SCADA<br>
measurements incorrectly identify parameters [13], [14]. For<br>
transmission Incorporating PMU measurements can improve the line<br>parameter identification, especially when SCADA<br>measurements incorrectly identify parameters [13], [14]. For<br>transmission line parameters identification, authors [15] use parameter identification, especially when SCADA<br>measurements incorrectly identify parameters [13], [14]. For<br>transmission line parameters identification, authors [15] used<br>an augmented state-parameter hybrid weighted least measurements incorrectly identify parameters [13], [14]. For<br>transmission line parameters identification, authors [15] used<br>an augmented state-parameter hybrid weighted least squares<br>state estimator that was based on SCADA transmission line parameters identification, authors [15] used<br>an augmented state-parameter hybrid weighted least squares<br>state estimator that was based on SCADA and PMU<br>measurements to update the approach proposed in [16] an augmented state-parameter hybrid weighted least squares<br>state estimator that was based on SCADA and PMU<br>measurements to update the approach proposed in [16]. In [5],<br>the line parameter estimation method required PMU<br>mea state estimator that was based on SCADA and PMU<br>measurements to update the approach proposed in [16]. In [5],<br>the line parameter estimation method required PMU<br>measurements at one end of a given line and SCADA<br>measurements measurements to update the approach proposed in [16]. In [5],<br>the line parameter estimation method required PMU<br>measurements at one end of a given line and SCADA<br>measurements at the other. During the short collection inter the line parameter estimation method required PMU measurements at one end of a given line and SCADA measurements of the PMU and SCADA measurements, the magnitude of the voltage and current did not exhibit significant wavef measurements at one end of a given line and SCADA<br>measurements at the other. During the short collection interval<br>of the PMU and SCADA measurements, the magnitude of the<br>voltage and current did not exhibit significant wave measurements at the other. During the short collection interval<br>of the PMU and SCADA measurements, the magnitude of the<br>voltage and current did not exhibit significant waveform<br>changes; therefore, the time skew of the meas of the PMU and SCADA measurements, the magnitude of the voltage and current did not exhibit significant waveform changes; therefore, the time skew of the measurements was ignored. Considering the inconsistent sampling time voltage and current did not exhibit significant waveform<br>changes; therefore, the time skew of the measurements was<br>ignored. Considering the inconsistent sampling time of the<br>PMU and SCADA measurements in a real system, the changes; therefore, the time skew of the measurements was ignored. Considering the inconsistent sampling time of the PMU and SCADA measurements in a real system, the PMU and SCADA measurement systems were discussed separat ignored. Considering the inconsistent sampling time of the PMU and SCADA measurements in a real system, the PMU and SCADA measurement systems were discussed separately in [17]. A method for estimating the self and mutual z PMU and SCADA measurements in a real system, the PMU<br>and SCADA measurement systems were discussed separately<br>in [17]. A method for estimating the self and mutual<br>zero-sequence impedances for mutually coupled transmission<br>l and SCADA measurement systems were discussed separately<br>in [17]. A method for estimating the self and mutual<br>zero-sequence impedances for mutually coupled transmission<br>lines was proposed using the unsynchronized three-phas in [17]. A method for estimating the self and mutual<br>zero-sequence impedances for mutually coupled transmission<br>lines was proposed using the unsynchronized three-phase<br>current and voltage signals measured during the fault zero-sequence impedances for mutually coupled transmission<br>lines was proposed using the unsynchronized three-phase<br>current and voltage signals measured during the fault period.<br>The unsynchronization using a Time Time-trans lines was proposed using the unsynchronized three-phase<br>current and voltage signals measured during the fault period.<br>The unsynchronized data were aligned to complete the<br>synchronization using a Time Time-transform (TT-tra current and voltage signals measured during the fault period.<br>The unsynchronized data were aligned to complete the<br>synchronization using a Time Time-transform (TT-transform)<br>based on abrupt change detection [22]. Based on The unsynchronized data were aligned to complete the<br>synchronization using a Time Time-transform (TT-transform)<br>based on abrupt change detection [22]. Based on the magnitude<br>measurements, a non-iterative estimation of the synchronization using a Time Time-transform (TT-transform)<br>based on abrupt change detection [22]. Based on the magnitude<br>measurements, a non-iterative estimation of the transmission<br>line and transformer parameters was prop based on abrupt change detection [22]. Based on the magnitude<br>measurements, a non-iterative estimation of the transmission<br>line and transformer parameters was proposed using SCADA<br>data [23]. Based on PMU measurements, a tr measurements, a non-iterative estimation of the transmission<br>line and transformer parameters was proposed using SCADA<br>data [23]. Based on PMU measurements, a transmission line<br>parameter estimation by at least one PMU was p line and transformer parameters was proposed using SCADA<br>data [23]. Based on PMU measurements, a transmission line<br>parameter estimation by at least one PMU was proposed by<br>using several measurement snapshots from PMUs and<br> data [23]. Based on PMU measurements, a transmission line<br>parameter estimation by at least one PMU was proposed by<br>using several measurement snapshots from PMUs and<br>estimated states provided by a hybrid state estimator, wh parameter estimation by at least one PMU was proposed by<br>using several measurement snapshots from PMUs and<br>estimated states provided by a hybrid state estimator, which<br>used conventional magnitude measurements and available using several measurement snapshots from PMUs and<br>estimated states provided by a hybrid state estimator, which<br>used conventional magnitude measurements and available<br>PMU synchronized measurements [4]. Furthermore, based on estimated states provided by a hybrid state estimator, which<br>used conventional magnitude measurements and available<br>PMU synchronized measurements [4]. Furthermore, based on<br>PMU measurements, an adaptive linear neuron (ADAL used conventional magnitude measurements and available<br>PMU synchronized measurements [4]. Furthermore, based on<br>PMU measurements, an adaptive linear neuron (ADALINE)<br>and IGG (Institute of Geodesy & Geophysics, Chinese<br>Acad PMU synchronized measurements [4]. Furthermore, based on<br>PMU measurements, an adaptive linear neuron (ADALINE)<br>and IGG (Institute of Geodesy & Geophysics, Chinese<br>Academy of Sciences) methods [24], robust identification<br>me PMU measurements, an adaptive linear neuron (ADALINE)<br>
and IGG (Institute of Geodesy & Geophysics, Chinese<br>
Academy of Sciences) methods [24], robust identification<br>
methods [25]-[29], the least trimmed squares estimation<br> and IGG (Institute of Geodesy & Geophysics, Chinese<br>Academy of Sciences) methods [24], robust identification<br>methods [25]-[29], the least trimmed squares estimation<br>method [30], a robust M-estimator method [31], and a<br>maxi Academy of Sciences) methods [24], robust identification<br>methods [25]-[29], the least trimmed squares estimation<br>method [30], a robust M-estimator method [31], and a<br>maximum likelihood estimation method [32] were proposed methods [25]-[29], the least trimmed squares estimation<br>method [30], a robust M-estimator method [31], and a<br>maximum likelihood estimation method [32] were proposed to<br>identify line parameters. These methods can address PM [36]. in in likelihood estimation method [32] were proposed to<br>entify line parameters. These methods can address PMU<br>assurement errors [24], PMU measurement outliers [25], [30],<br>1], the uncertainty in PMU measurements [32], inst identify line parameters. These methods can address PMU<br>measurement errors [24], PMU measurement outliers [25], [30],<br>[31], the uncertainty in PMU measurements [32], instrument<br>transformers errors [26]-[28], and PMU phase measurement errors [24], PMU measurement outliers [25], [30], [31], the uncertainty in PMU measurements [32], instrument transformers errors [26]-[28], and PMU phase angle error [29]. In addition, many other methods for tr [31], the uncertainty in PMU measurements [32], instrument transformers errors [26]-[28], and PMU phase angle error [29].<br>In addition, many other methods for transmission line parameter identification [33]-[35] have been transformers errors [26]-[28], and PMU phase angle error [29].<br>In addition, many other methods for transmission line<br>parameter identification [33]-[35] have been proposed using<br>PMU measurements. Moreover, a measurement-bas In addition, many other methods for transmission line<br>parameter identification [33]-[35] have been proposed using<br>PMU measurements. Moreover, a measurement-based<br>transmission line parameter estimation with an adaptive data

JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE<br>SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize<br>same time section based on the instantane JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PMU A<br>SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter dete JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PM<br>SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter detecti JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PY SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter detecs<br> JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter<br>same time secti JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter<br>same time secti JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS<br>SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter<br>same time secti JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PMU A<br>SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter dete JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PMU ASCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>stamp of the PMU to align the SCADA measurement data at the realize line parameter detect JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PSCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>
stamp of the PMU to align the SCADA measurement data at the realize line parameter detectio JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PISCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>
stamp of the PMU to align the SCADA measurement data at the realize line parameter detects<br> DRATION DESCRIPTION GRIDS<br>
SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>
stamp of the PMU to align the SCADA measurement data at the realize line parameter dets<br>
same time section based on the instantaneous voltage values and stamp of the PMU to align the SCADA measurement data at the realize line paramete<br>same time section based on the instantaneous voltage values 2) A PPII of the 1<br>and the line parameter can be identified [37]. As is well kno stamp of the PMU to align the SCADA measurement data at the<br>
same time section based on the instantaneous voltage values<br>
2) A PPII of the line parameter can be identified [37]. As is well known, on the probability density same time section based on the instantaneous voltage values<br>
2) A PPII of the line<br>
and the line parameter can be identified [37]. As is well known, on the probability den<br>
SCADA renders voltage and current magnitude measu and the line parameter can be identified [37]. As is well known, on the probability density func<br>SCADA renders voltage and current magnitude measurements; measurements. The PPII contatus, we will investigate the SCADA magn SCADA renders voltage and current magnitude measurements; measurements. The PPII coronus, we will investigate the SCADA magnitude measurements, comparing the PPII with a three Their tracking of series parameters [21] and thus, we will investigate the SCADA magnitude measurements. parameter and can be used<br>in distribution grids, based on magnitude measurements, comparing the PPII with a<br>off-line tracking of series parameters [21] and regres In distribution grids, based on magnitude measurements, comparing the PPII with a three micelaries parameters [21] and regressing of the determine whether the line prarmeters with the parameters with the proposed detectio off-line tracking of series parameters [21] and regressing of the determine whether the line parametical infermation coverage drop amplificule and current [20] were used to identify errors of the resistance and the rolline line impedance using the approximate relationship between the<br>voltage drop amplitude and current [20] were used to identify<br>errors of the resistance and the line parameters. In addition, others have proposed a discrete<br>err voltage drop amplitude and current [20] were used to identify<br>
line parameters. In addition, others have proposed a discrete<br>
errors as a whole.<br>
dynamic Bayesian network method with advanced metering 3) A power-loss P<br>
in line parameters. In addition, others have proposed a discrete errors as a whole.<br>
dynamic Bayesian network method with advanced metering 3) A power-loss PDF with P<br>
infrastructure (AMI) measurements and weaker measurements dynamic Bayesian network method with advanced metering 3) A power-loss PDF with P<br>infrastructure (AMI) measurements and weather measurements model the correlation between<br>138] and a parameter estimation scheme that conside infrastructure (AMI) measurements and weather measurements model the correlation between<br>
[38] and a parameter estimation scheme that considers the stamps, and a power-loss of<br>
influence of measurements and instrument tran [38] and a parameter estimation scheme that considers the<br>
influence of measurement and instrument transformer model the chronologica<br>
uncertainties with SCADA measurements [42]. Moreover, an build a joint PDF b<br>
automate influence of measurement and instrument transformer model the chronological correl<br>uncertainties with SCADA measurements [42]. Moreover, an build a joint PDF between<br>automated determination of topology and line parameters uncertainties with SCADA measurements [42]. Moreover, an build a joint PDF betwee<br>automated determination of topology and line parameters with measurements with the PML<br>smart meters measurements [39], the identification of automated determination of topology and line parameters with measurements with the PMU smart meters measurements [39], the identification of topology the power loss at the prior time and line parameters with time-stamped v smart meters measurements [39], the identification of topology<br>
imped voltage magnitude and<br>
injection samples of leaf nodes [40], and the identification of loss can be obtained.<br>
topology and line parameters without the i and line parameters with time-stamped voltage magnitude and<br>
injection samples of leaf nodes [40], and the identification of loss can be obtained.<br>
topology and line parameters without the information of 4) The power-loss injection samples of leaf nodes [40], and the identification of<br>topology and line parameters without the information of<br>voltage angles [41] can realize the parameter identification.<br>Based on PMU measurements, iterations be bey and line parameters without the information of 4) The power-loss sant<br>age angles [41] can realize the parameter identification. chronological correlation<br>sed on PMU measurements, iterations between the power loss based voltage angles [41] can realize the parameter identification. Chronological correlations and<br>Based on PMU measurements, iterations between the power loss based on the<br>parameter estimation and topology estimation, which cur Based on PMU measurements, iterations between the power loss based on the parameter estimation and topology eidentification were used for parameter is identified by the the joint line parameter and topology estimation, whi parameter estimation and topology identification were used for<br>
the joint line parameter and topology estimation, which current measurements. Har<br>
combined PMUs and AMI measurements [18]. A PMU-based<br>
iterative line parame the joint line parameter and topology estimation,<br>combined PMUs and AMI measurements [18]. A PMU<br>iterative line parameter estimation algorithm using only<br>data was presented, which included in the estimation<br>systematic meas

presented a classification identification method based on PMU details the method for dues<br>
measurements for line parameter identification under<br>
However, current approaches to the line parameter PDF of the measurement<br>
How measurements for line parameter identification under the PMU and SCADA measurem<br>
insufficient measurement conditions.<br>
However, current approaches to the line parameter por of the measurements, respectively<br>
identification insufficient measurement conditions.<br>
Gaussian mixture model (GMM<br>
However, current approaches to the line parameter PDF of the measurements, respectively<br>
dimitations of hybrid measurements still pose serious the line par However, current approaches to the line parameter PDF of the measurement<br>identification of hybrid measurements still pose serious the line parameter detect<br>imitations in distribution grids. For example, PMU PDFs. Section V identification of hybrid measurements still pose serious the line parameter detectic<br>limitations in distribution grids. For example, PMU PDFs. Section V describes<br>measurements do not.<br>measurements of the sum over-loss PDF limitations in distribution grids. For example, PMU PDFs. Section V de<br>measurements have exact time stamps, whereas SCADA parameter identifica<br>measurements do not.<br>In this paper, we propose a measurement-based method for c measurements have exact time stamps, whereas SCADA parameter identification. We demonstrements do not i.e., a power-loss PDF with PMI<br>
In this paper, we propose a measurement-based method for chronological PDF. We introduc i.e., a power-loss PDF with PM<br>
In this paper, we propose a measurement-based method for chronological PDF. We introduced<br>
PMU and identification of parameters of a line with detection and identified by the PMU<br>
PMU and st In this paper, we propose a measurement-based method for chronological PDF. We intro<br>the detection and identification of parameters of a line with sample power-loss samples<br>PMU and unsynchronized SCADA measurements in iden the detection and identification of parameters of a line with sample power-loss samples.<br>
PMU and unsynchronized SCADA measurements in identified by the PMU curdistribution systems. Owing to the nonsynchronization of PMU PMU and unsynchronized SCADA measurements in identified by the PMU curr<br>
distribution systems. Owing to the nonsynchronization of the power-loss samples with the feat<br>
PMU and SCADA measurements, we analyze the probabilit follows: A SCADA measurements, we analyze the probability<br>
and chronological correlatic<br>
tribution of PMU and SCADA measurements based on<br>
hardware simulation results of<br>
babilistic approaches, respectively. The suspicious line<br>
pa distribution of PMU and SCADA measurements based on hardware simulation results<br>probabilistic approaches, respectively. The suspicious line parameter detection and<br>parameter is detected using a probability parameter analys probabilistic approaches, respectively. The suspicious line parameter detection and identification index (PPII). The PPII is the sum of relative analyses. Section VII presents identification index (PPII). The PPII is the parameter is detected using a probability parameter analyses. Section VII presents or detectrication index (PPII). The PPII is the sum of relative massurements.<br>
Based on the probability distribution of measurements, we ME identification index (PPII). The PPII is the sum of relative<br>errors of the means of the voltage magnitude measurements.<br>
Based on the probability distribution of measurements, we<br>
generate samples of the power loss with P

F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED<br>
realize line parameter detection and identification.<br>
2) A PPII of the line parameter detection is proposed based<br>
on the probability density function (PDF) parameters of the INE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>
alize line parameter detection and identification.<br>
2) A PPII of the line parameter detection is proposed based<br>
the probability density function (PDF) parameters of the line<br> F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>realize line parameter detection and identification.<br>2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the<br>m F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>realize line parameter detection and identification.<br>2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the<br>m F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>realize line parameter detection and identification.<br>2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the<br>m F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>realize line parameter detection and identification.<br>2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the<br>m FLINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>realize line parameter detection and identification.<br>2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the li FLINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>realize line parameter detection and identification.<br>2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the<br>me FLINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 3<br>realize line parameter detection and identification.<br>2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the<br>me F LINE PARAMETERS WITH PMU AND UNSYNCHRON<br>realize line parameter detection and identification<br>2) A PPII of the line parameter detection is pr<br>on the probability density function (PDF) parameasurements. The PPII contains th The FANAWELERS with FMO RID ORSTRETINGORIZED<br>2) A PPII of the line parameter detection is proposed based<br>the probability density function (PDF) parameters of the<br>assurements. The PPII contains the features of the line<br>rame realize line parameter detection and identification.<br>
2) A PPII of the line parameter detection is proposed based<br>
on the probability density function (PDF) parameters of the<br>
measurements. The PPII contains the features o realize line parameter detection and identification.<br>
2) A PPII of the line parameter detection is proposed based<br>
on the probability density function (PDF) parameters of the<br>
measurements. The PPII contains the features o 2) A PPII of the line parameter detection is proposed based<br>on the probability density function (PDF) parameters of the<br>measurements. The PPII contains the features of the line<br>parameter and can be used to detect the line

on the probability density function (PDF) parameters of the measurements. The PPII contains the features of the line parameter and can be used to detect the line parameter. When comparing the PPII with a threshold many tim measurements. The PPII contains the features of the line<br>parameter and can be used to detect the line parameter. When<br>comparing the PPII with a threshold many times over, we can<br>determine whether the line parameter is corr parameter and can be used to detect the line parameter. When<br>comparing the PPII with a threshold many times over, we can<br>determine whether the line parameter is correct. However, the<br>proposed detection method cannot distin comparing the PPII with a threshold many times over, we can<br>determine whether the line parameter is correct. However, the<br>proposed detection method cannot distinguish between the<br>errors of the resistance and the reactance, determine whether the line parameter is correct. I<br>proposed detection method cannot distinguish<br>errors of the resistance and the reactance, but it c.<br>errors as a whole.<br>3) A power-loss PDF with PMU time stamps<br>model the co posed detection method cannot distinguish between the<br>ors of the resistance and the reactance, but it can detect the<br>ors as a whole.<br>3) A power-loss PDF with PMU time stamps is derived to<br>odel the correlation between the p errors of the resistance and the reactance, but it can detect the<br>errors as a whole.<br>3) A power-loss PDF with PMU time stamps is derived to<br>model the correlation between the power loss and PMU time<br>stamps, and a power-loss errors as a whole.<br>
3) A power-loss PDF with PMU time stamps is derived to<br>
model the correlation between the power loss and PMU time<br>
stamps, and a power-loss chronological PDF is derived to<br>
model the chronological corre 3) A power-loss PDF with PMU time stamps is derived to model the correlation between the power loss and PMU time stamps, and a power-loss chronological PDF is derived to model the chronological correlation of the power los model the correlation between the power loss and PMU time<br>stamps, and a power-loss chronological PDF is derived to<br>model the chronological correlation of the power loss. First, we<br>build a joint PDF between the power loss a

stamps, and a power-loss chronological PDF is derived to model the chronological correlation of the power loss. First, we build a joint PDF between the power loss and current measurements with the PMU time stamps, and a jo model the chronological correlation of the power loss. First, we build a joint PDF between the power loss and current measurements with the PMU time stamps, and a joint PDF of the power loss at the prior time stamp and the build a joint PDF between the power loss and current<br>measurements with the PMU time stamps, and a joint PDF of<br>the power loss at the prior time stamp and the following time<br>stamp. Then, using the conditional PDF, two PDFs examing with the PMU time stamps, and a joint PDF of<br>
power loss at the prior time stamp and the following time<br>
mp. Then, using the conditional PDF, two PDFs of power<br>
scan be obtained.<br>
4) The power-loss samples with the the power loss at the prior time stamp and the following time<br>stamp. Then, using the conditional PDF, two PDFs of power<br>loss can be obtained.<br>4) The power-loss samples with the PMU time stamps and<br>chronological correlation stamp. Then, using the conditional PDF, two PDFs of power<br>loss can be obtained.<br>4) The power-loss samples with the PMU time stamps and<br>chronological correlations are generated by the two PDFs of the<br>power loss based on the loss can be obtained.<br>
4) The power-loss samples with the PMU time stamps and<br>
chronological correlations are generated by the two PDFs of the<br>
power loss based on the sampling algorithm. The line<br>
parameter is identified

mbined PMUs and AMI measurements [18]. A PMU-based<br>
proposed method is substantial<br>
rative line parameter estimation algorithm using only PMU<br>
detection and identification whe<br>
tate was presented, which included in the est iterative line parameter estimation algorithm using only PMU detection and identification which are detailed in the estimation model and PMU measurements do not assigned a classification identification method based on PMU data was presented, which included in the estimation model<br>systematic measurement errors [43]. Our previous work [44] The remainder of this paper presented a classification identification method based on PMU details the me systematic measurement errors [43]. Our previous work [44] The remainder of this paper presented a classification identification method based on PMU details the method for dealing uneasurements for line parameter identific 4) The power-loss samples with the PMU time stamps and<br>chronological correlations are generated by the two PDFs of the<br>power loss based on the sampling algorithm. The line<br>parameter is identified by the power-loss samples chronological correlations are generated by the two PDFs of the<br>power loss based on the sampling algorithm. The line<br>parameter is identified by the power-loss samples and PMU<br>current measurements. Hardware simulations show power loss based on the sampling algorithm. The line<br>parameter is identified by the power-loss samples and PMU<br>current measurements. Hardware simulations show the<br>proposed method is substantially effective for line paramet parameter is identified by the power-loss samples and PMU<br>current measurements. Hardware simulations show the<br>proposed method is substantially effective for line parameter<br>detection and identification when considering that current measurements. Hardware simulations show the proposed method is substantially effective for line parameter detection and identification when considering that the SCADA and PMU measurements do not match. The remainde proposed method is substantially effective for line parameter<br>detection and identification when considering that the SCADA<br>and PMU measurements do not match.<br>The remainder of this paper proceeds as follows: Section III<br>det detection and identification when considering that the SCADA<br>and PMU measurements do not match.<br>The remainder of this paper proceeds as follows: Section III<br>details the method for dealing with the nonsynchronization of<br>the and PMU measurements do not match.<br>
The remainder of this paper proceeds as follows: Section III<br>
details the method for dealing with the nonsynchronization of<br>
the PMU and SCADA measurements. Section IV considers the<br>
Gau The remainder of this paper proceeds as follows: Section III<br>details the method for dealing with the nonsynchronization of<br>the PMU and SCADA measurements. Section IV considers the<br>Gaussian mixture model (GMM) PDF and the G details the method for dealing with the nonsynchronization of<br>the PMU and SCADA measurements. Section IV considers the<br>Gaussian mixture model (GMM) PDF and the Gaussian model<br>PDF of the measurements, respectively. We deriv the PMU and SCADA measurements. Section IV considers the Gaussian mixture model (GMM) PDF and the Gaussian model PDF of the measurements, respectively. We derive a PPII for the line parameter detection based on the paramet Gaussian mixture model (GMM) PDF and the Gaussian model<br>
PDF of the measurements, respectively. We derive a PPII for<br>
the line parameter detection based on the parameters of the<br>
PDFs. Section V describes the proposed appr PDF of the measurements, respectively. We derive a PPII for<br>the line parameter detection based on the parameters of the<br>PDFs. Section V describes the proposed approach for the line<br>parameter identification. We derive two P Fs. Section V describes the proposed approach for the line ameter identification. We derive two PDFs of the power loss, a power-loss PDF with PMU time stamps and a power-loss prological PDF. We introduce two sampling algor a a power-loss PDF with PMU time stamps and a power-loss<br>conological PDF. We introduce two sampling algorithms to<br>mple power-loss samples. Then, the line parameter is<br>entified by the PMU current measurements and the<br>wer-lo chronological PDF. We introduce two sampling algorithms to<br>sample power-loss samples. Then, the line parameter is<br>identified by the PMU current measurements and the<br>power-loss samples with the features of the PMU time stam sample power-loss samples. Then, the line parameter is<br>identified by the PMU current measurements and the<br>power-loss samples with the features of the PMU time stamps<br>and chronological correlations. Section VI presents the<br>

# MEASUREMENTS SAMPLES

identified by the PMU current measurements and the<br>power-loss samples with the features of the PMU time stamps<br>and chronological correlations. Section VI presents the<br>hardware simulation results of the proposed approach f prower-loss samples with the features of the PMU time stamps<br>and chronological correlations. Section VI presents the<br>hardware simulation results of the proposed approach for line<br>parameter detection and identification, and and chronological correlations. Section VI presents the<br>hardware simulation results of the proposed approach for line<br>parameter detection and identification, and comparison<br>analyses. Section VII presents our conclusions.<br>I hardware simulation results of the proposed approach for line<br>parameter detection and identification, and comparison<br>analyses. Section VII presents our conclusions.<br>III. PMU MEASUREMENTS POPULATION AND SCADA<br>MEASUREMENTS parameter detection and identification, and comparison<br>analyses. Section VII presents our conclusions.<br>III. PMU MEASUREMENTS POPULATION AND SCADA<br>MEASUREMENTS SAMPLES<br>When a SCADA meter rather than a PMU meter is installe analyses. Section VII presents our conclusions.<br>
III. PMU MEASUREMENTS POPULATION AND SCADA<br>
MEASUREMENTS SAMPLES<br>
When a SCADA meter rather than a PMU meter is installed<br>
at one bus, we analyze how PMU measurements of th III. PMU MEASUREMENTS POPULATION AND SCADA<br>MEASUREMENTS SAMPLES<br>When a SCADA meter rather than a PMU meter is installed<br>at one bus, we analyze how PMU measurements of this bus can<br>be expressed by SCADA measurements. One m

CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>as the population, and one SCADA measurement (the time CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>as the population, and one SCADA measurement (the time Fig. 2. PMU and SCAD<br>stamp is  $tx1$  in Fig. 1) is taken as a sample of the subpopulation When a PMU meter is installed<br>of 50 P CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>as the population, and one SCADA measurement (the time<br>stamp is *tx*1 in Fig. 1) is taken as a sample of the subpopulation When a PMU met<br>of 50 PMU measurements (the time stamps ar CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time Fig. 2. PMU and SCADA measurement<br>
stamp is  $tx1$  in Fig. 1) is taken as a sample of the subpopulation When a PMU meter is in CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time<br>
stamp is tx1 in Fig. 1) is taken as a sample of the subpopulation<br>
of 50 PMU measurements (the time stamps are t1, t2, ... CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time<br>
stamp is tx1 in Fig. 1) is taken as a sample of the subpopulation<br>
of 50 PMU measurements (the time stamps are t1, t2, ... CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time<br>
stamp is xt in Fig. 1) is taken as a sample of the subpopulation<br>
of 50 PMU measurements (the time stamps are  $t1$ ,  $t2$ , . CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time<br>
stamp is  $x1$  in Fig. 1) is taken as a sample of the subpopulation<br>
of 50 PMU measurements (the time stamps are  $t1$ ,  $t2$ , CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time<br>
stamp is tx1 in Fig. 1) is taken as a sample of the subpopulation<br>
of 50 PMU measurements (the time stamps are t1, t2, ... CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time<br>
stamp is  $\kappa 1$  in Fig. 1) is taken as a sample of the subpopulation<br>
of 50 PMU measurements (the time stamps are  $t1$ ,  $t$ CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
as the population, and one SCADA measurement (the time<br>
stamp is *tx*1 in Fig. 1) is taken as a sample of the subpopulation<br>
of 50 PMU measurements (the time stamps are *t*1, *t*2 as the population, and one SCADA measurement (the time<br>stamp is *tx* l in Fig. 1) is taken as a sample of the subpopulation when a PMU meter is installed at is<br>of 50 PMU measurements (the time stamps are *t*1, *t2*, ... as the population, and one SCADA measurement (the time<br>stamp is  $\kappa 1$  in Fig. 1) is taken as a sample of the subpopulation<br>of 50 PMU measurements (the time stamps are  $t1$ ,  $t2$ , ...  $t50$  in<br>SCADA meter is installed<br>Fi as the population, and one SCADA measurement (the time<br>stamp is  $\kappa$ 1 in Fig. 1) is taken as a sample of the subpopulation<br>of 50 PMU measurements (the time stamps are  $t1$ ,  $t2$ , ...  $t50$  in SCADA meter is installed a<br>f stamp is  $\kappa$ 1 in Fig. 1) is taken as a sample of the subpopulation<br>of 50 PMU measurements (the time stamps are  $t1$ ,  $t2$ , ...  $t50$  in SCADA meter is installed at a<br>Fig. 1) in the first second. Therefore, an unbiased e of 50 PMU measurements (the time stamps are  $t1$ ,  $t2$ , ...  $t50$  in<br>
Fig. 1) in the first second. Therefore, an unbiased estimator of<br>
the PMU mad SCADA measurements and the PMU measurements are botained<br>
the poultaion m Fig. 1) in the first second. Therefore, an unbiased estimator of the parameter can be detected<br>the population mean of the PMU measurements can be obtained the PMU at SCADA measurement<br>from the sample manusum is in the SCA the population mean of the PMU measurements can be obtained<br>
from the sample mean of the SCADA measurements in the the analysis. In Fig. 2, a PMU<br>
abundant measurement samples. The population distribution<br>
abundant measur measurements.



[48]-[52].

PMU<br>
Population differ. At *bus j*, the PDF c<br>
Fig. 1. Inconsistent sampling time of PMU and SCADA measurements<br>
Fig. 1. Inconsistent sampling time of PMU and SCADA measurements<br>
Population  $|U_j|'$ , we propose a PPII<br>
IV. Population 11 2 150 151 152 1100<br>
an be expressed us<br>  $\frac{1}{2}$  time<br>  $\frac{1}{2$ Example the Fig. 1. Inconsistent sampling time of PMU and SCADA measurements<br>
Fig. 1. Inconsistent sampling time of PMU and SCADA measurements<br>
IV. LINE PARAMETER DETECTION<br>
A. PDF Parameters of Measurements<br>
The GMM is t Fig. 1. Inconsistent sampling time of PMU and SCADA measurements<br>
TV. LINE PARAMETER DETECTION<br>
The GMM is the weighted finite sum of several Gaussian<br>
The GMM is the weighted finite sum of several Gaussian<br>
The GMM is th EV. INSERT SURFAINETER DETECTION<br>  $\mu$  and  $\mu$  an IV. LINE PARAMETER DETECTION<br>
A. PDF Parameters of Measurements<br>
The GMM is the weighted finite sum of several Gaussian<br>
The CMM is the weighted finite sum of several Gaussian<br>
1991– $\sum_{k=1}^{K} 100 \times$ <br>
1991– $\sum_{k=1}^{K} 10$ A. PDF Parameters of Measurements<br>
The GMM is the weighted finite sum of several Gaussian<br>
There, K can be determined by<br>
components. Mathematically, the PDF can be expressed as in<br>
is influenced by load fluctuation<br>
[48] A. PDF Parameters of Measurements<br>
The GMM is the weighted finite sum of several Gaussian<br>
The CMM is the weighted finite sum of several Gaussian<br>
is influenced by load fluctuation.<br>
[48]-[52].<br>
We assume that the PDF of The GMM is the weighted finite sum of several Gaussian<br>
verg K can be determined by the v<br>
(48)-[52].<br>
We assume that the PDF of the measurement data is the<br>
distribution, if the PPII is  $K$  in  $\frac{1}{2}$ <br>
Gaussian PDF or components. Mathematically, the PDF can be expressed as in is influenced by load fluctuation magnitude is a Gaussian PDI<br>We assume that the PDF of the measurement data is the distribution, if the PPII is green<br>Gaussian PD [48]-[52]. magnitude is a Gaussian PI<br>
We assume that the PDF of the measurement data is the distribution, if the PPII is gre<br>
Gaussian PDF or the GMM PDF. The advantage of the GMM<br>
distribution, if the PPII is gre<br>
distr We assume that the PDF of the measurement data is the distribution, if the PPII is<br>Gaussian PDF or the GMM PDF. The advantage of the GMM<br>distributions can be fairly represented by several normal threshold experimentally.<br> Gaussian PDF or the GMM PDF. The advantage of the GMM<br>
cases, this line param<br>
approach is that the different types of the measurement<br>
distributions can be fairly represented by several normal<br>
distributions. The paramet approach is that the different types of the measurement threshold experimentally. For distributions can be fairly represented by several normal therehold of PPII is K mult distributions. The parameters of the GMM PDF can distributions can be fairly represented by several normal<br>distributions. The parameters of the GMM PDF can be<br>determined using the RNM algorithm [53]. The EM algorithm obtains the parameter set by<br>algorithm [53]. The EM a distributions. The parameters of the GMM PDF can be<br>determined using the expectation maximization (EM)<br>algorithm [53]. The EM algorithm obtains the parameters et by<br>iterating between the E-step and M-step until convergenc determined using the expectation maximization (EM)<br>algorithm [53]. The EM algorithm obtains the parameter set by<br>tierating between the Estep and M-step until convergence has<br>been reached (49), [54], [55]. However, the fin *B. PPII of Line Parameter Detection*<br>*B. PPII of Line Parameter Set operation reading between the E-step and M-step unil convergence has*<br>been reached [49], [54], [55]. However, the final solution is<br>very sensitive to the



Fig. 2. PMU and SCADA measurements of the line<br>PMU meter is installed at one bus of the line and a<br>neter is installed at another bus of the same line, the<br>eter can be detected and identified. The location of Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>'ADA meter is installed at another bus of the same line, the<br>e parameter can be detected and identified. The locatio Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The loc Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The lo Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The loc Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The loc Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The loc Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The loc Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA measurements of the similar another bus of the same line, the<br>line parameter can be detected and identified. Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line<br>SCADA meter is installed at another bus of the same l<br>line parameter can be detected and identified. The locitie PMU and Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>'ADA meter is installed at another bus of the same line, the<br>e parameter can be detected and identified. The locati Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The lo Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA measurements installed another bus of the same line, the<br>line parameter can be detected and identified. The l SCADA meter is installed at another bus of the same line, the<br>sCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The location of<br>the PMU and SCADA measurements in Fig. 2. PMU and SCADA measurements of the line<br>When a PMU meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The lo MU and SCADA measurements of the line<br>meter is installed at one bus of the line and a<br>installed at another bus of the same line, the<br>h be detected and identified. The location of<br> $SDA$  measurements in Fig. 2 is an example Fig. 2. PMU and SCADA measurements of the line<br>SCADA meter is installed at one bus of the line and a<br>SCADA meter is installed at another bus of the same line, the<br>line parameter can be detected and identified. The locatio

$$
|U_j|' = |U_i - I_{ij}(R + jX)| \tag{1}
$$

i, the theory of the proposed method is similar to that of the locations in Fig. 2.<br>
According to Section III, in the abundant measurement<br>
snapshots,  $U_i$  and  $I_{ij}$  are the population of the voltage phasor<br>
and current locations in Fig. 2.<br>According to Section III, in the abundant measurement<br>snapshots,  $U_i$  and  $I_{ij}$  are the population of the voltage phasor<br>and current phasor, respectively, and  $|U_j|$  is the samples of<br>voltage magnitu According to Section III, in the abundant measurement<br>snapshots,  $U_i$  and  $I_{ij}$  are the population of the voltage phasor<br>and current phasor, respectively, and  $|U_j|$  is the samples of<br>voltage magnitude. According to Ohm' line parameter can be detected and identited. The location of<br>the PMU and SCADA measurements in Fig. 2 is an example of<br>the analysis. In Fig. 2, a PMU meter is installed at *bus j*, and a<br>scADA meter is installed at *bus* not rive and so-rxibr measurements in rig.  $z$  is an example of<br>the analysis. In Fig. 2, a PMU meter is installed at *bus i*, and a<br>SCADA meter is installed at *bus j* and a SCADA meter is installed at *bus*<br>*i*, the voltage magnitude. According to Ohm's law, the  $|U_j|$  based on the line impedance is given as  $|U_j|' = |U_i - I_{ij}(R + jX)|$ <br>If the line impedance is correct, the mean of the is the same as the mean of the population  $|U_j|'$ . H<br>li at bus j and a SCADA meter is installed at bus<br>
e proposed method is similar to that of the<br>
.<br>
.<br>
.<br>
Section III, in the abundant measurement<br>  $\int_{l_a}$  are the population of the voltage phasor<br>  $r$ , respectively, and  $|U$  $U_i - I_{ij}(R + jX)$  (1)<br>
s correct, the mean of the samples  $|U_j|$ <br>
f the population  $|U_j|'$ . However, if the<br>
rect, the means of the samples and<br> *i*, the PDF of the voltage magnitude<br>
a GMM PDF or a Gaussian PDF.<br>
the sample *f*(1)<br> *k* mean of the samples  $|U_j|$ <br>
lation  $|U_j|'$ . However, if the<br>
means of the samples and<br> *F* of the voltage magnitude<br>
PDF or a Gaussian PDF.<br> *k*  $|U_j|$  with the mean of the<br>
PII to realize incorrect line<br>
PII *Five meta is instanted at bus <i>j*, Mote that when a PMU and a SCADA meter is installed at *bus*  $\mu$ . Note that when a PMU and a SCADA meter is installed at *bus* obosed method is similar to that of the 1 III, in the abu alled at *bus j.* Note that when a PMU<br> *sj* and a SCADA meter is installed at *bus*<br>
oposed method is similar to that of the<br>
oposed method is similar to that of the<br>
oposed method is similar to that of the<br>
oposed metho If the line impedance is correct, the mean of the samples  $|U_j|$ <br>the same as the mean of the population  $|U_j|'$ . However, if the<br>e impedance is incorrect, the means of the samples and<br>pulation differ. At *bus j*, the PDF is the same as the mean of the population  $|U_j|'$ . However, if the<br>line impedance is incorrect, the means of the samples and<br>population differ. At *bus j*, the PDF of the voltage magnitude<br>can be expressed using a GMM PDF is the same as the mean of the population  $|U_j|$ . However, if the<br>line impedance is incorrect, the means of the samples and<br>population differ. At *bus j*, the PDF of the voltage magnitude<br>can be expressed using a GMM PDF

$$
PPII = \sum_{k=1}^{K} 100 \times \frac{\left| \mu_k^j \right|^{r} - \mu_k^j}{\mu_k^j}
$$
 (2)

line impedance is incorrect, the means of the samples and<br>population differ. At *bus j*, the PDF of the voltage magnitude<br>can be expressed using a GMM PDF or a Gaussian PDF.<br>Comparing the mean of the samples  $|U_j|$  with t population differ. At *bus j*, the PDF of the voltage magnitude<br>can be expressed using a GMM PDF or a Gaussian PDF.<br>Comparing the mean of the samples  $|U_j|$  with the mean of the<br>population  $|U_j|'$ , we propose a PPII to re can be expressed using a GMM PDF or a Gaussian PDF.<br>Comparing the mean of the samples  $|U_j|$  with the mean of the<br>population  $|U_j|'$ , we propose a PPII to realize incorrect line<br>parameter detection:<br> $PPII = \sum_{k=1}^{K} 100 \times \$ Comparing the mean of the samples  $|U_j|$  with the mean of the<br>population  $|U_j|$ , we propose a PPII to realize incorrect line<br>parameter detection:<br> $PPII = \sum_{k=1}^{K} 100 \times \frac{||\mu_k^j||^2 - \mu_k^j||}{\mu_k^j}$  (2)<br>Here, *K* can be deter population  $|U_j|'$ , we propose a PPII to realize<br>parameter detection:<br> $PPII = \sum_{k=1}^{K} 100 \times \frac{||\mu_k||' - \mu_k||}{|\mu_k|}$ <br>Here, K can be determined by the voltage mag<br>is influenced by load fluctuation. When the PDF<br>magnitude is a etection:<br>
PPII =  $\sum_{k=1}^{K} 100 \times \frac{||\mu_k^j||^2 - \mu_k^j||}{\mu_k^j}$  (2)<br>
an be determined by the voltage magnitude, which<br>
d by load fluctuation. When the PDF of the voltage<br>
is a Gaussian PDF, K is one. For a Gaussian<br>
if the **PPII** =  $\sum_{k=1}^{n} 100 \times \frac{P^2 + 2k}{\mu_k^2}$  (2)<br>
Here, *K* can be determined by the voltage magnitude, which<br>
is influenced by load fluctuation. When the PDF of the voltage<br>
magnitude is a Gaussian PDF, *K* is one. For a Here, *K* can be determined by the voltage magnitude, which<br>influenced by load fluctuation. When the PDF of the voltage<br>ignitude is a Gaussian PDF, *K* is one. For a Gaussian<br>itribution, if the PPII is greater than one th Fractal single and the sample of the samples  $|U_j|$  with the mean of the population  $|U_j|'$ , we propose a PPII to realize incorrect line<br>population  $|U_j|'$ , we propose a PPII to realize incorrect line<br>parameter detection: tribution, if the PPII is greater than one threshold in most<br>ses, this line parameter is incorrect. We determine this<br>reshold experimentally. For the GMM distribution, this<br>eshold of PPII is K multiplied by the threshold

$$
I_{ii}^{2}(R + jX) = \Delta P + \Delta Q = (P_{i} - P_{j}) + j(Q_{i} - Q_{j})
$$
 (3)

cases, this line parameter is incorrect. We determine this<br>threshold experimentally. For the GMM distribution, this<br>threshold of PPII is K multiplied by the threshold of the<br>Gaussian PDF.<br>V. LINE PARAMETER IDENTIFICATION<br> threshold experimentally. For the GMM distribution, this<br>threshold of PPII is K multiplied by the threshold of the<br>Gaussian PDF.<br>V. LINE PARAMETER IDENTIFICATION<br>A. PDF Parameters of Active and Reactive Power Loss<br>In Fig. threshold of PPII is K multiplied by the threshold of the<br>
Gaussian PDF.<br>
V. LINE PARAMETER IDENTIFICATION<br>
A. PDF Parameters of Active and Reactive Power Loss<br>
In Fig. 2, the expression of the line parameter identificati Gaussian PDF.<br>
V. LINE PARAMETER IDENTIFICATION<br>
A. PDF Parameters of Active and Reactive Power Loss<br>
In Fig. 2, the expression of the line parameter identification<br>
can be given as<br>  $I_{ij}^2(R + jX) = \Delta P + \Delta Q = (P_i - P_j) + j(Q_i - Q_j)$  V. LINE PARAMETER IDENTIFICATION<br> *PDF Parameters of Active and Reactive Power Loss*<br>
In Fig. 2, the expression of the line parameter identification<br>
n be given as<br>  $I_{ij}^2(R + jX) = \Delta P + \Delta Q = (P_i - P_j) + j(Q_i - Q_j)$  (3)<br>
However, the

V. LINE PARAMETER IDENTIFICATION<br>
A. PDF Parameters of Active and Reactive Power Loss<br>
In Fig. 2, the expression of the line parameter identification<br>
can be given as<br>  $I_{ij}^2(R + jX) = \Delta P + \Delta Q = (P_i - P_j) + j(Q_i - Q_j)$  (3)<br>
However, t A. PDF Parameters of Active and Reactive P<br>In Fig. 2, the expression of the line parame<br>can be given as<br> $I_{ij}^2(R + jX) = \Delta P + \Delta Q = (P_i - P_j) + j(Q$ <br>However, the active and reactive power<br>precisely determined owing to the SCADA m<br>do *ij <sup>I</sup>* population, the GMM PDF parameters of the In Fig. 2, the expression of the line parameter identification<br>can be given as<br> $I_{\theta}^{2}(R + jX) = \Delta P + \Delta Q = (P_{i} - P_{j}) + j(Q_{i} - Q_{j})$  (3)<br>However, the active and reactive power loss cannot be<br>precisely determined owing to the SCAD can be given as<br>  $I_{ij}^2(R + jX) = \Delta P + \Delta Q = (P_i - P_j) + j(Q_i - Q_j)$  (3)<br>
However, the active and reactive power loss cannot be<br>
precisely determined owing to the SCADA measurements that<br>
do not match with the PMU measurements. First,  $I_{ij}^2(R + jX) = \Delta P + \Delta Q = (P_i - P_j) + j(Q_i - Q_j)$  (3)<br>However, the active and reactive power loss cannot be<br>precisely determined owing to the SCADA measurements that<br>do not match with the PMU measurements. First, we analyze<br>the PDF p *is K* multiplied by the threshold of the<br> *E* PARAMETER IDENTIFICATION<br> *is of Active and Reactive Power Loss*<br>
ression of the line parameter identification<br>  $= \Delta P + \Delta Q = (P_i - P_j) + j(Q_i - Q_j)$  (3)<br>
tive and reactive power loss

$$
\omega_k^{\Delta P} = \omega_k^{I_{ij}^2} = \omega_k^{P_i} = \omega_k^{P_j} \tag{4}
$$

$$
\mu_k^{\Delta P} = \mu_k^{T_i} - \mu_k^{T_j}
$$
\n
$$
\tau^{\Delta P} \approx \tau^{\frac{T_g^2}{2}}
$$
\n(6)

*j*  $\mu_k^{\Delta P} = \mu_k^{P_i} - \mu_k^{P_j}$  (5) time stamp and  $\sigma_k^{\Delta P} \approx \sigma_k^{I_{ij}^2}$  (5)  $\mu_k^{\Delta P} = \mu_k^{P_j} - \mu_k^{P_j}$  (5) time stamp and  $\sigma_k^{\Delta P} \approx \sigma_k^{I_{ij}^2}$  (6) measurements.<br>viation  $\sigma_k^{\Delta P}$  is equal to  $\sqrt{R^2 \times (\sigma_k^{I_{ij}^2})^2$ **EXECUTE AND IDENTIFICATION OF LINE PARAM**<br> **V** DISTRIBUTION GRIDS<br>  $P = \mu_k^p - \mu_k^{p_j}$  (5) time stamp a<br>  $\sigma_k^{\Delta P} \approx \sigma_k^{l_{\hat{B}}^2}$  (6) measurement<br>
tion  $\sigma_k^{\Delta P}$  is equal to  $\sqrt{R^2 \times (\sigma_k^{l_{\hat{B}}^2})^2}$ , and section, we JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARA<br>
SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>  $\mu_k^{\Delta P} = \mu_i^P_i - \mu_k^{P_i}$  (5) time stamp<br>  $\sigma_k^{\Delta P} \approx \sigma_k^{I_{ij}^2}$  (6) measurement<br>
Where the standard JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LIN<br>
SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>  $\mu_k^{\Delta P} = \mu_k^P - \mu_k^P$  (5) time<br>  $\sigma_k^{\Delta P} \approx \sigma_k^{l_k^2}$  (6) mean<br>
Where the standard deviation  $\sigma_k^{\Delta P}$  is

JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION<br>
SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>  $\mu_k^{\Delta P} = \mu_k^P - \mu_k^P$  (5)<br>  $\sigma_k^{\Delta P} \approx \sigma_k^{I_{\ell}^{\dagger}}$  (6)<br>
Where the standard deviation  $\sigma_k^{\Delta P}$  is equal to  $\sqrt$ *B.*  $\mu_k^{N} = \mu_k^{p_i} - \mu_k^{p_j}$  (5) time standard deviation  $\sigma_k^{N} \approx \sigma_k^{l_i^2}$  (6) measure phasor<br>
Where the standard deviation  $\sigma_k^{N}$  is equal to  $\sqrt{R^2 \times (\sigma_k^{l_i^2})^2}$ , and section, the standard deviation  $\sigma_k^{N}$  is a

 $\sigma_k^{ab} \approx \sigma_k^{i\frac{1}{2}}$  (6) measurements. The PMUs pro-<br>
Where the standard deviation  $\sigma_k^{ab}$  is equal to  $\sqrt{R^2 \times (\sigma_k^{i_1})^2}$ , and section, we obtain the PDF of  $\Delta P$ <br>
the standard deviation  $\sigma_k^{ab}$  is approximately eq Where the standard deviation  $\sigma_k^{AP}$  is equal to  $\sqrt{R^2 \times (\sigma_k^{I_0^+})^2}$ , and<br>the standard deviation  $\sigma_k^{AP}$  is approximately equal to  $\sigma_k^{I_0^+}$  when PMU measurements. The current<br>the resistance value in per-unit (p. where the standard deviation  $\sigma_k^{\alpha}$  is equal to  $\sqrt{k} \times (\sigma_k^*)^*$ , and section, we obtain the PDF of<br>the standard deviation  $\sigma_k^{\alpha}$  is approximately equal to  $\sigma_k^{\beta}$  when PMU measurements. The curr<br>the resistance val the standard deviation  $\sigma_x^{AP}$  is approximately equal to  $\sigma_x^{I_0}$  when PMU measurements. The current<br>the resistance value in per-unit (p.u.) is approximately one. with exact time stamps, and thus<br> $\Delta P$  based on the PDF the resistance value in per-unit (p.u.) is approximately one. with exact time stamps, and<br>
We can determine the GMM PDF of the active power loss<br>  $\Delta P$  based on the PDF parameters. Using the same method, the<br>
GMM PDF and We can determine the GMM PDF of the active power loss<br>  $\Delta P$  based on the PDF parameters. Using the same method, the<br>
GMM PDF and GMM PDF parameters of the reactive power<br>
the PMU time stamps can<br>
loss  $\Delta Q$  can be determ  $\Delta P$  based on the PDF parameters. Using the same method, the the exact time stamps. In economy<br>
GMM PDF and GMM PDF parameters of the reactive power<br>  $B$ . Nonparametric Kernel Density Estimation<br>  $P(\Delta P_i | I_i^2) = \frac{P(\Delta P_i)}{P$ GMM PDF and GMM PDF parameters of<br>loss  $\Delta Q$  can be determined.<br>B. Nonparametric Kernel Density Estimation<br>The PDF of the measurements can be<br>nonparametric kernel density estimation (<br>data-driven method. In a univariate K *Nonparametric Kernel Density Estimation*<br>
In the PDF of the measurements can be obtained from the<br>
parametric kernel density estimation (KDE), which is a<br>
dta-driven method. In a univariate KDE [56]-[58], the type of<br>
in *B. Nonparametric Kernel Density Estimation*  $P(\Delta P_r | I_r^2)$ <br>
The PDF of the measurements can be obtained from the<br>
nonparametric kernel density estimation (KDE), which is a<br>
data-driven method. In a univariate KDE [56]-[58 *B. Nonparametric Kernel Density Estimation*  $P(\Delta t)$ <br>
The PDF of the measurements can be obtained from the<br>
nonparametric kernel density estimation (KDE), which is a<br>
data-driven method. In a univariate KDE [56]-[58], the The PDF of the measurements can be obtained from the<br>nonparametric kernel density estimation (KDE), which is a<br>data-driven method. In a univariate KDE [56]-[58], the type of<br>interval [1, tm], and  $P(l$ <br>kernel function has nonparametric kernel density estimation (KDE), which is a<br>
data-driven method. In a univariate KDE [56]-[58], the type of interval [1, *tm*], and<br>
kernel function has very little effect on the accuracy of the KDE.<br>
Furthe data-tinven include. In a dinvariance KDE [50]-[50], the type of<br>
kernel function has very little effect on the accuracy of the KDE.<br>
Furthermore, the Gaussian kernel function has a wide range of<br>
applications [57], [59]-[ Furthermore, the Gaussian kernel function has a wide range of<br> *applications* [57], [59]-[62]. In this study, a Gaussian kernel<br>
function is selected as the kernel function. For a Gaussian<br>
kernel, the optimal bandwidth c

The active power loss at time *<sup>t</sup>*-1 affects the loss at time *<sup>t</sup>*, and

Francian in Fright, 1971 (160), the active power loss at time *t* affects that at time *t*-1. In this section, the condition [58], [63].<br>
In this study, a multivariate KDE with two-dimensional reflect the effects of the e where the optimal bandwidth can be determined as given in<br>
[58], [63].<br>
In this study, a multivariate KDE with two-dimensional<br>
reflect the effects of the<br>
In this study, a multivariate KDE with two-dimensional<br>
with the **EXECT THE STATE CONSTRANGE THE STATE STATE AT A SET AND THE SET AND THE SET AND IT IS SERIOR, IT IS USED IT IS** power loss at time  $\epsilon$  and at time stamp *t* and  $\epsilon$  are time stamps and a chronological probability model in this study, a multivariate normal distribution kernel, From the mass of and the multivariate interaction of  $\Delta P_i$ . The probability of  $\Delta P_i$  can be expressed as<br>
of  $\Delta P_i$  can be expressed as<br>  $\Delta P_i$  of  $\Delta P_i$  can be expressed as<br>  $\Delta P_i$  can be expressed as<br>  $\Delta P_i$  can be ex with the PMU time stamps and a chronological probability<br>model of the data. For a multivariate normal distribution kernel,<br>the optimal bandwidth can be determined as given in [64].<br>C. *Probability Model of Power Loss*<br>*1)* model of the data. For a multivariate normal distribution kernel,<br>the optimal bandwidth can be determined as given in [64].<br>*C. Probability Model of Power Loss*<br>*1) Chronological Probability Model*<br>The active power loss a *s*<br> *technique*<br> *distributio*<br> *ffects the loss at time t, and<br>
<i>s* that at time t+1. In other<br>
eceding time stamp affects<br>
(MCMC)<br>
onsider the pair of active<br>
d at time stamp t as an<br>
n of  $\Delta P_{t-1}$  has an impact on<br> *of Power Loss*<br> *bability Model*<br> *t*s at time *t*-1 affects the loss at time *t*, and<br> *t* time *t* affects that at time *t*+1. In other<br> *r* loss at the preceding time stamp affects<br>
ime stamp. Consider the pair of act *P*( $\Delta Q_i | I_i^2$ ) **a** and words the kennel function. For a Gaussian  $P(\Delta Q_i | I_i^2) = \frac{I(\Delta Q_i)}{P(\Delta Q_i | I_i^2)}$ <br> **a** multivariate KDE with two-dimensional reflect the effects of the exact [57] is used to develop a probability mode ussian kernel tunction has a wide range of<br>
Similary, we can<br>
bandwidth can be study, a Gaussian kernel<br>
as the kernel function. For a Gaussian<br>
bandwidth can be determined as given in<br>
multivariate KDE with two-dimension SI, [63].<br>
In this study, a multivariate KDE with two-dimensional<br>
melhed the exhibition wratelest EST] is used to develop a probability model<br>
measurement<br>
the the NNU time stamps and a chronological probability model<br>
o Probability Model<br>
loss at time t-1 affects the loss at time t, and<br>
sat time t-1 affects that at time t+1. In other<br>
sat time t affects that at time t+1. In other<br>
algorithm [67]-[69] is a<br>
wer loss at the preceding time [58], [63], [63], [63], [63], [63], [63], [63], [63], [63], [63], [63], [63], [63], [63], [1, *tm*], and correct interval measurements. Therefore, pDF's (9) and (10) and interval for this study, a multivariate KDE with tw the active power loss at time *t* affects that at time *t*+1. In other<br>words, the active power loss at the preceding time stamp affects<br>what at the following time stamp consider the pair of active<br>power losses at time sta

$$
P(\Delta P_t | \Delta P_{t-1}) = \frac{P(\Delta P_t, \Delta P_{t-1})}{P(\Delta P_{t-1})}
$$
\n<sup>(7)</sup>

words, the active power loss at the preceding time stamp articets<br>
that at the following time stamp. Consider the pair of active<br>
hould generate random view losses at time stamp *t*-1 and at time stamp it as an<br>
example. that at the following time stamp. Consider the parameter power losses at time stamp  $t$ -1 and at time stand example. The probability distribution of  $_{\Delta P_t}$ . The conditiona of  $_{\Delta P_t}$  can be expressed as  $P(\Delta P_t | \Delta P_{t-1})$ are data within the time interval [1,  $t \rightarrow P(AP_{i-1})$ ] are calculated using the and the stamp of  $\Delta P_{i-1}$  has an impact on  $\int_{0}^{2\pi} \frac{P(\Delta P_{i} \Delta P_{i-1})}{P(\Delta P_{i-1})}$  (7) The expression of the power later *Parameter Identif* model of the data. For a multivariate normal distribution kernel, *D. Sampling Alg*<br>
the optimal bandwidth can be determined as given in [64]. Acceptance-rej<br> *C. Probability Model of Power Loss*<br> *D. Chronological Probab Acceptance-rejection* sample the distribution, and then these termine as given in [0+j).<br> *Acceptance-rejection* sample the distribution, and then these valid distribution, and then these valid at time *t*-1 affects the are time stamp t as an distribution as the proposal PE<br>
e conditional PDF value<br>
constant variance  $\sigma_q$ .<br>
E. Line Parameter Identification<br>
based on the univariate<br>  $\left[\begin{matrix}I_{ij}^2 & I_{ij}\end{matrix}\right] \left[\begin{matrix}R\end{matrix}\right]$ <br>
(7) The expr the probability distribution of  $\Delta P_i$ . The conditional PDF value<br>
of  $\Delta P_i$  can be expressed as<br>  $P(\Delta P_i | \Delta P_{i-1}) = \frac{P(\Delta P_i, \Delta P_{i-1})}{P(\Delta P_{i-1})}$  (7) The expression of the 1<br>
Where  $P(\Delta P_{i-1})$  can be calculated based on the of  $\Delta P_i$  can be expressed as<br>  $P(\Delta P_i | \Delta P_{i-1}) = \frac{P(\Delta P_i, \Delta P_{i-1})}{P(\Delta P_{i-1})}$ <br>
Where  $P(\Delta P_{i-1})$  can be calculated based on the<br>
KDE for the time interval [1, *tm*], and  $P(\Delta P_i, \Delta P_{i-1})$ <br>
calculated based on the multivaria  $\Delta P_i$  can be expressed as<br>  $P(\Delta P_i \mid \Delta P_{i-1}) = \frac{P(\Delta P_i, \Delta P_{i-1})}{P(\Delta P_{i-1})}$  (7) The expression of the p<br>
matrix equation:<br>
Where  $P(\Delta P_{i-1})$  can be calculated based on the univariate<br>
DE for the time interval [1, *tm*], an st at time t affects that time  $t = 1$ , nother<br>
state preceding time stamp affects (MCMC) scheme. For MH sampling, the<br>
state preceding time stamp affects the pair of active<br>
should generate random variates conver<br>
g time consider the pair of active<br>
should generate random variates consider the pair of active<br>
of a t time stamp t as an fixed distribution [70]. In this study<br>
of  $\Delta P_{r-1}$  has an impact on<br>  $\frac{1}{2}$ . Line Parameter Identif matrix equa<br>based on the univariate<br>
nd  $P(\Delta P_r, \Delta P_{r-1})$  can be<br>
DE for the time interval<br>
e not time series samples, stamps and<br>
within the time interval [1, PDFs of (<br>
are calculated using the measuremer<br>
e sample in th *t* be calculated based on the univariate<br> *t*rval [1, *tm*], and  $P(\Delta P_t, \Delta P_{t-1})$  can be<br> *t* multivariate KDE for the time interval<br> *xer*-loss data are not time series samples,<br>  $\Delta P_{t-1}$  are data within the time inte **EXECTE AS at the** *T* at the *F* at the *F* and the *F* and the *F* and the measurement radio and the mannous obver loss at the preceding time stamp a fifted showed generate radio in tracks consider the pair of active sh preceding time stamp attects<br>
consider the pair of active<br>
and at time stamp t as an invact on<br>
time stamp t as an invact on<br>  $P_{r_1}$ ,  $\Delta P_{r_{r-1}}$  has an impact on<br>  $P_{r_2}$ ,  $\Delta P_{r_{r-1}}$  has an impact on<br>  $P_{r_1}$ ,  $P_{$ loss at time *t*-1 affects the loss at time *t*, and<br>according to a crute<br>as at time *t*-1. In other<br>as the preceding time stamp affects that at time *t*-1. In other<br>wer loss at the preceding time stamp *t* as an fixed di Where  $P(AP_{i-1})$  can be calculated based on the univariate<br>
DE for the time interval [1, tm], and  $P(\Delta P_i, \Delta P_{i-1})$  can be<br>
culated based on the multivariate KDE for the time interval<br>
By MH sampling, a lot<br>
tm]. Because t KDE for the time interval [1, *tm*], and  $P(\Delta P_i, \Delta P_{i-1})$  can be<br>calculated based on the multivariate KDE for the time interval<br>[1, *tm*]. Because the power-loss data are not time series samples, stam<br>the samples of  $\Delta P_i$ calculated based on the multivariate KDE for the time interval<br>
[1, *tm*]. Because the power-loss data are not time series samples, stamps and<br>
the samples of  $\Delta P_r$  and  $\Delta P_{r-1}$  are data within the time interval [1, PD *tm*]. Because the power-loss data are not time series samples, stamps and chronological corresamples of  $\Delta P_i$  and  $\Delta P_{i-1}$  are data within the time interval [1, PDFs of (7), (8), (9), and <br>J when  $P(\Delta P_i, \Delta P_{i-1})$  and the samples of  $\Delta P_i$  and  $\Delta P_{i-1}$  are data within the time interval [1, PDFs of (7), (8), (9)<br> *tm*] when  $P(\Delta P_i, \Delta P_{i-1})$  and  $P(\Delta P_{i-1})$  are calculated using the sampshots, Equation (11)<br>
measurement data.<br>
Similarly

$$
P(\Delta Q_{t} | \Delta Q_{t-1}) = \frac{P(\Delta Q_{t}, \Delta Q_{t-1})}{P(\Delta Q_{t-1})}
$$
 (8) can be taken into

TECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PMU AND UNSYNCHRONIZ<br>
UTION GRIDS<br>
(5) time stamp and do not contain the time stamps c<br>
(6) measurements. The PMUs provide accurate sy<br>
is equal to  $\sqrt{R^2 \times (\sigma_k^{l_s^2})^2}$ ATION OF LINE PARAMETERS WITH PMU A<br>
(5) time stamp and do not contain<br>
measurements. The PMUs p<br>
phasor measurements and have<br>
section, we obtain the PDF of<br>
when PMU measurements. The currency<br>
with exact time stamps, a VEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WI<br>  $= \mu_k^{p_i} - \mu_k^{p_j}$  (5) time stamp and do not<br>  $\sigma_k^{\Delta P} \approx \sigma_k^{l_0^2}$  (6) measurements. The l<br>
phasor measurements<br>
on  $\sigma_k^{\Delta P}$  is equal to  $\sqrt{R^2 \times (\sigma_k^{l_0^2})^2}$ , the standard deviation  $\sigma_k^{\Delta P}$  is approximately equal to  $\sigma_k^{I_{ij}^2}$  when PMU measurements. The current  $I_{ij}$  is the PMU measurements JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH P<br>
SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>  $\mu_k^{\Delta F} = \mu_k^{\mu} - \mu_k^{\mu}$  (5) time stamp and do not co<br>  $\sigma_k^{\Delta F} \approx \sigma_k^{\ell_k^1}$  (6) measu PING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PMU.<br>
ADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>  $\mu_k^{A^P} = \mu_k^{P_i} - \mu_k^{P_i}$  (5) time stamp and do not contain<br>
there the standard deviation *<sup>P</sup>* based on the PDF parameters. Using the same method, the JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PM<br>
SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>  $\mu_k^{ab} = \mu_k^{r_i} - \mu_k^{r_i}$  (5) time stamp and do not cont<br>  $\sigma_k^{ab} \approx \sigma_k^{r_i}$  (6) measureme  $\mu_k^{2\nu} = \mu_k^{i\ell} - \mu_k^{i\ell}$  (5) time stamp and do not contain<br>  $\sigma_k^{2\nu} \approx \sigma_k^{i\ell}$  (6) measurements. The PMUs pri<br>
here the standard deviation  $\sigma_k^{2\nu}$  is equal to  $\sqrt{R^2 \times (\sigma_k^{i\ell})^2}$ , and section, we obtain the PDF F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>sect F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>sect F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>sect F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>sect F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>sect *i* JUNSYNCHRONIZED 5<br> *i* the time stamps of the PMU<br> *i* vide accurate synchronized<br> *i* high sampling rate. In this<br> *i* with the time stamps of the<br> *i*<sub>*i*</sub> is the PMU measurements<br> *i*<sub>*i*</sub> is the measurements with<br> F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>sect **i** UNSYNCHRONIZED 5<br> **i** if the measurements of the PMU<br> **ide** accurate synchronized<br>
high sampling rate. In this<br>
with the time stamps of the<br>  $I_{ij}$  is the PMU measurements<br>  $I_{ij}^2$  is the measurements with<br>
onal PDF F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>sect FLINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>secti the PMU time stamps can be obtained when the current  $I_{ii}$  is FLINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>secti EXECT: WITH PMU AND UNSYNCHRONIZED 5<br>
2 (or to contain the time stamps of the PMU<br>
2 (PMUs provide accurate synchronized<br>
2 (or the PDF of  $\Delta P_i$  with the time stamps of the<br>
3. The current  $I_{ij}$  is the PMU measurements<br> (a) UNSYNCHRONIZED 5<br>
the time stamps of the PMU<br>
ovide accurate synchronized<br>
a high sampling rate. In this<br>  $P_t$  with the time stamps of the<br>  $I_y$  is the PMU measurements<br>  $I_y^2$  is the measurements with<br>
tional PDF val The stamps of the PMU<br>
ide accurate synchronized<br>
high sampling rate. In this<br>
with the time stamps of the<br>  $I_{ij}$  is the PMU measurements<br>  $I_{ij}^2$  is the measurements with<br>
ional PDF value of  $\Delta P_i$  with<br>
inned when the *t* contain the time stamps of the PMI<br>
PMUs provide accurate synchronize<br>
and have a high sampling rate. In this<br>
PDF of  $\Delta P_i$  with the time stamps of th<br>
the current  $I_{ij}$  is the PMU measurements<br>
is, and thus,  $I_{ij}^$ *thereta in the time stamps of the PMU*<br> *the PMUs provide accurate synchronized*<br> *the PMUs provide accurate synchronized*<br> *ents and have a high sampling rate. In this the PDF of*  $\Delta P_i$  *with the time stamps of the ts. T* **Example 10**<br> **P** I the time stamps of the PMU<br> **P** rovide accurate synchronized<br> **P** a high sampling rate. In this<br>  $\Delta P_i$  with the time stamps of the<br> **P**  $I_{ij}$  is the PMU measurements<br> **S**,  $I_{ij}^2$  is the measurement NE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>
e stamp and do not contain the time stamps of the PMU<br>
asurements. The PMUs provide accurate synchronized<br>
asor measurements and have a high sampling rate. In this<br>
tion, we o FLINE PARAMETERS WITH PMU AND UNSYNCHRONIZED 5<br>time stamp and do not contain the time stamps of the PMU<br>measurements. The PMUs provide accurate synchronized<br>phasor measurements and have a high sampling rate. In this<br>pecti section, we obtain the PDF of  $\Delta P_i$  with the time stamps of the<br>PMU measurements. The current  $I_{ij}$  is the PMU measurements<br>with exact time stamps, and thus,  $I_{ij}^2$  is the measurements with<br>the exact time stamps. The AU measurements. The current  $I_y$  is the PMU measurements<br>th exact time stamps, and thus,  $I_y^2$  is the measurements with<br>exact time stamps. The conditional PDF value of  $\Delta P_i$  with<br>PMU time stamps can be obtained when th If the model of the exact the stamps of the PMU<br>
2 (PMUs provide accurate synchronized<br>
2 (PMUs provide accurate synchronized<br>
this and have a high sampling rate. In this<br>
3. The current  $I_{ij}$  is the PMU measurements<br>
mp he time stamps of the PMU<br>vide accurate synchronized<br>a high sampling rate. In this<br>; with the time stamps of the<br> $I_y$  is the PMU measurements<br> $I_y^2$  is the measurements with<br>ional PDF value of  $\Delta P_i$  with<br>ained when the c  $t_{ij}$  and PDF value of  $\Delta P_i$  with<br>
red when the current  $I_{ij}$  is<br>
red at *bus i*.<br>  $\left(\frac{I_i^2}{2}\right)$  (9)<br>
univariate KDE for the time<br>
is calculated based on<br>
val [1, *tm*].<br>
ditional PDF value of  $\Delta Q_i$ .<br>  $\frac{I_i^2}{I_i^2$ The conditional PDF value of  $\Delta P_t$  with<br>can be obtained when the current  $I_y$  is<br>neter installed at *bus i*.<br> $|I_t^2| = \frac{P(\Delta P_t, I_t^2)}{P(I_t^2)}$  (9<br>assed on the univariate KDE for the time<br> $P(\Delta P_t, I_t^2)$  is calculated based on **thereoff The EXECT CONDUCTE THE CONDUCTE AND UNSYNCHRONIZED** 5<br> **to** not contain the time stamps of the PMU<br>
the PMUs provide accurate synchronized<br>
the PDF of  $\Delta P$ , with the time stamps of the<br>
ths. The current  $I_{ij}$ 

$$
P(\Delta P_t | I_t^2) = \frac{P(\Delta P_t, I_t^2)}{P(I_t^2)}
$$
\n(9)

.

$$
P(\Delta Q_t | I_t^2) = \frac{P(\Delta Q_t, I_t^2)}{P(I_t^2)}\tag{10}
$$

In this section, the conditional PDF values of  $\Delta P$ , the PMU ime stamps can be obtained when the current  $I_{ij}$  is obtained from a PMU meter installed a *bus i*.<br>  $P(\Delta P_i | I_i^2) = \frac{P(\Delta P_i, I_i^2)}{P(I_i^2)}$  (9)<br>  $P(I_i^2)$  is calc obtained from a PMU meter installed at *ous t*.<br>  $P(\Delta P_r | I_r^2) = \frac{P(\Delta P_r, I_r^2)}{P(I_r^2)}$  (9)<br>  $P(I_r^2)$  is calculated based on the univariate KDE for the time<br>
interval [1, *tm*], and  $P(\Delta P_r, I_r^2)$  is calculated based on<br>
mult  $P(\Delta P_i | I_i^2) = \frac{P(\Delta P_i, I_i^2)}{P(I_i^2)}$  (<br>  $P(I_i^2)$  is calculated based on the univariate KDE for the tin<br>
interval [1, *tm*], and  $P(\Delta P_i, I_i^2)$  is calculated based (<br>
multivariate KDE for the time interval [1, *tm*].<br>
Simila *P*( $I_i^2$ ) is calculated based on the univariate KDE for the<br>interval [1, *tm*], and *P*( $\Delta P_i, I_i^2$ ) is calculated based<br>multivariate KDE for the time interval [1, *tm*].<br>Similarly, we can obtain the conditional PDF val

a chronological probability<br>
te normal distribution kernel,<br>
te normal distribution kernel,<br>
mined as given in [64]. Acceptance-rejection same<br>
del distribution, and then these<br>
affects the loss at time t, and<br>
according 2) (3) and some solution of a criterion. For a Gaussian<br>
at as the kernel function. For a Gaussian<br>
this section, the conditional PDF<br>
multivariate KDE with two-dimensional<br>
reflect the effects of the exact tim<br>
77] is u Francoin: To a Coalassian<br>
DE with two-dimensional reflect the effects of the exact time<br>
lobe determined as given in In this section, the conditional PIC,<br>
chronological probability model measurements. Therefore, PDFs (9 e *t*, and<br>
n other<br>
algorithm [67]-[69] is a famous<br>
affects<br>
(MCMC) scheme. For MH samp<br>
should generate random variates<br>
as an<br>
distribution as the proposal PD<br>
constant variance  $\sigma_q$ .<br>
E. Line Parameter Identificatio erval [1, *tm*], and  $P(\Delta P_i, I_i^2)$  is calculated based on<br>ultivariate KDE for the time interval [1, *tm*].<br>Similarly, we can obtain the conditional PDF value of  $\Delta Q_i$ .<br> $P(\Delta Q_i | I_i^2) = \frac{P(\Delta Q_i, I_i^2)}{P(I_i^2)}$  (10)<br>In this sec the random variate KDE for the time interval [1, tm].<br>
Similarly, we can obtain the conditional PDF value of  $\Delta Q_i$ .<br>  $P(\Delta Q_i | I_i^2) = \frac{P(\Delta Q_i, I_i^2)}{P(I_i^2)}$  (10)<br>
In this section, the conditional PDF values of  $\Delta P_i$  and  $\Delta$ multivariate KDE for the time interval [1, *m*].<br>
Similarly, we can obtain the conditional PDF value of  $\Delta Q_i$ .<br>  $P(\Delta Q_i | I_i^2) = \frac{P(\Delta Q_i, I_i^2)}{P(I_i^2)}$  (10)<br>
In this section, the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br> Similarly, we can obtain the conditional PDF value of  $\Delta Q_i$ .<br>  $P(\Delta Q_i | I_i^2) = \frac{P(\Delta Q_i, I_i^2)}{P(I_i^2)}$  (10)<br>
In this section, the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>
reflect the effects of the exact time stamps of th  $P(\Delta Q_i | I_i^2) = \frac{P(\Delta Q_i, I_i^2)}{P(I_i^2)}$  (10)<br>
In this section, the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>
reflect the effects of the exact time stamps of the PMU<br>
measurements. Therefore, PDFs (9) and (10) are power-los In this section, the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>reflect the effects of the exact time stamps of the PMU<br>measurements. Therefore, PDFs (9) and (10) are power-loss<br>PDFs with PMU time stamps.<br>D. *Sampling Al* In this section, the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>reflect the effects of the exact time stamps of the PMU<br>measurements. Therefore, PDFs (9) and (10) are power-loss<br>PDFs with PMU time stamps.<br>*D. Sampling Al* reflect the effects of the exact time stamps of the PMU<br>measurements. Therefore, PDFs (9) and (10) are power-loss<br>PDFs with PMU time stamps.<br>D. Sampling Algorithm<br>Acceptance-rejection sampling (ARS) [65]-[66] is a<br>distrib interval [1, *tm*], and  $P(\Delta P_r, I_r^2)$  is calculated based on<br>multivariate KDE for the time interval [1, *tm*].<br>Similarly, we can obtain the conditional PDF value of  $\Delta Q_r$ .<br> $P(\Delta Q_r | I_r^2) = \frac{P(\Delta Q_r, I_r^2)}{P(I_r^2)}$  (10)<br>In this PDFs with PMU time stamps.<br>
D. *Sampling Algorithm*<br>
Acceptance-rejection sampling (ARS) [65]-[66] is a<br>
technique for generating random variates from an alternative<br>
distribution, and then these variates are accepted or *D. Sampling Algorithm*<br>
Acceptance-rejection sampling (ARS) [65]-[66] is a<br>
technique for generating random variates from an alternative<br>
distribution, and then these variates are accepted or rejected<br>
according to a cri Acceptance-rejection sampling (ARS) [65]-[66] is a<br>
shnique for generating random variates from an alternative<br>
stribution, and then these variates are accepted or rejected<br>
cording to a criterion. The Metropolis-Hastings technique for generating random variates frequencies distribution, and then these variates are according to a criterion. The Metropolis algorithm [67]-[69] is a famous Markov ch (MCMC) scheme. For MH sampling, the proposi of the exact time stamps of the PMU<br>erefore, PDFs (9) and (10) are power-loss<br>me stamps.<br>*iihm*<br>tion sampling (ARS) [65]-[66] is a<br>*iihm*<br>tion sampling (ARS) [65]-[66] is a<br>arating random variates from an alternative<br>enen the exact time stamps of the PMU<br> *I* rec, PDFs (9) and (10) are power-loss<br>
tamps.<br> *n*<br> **I** sampling (ARS) [65]-[66] is a<br> *I* sampling (ARS) [65]-[66] is a<br> *I* contractive these variates are accepted or rejected<br> *I*  $P(I_i^-)$ <br>
the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>
s of the exact time stamps of the PMU<br>
enerefore, PDFs (9) and (10) are power-loss<br>
ime stamps.<br>
orithm<br>
ection sampling (ARS) [65]-[66] is a<br>
erating random varia the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>s of the exact time stamps of the PMU<br>enerefore, PDFs (9) and (10) are power-loss<br>ime stamps.<br>*orithm*<br>ection sampling (ARS) [65]-[66] is a<br>erating random variates from an a litional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>
exact time stamps of the PMU<br>
PDFs (9) and (10) are power-loss<br>
pps.<br>
sampling (ARS) [65]-[66] is a<br>
andom variates from an alternative<br>
se variates are accepted or rejected<br>
. Th the conditional PDF values of  $\Delta P_i$  and  $\Delta Q_i$ <br>s of the exact time stamps of the PMU<br>enerefore, PDFs (9) and (10) are power-loss<br>ime stamps.<br>orithm<br>erection sampling (ARS) [65]-[66] is a<br>ecrating random variates from an by MH sampling, the moreover than the proposal distribution<br>
CIOC scheme. For MH sampling, the proposal distribution<br>
ould generate random variates conveniently and can be any<br>
ed distribution [70]. In this study, we choo **Example 12** and a method of rejected or rejected<br> **An**. The Metropolis-Hastings (MH)<br>
famous Markov chain Monte Carlo<br> **H** sampling, the proposal distribution<br>
variates conveniently and can be any<br> **In** this study, we

matrix equation: The expression of the power loss in  $(3)$  can be written as a

$$
\begin{bmatrix} I_{ij}^2 & I_{ij}^2 \end{bmatrix} \begin{bmatrix} R \\ X \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{11}
$$

should generate random variates conveniently and can be any<br>should generate random variates conveniently and can be any<br>fixed distribution [70]. In this study, we choose a normal<br>distribution as the proposal PDF  $q(x|X)$  w show given a faither and the matrix subseminary and can be any<br>fixed distribution as the proposal PDF  $q(x|X)$  with mean X and<br>distribution as the proposal PDF  $q(x|X)$  with mean X and<br>constant variance  $\sigma_q$ .<br>E. Line Param measurements can be proposal PDF  $q(x|X)$  with mean X and<br>
constant variance  $\sigma_q$ .<br>
E. Line Parameter Identification Algorithm<br>
The expression of the power loss in (3) can be written as a<br>
matrix equation:<br>  $\begin{bmatrix} I_q^2 \ I_q$ E. *Line Parameter Identification Algorithm*<br>
The expression of the power loss in (3) can be written as a<br>
matrix equation:<br>  $\begin{bmatrix} I_{ij}^2 & 0 \end{bmatrix} \begin{bmatrix} R \\ K \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$  (11)<br>
By MH sampling, a lot of power-Line Parameter Identification Algorithm<br>
The expression of the power loss in (3) can be written as a<br>
tirix equation:<br>  $\begin{bmatrix} I_i^2 & I_i^2 \end{bmatrix} \begin{bmatrix} R \\ X \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$  (11)<br>
By MH sampling, a lot of power-loss d

$$
x_{RX} = y_{PQ} \tag{12}
$$

Similarly, we can obtain the conditional PDF value of  $_{\Delta Q_i}$ . By using the total least squares (TLS) method, both the errors of the coefficient matrix A and observed data vector  $y_{pQ}$ The expression of the power loss in (3) can be written as a<br>matrix equation:<br> $\begin{bmatrix} I_{\vartheta}^2 & I_{\vartheta}^2 \end{bmatrix} \begin{bmatrix} R \\ R \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$  (11)<br>By MH sampling, a lot of power-loss data with PMU time<br>stamps and chrono matrix equation:<br>  $\begin{bmatrix} I_y^2 \\ I_y^2 \end{bmatrix} \begin{bmatrix} R \\ X \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$  (11)<br>
By MH sampling, a lot of power-loss data with PMU time<br>
stamps and chronological correlations are generated from the<br>
PDFs of (7), (8), (9  $\begin{bmatrix} I_{ij}^2 & 0 \ I_{ij}^2 & 0 \end{bmatrix} \begin{bmatrix} R \\ R \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$  (11)<br>By MH sampling, a lot of power-loss data with PMU time<br>stamps and chronological correlations are generated from the<br>PDFs of (7), (8), (9), and (10) By MH sampling, a lot of power-loss data with PMU time<br>stamps and chronological correlations are generated from the<br>PDFs of (7), (8), (9), and (10). Many current square<br>measurements can be obtained. In abundant measuremen *T<sub>q</sub>*  $\int_{a}^{T} \int_{a}^{T} F_{q}$ .<br> *T Identification Algorithm*<br>
of the power loss in (3) can be written as a<br>  $I_{ij}^{2} \left[ \begin{bmatrix} R \\ X \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$  (11)<br> *R<sub>i</sub>* a lot of power-loss data with PMU time<br>
logical co

$$
x_{RX} = (A^T A - \sigma_{T+1}^2 I)^{-1} A^T y_{PQ}
$$
 (13)

CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>where  $\sigma_{T+1}$  is the smallest singular value of the expanded time where  $\sigma_{T+1}$  is the smallest singular value of the expanded

CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>where  $\sigma_{r+1}$  is the smallest singular value of the expanded time references, but d<br>sample matrix  $[A, y_{PQ}]$ .<br>To show the proposed algorithm, the line parameter that of bus 1. The



generate  $\Delta P_i$  from  $P(\Delta P_i | \Delta P_{i-1})$  and  $P(\Delta P_i | P_i)$  by MH<br>output population of active power loss  $\Delta P_i$ <br>generate population of reactive power loss  $\Delta Q_i$  using the<br>same method in stage 1 and stage 2<br>identify line parame output population of active power loss  $\Delta P_i$ <br>
generate population of reactive power loss  $\Delta Q_i$  using the<br>
same method in stage 1 and stage 2<br>
identify line parameter identification)<br>
identify line parameter  $x_{\kappa x}$  by generate population of reactive power loss  $\Delta Q$ , using the<br>
same method in stage 1 and stage 2<br> **Stage 3**: (line parameter  $x_{\text{ex}}$  by TLS in (13)<br>
(See dientify line parameter  $x_{\text{ex}}$  by TLS in (13)<br>
VI. HARDWARE SIM shows the parameter identification in the hardware simulation in which the hardware simulation Settings<br>
A. Hardware Simulation Settings<br>
In this study, the PDF of the measurement data is assumed to<br>
be the Gaussian PDF o Stage 3: (line parameter identification)<br>
identify line parameter  $x_{xx}$  by TLS in (13)<br>
VI. HARDWARE SIMULATION RESULTS<br>
A. *Hardware Simulation Settings*<br>
In this study, the PDF of the measurement data is assumed to<br>
be identify line parameter  $x_{kX}$  by TLS in (13)<br>
VI. HARDWARE SIMULATION RESULTS<br>
A. *Hardware Simulation Settings*<br>
In this study, the PDF of the measurement data is assumed to<br>
be the Gaussian PDF or the GMM PDF; however Since II and the SIMULATION RESULTS<br>
A. Hardware Simulation Settings<br>
In this study, the PDF of the measurement data is assumed to<br>
be the Gaussian PDF or the GMM PDF; however, the PDF of<br>
the real measurements in the dist VI. HARDWARE SIMULATION RESULTS<br>
A. *Hardware Simulation Settings*<br>
In this study, the PDF of the measurement data is assumed to<br>
be the Gaussian PDF or the GMM PDF; however, the PDF of<br>
the real measurements in the distr A. Hardwide Simulation Settings<br>
In this study, the PDF of the measurement data is assumed to<br>
be the Gaussian PDF or the GMM PDF; however, the PDF of<br>
the real measurements in the distribution system is unknown.<br>
This se A. *Hardware Simulation Settings*<br>
In this study, the PDF of the measurement data is assumed to<br>
be the Gaussian PDF or the GMM PDF; however, the PDF of<br>
the real measurements in the distribution system is unknown.<br>
This In this study, the PDF of the measurement data is assumed to<br>be the Gaussian PDF or the GMM PDF; however, the PDF of<br>the real measurements in the distribution system is unknown.<br>This section discusses the performance of t be the Gaussian PDF or the GMM PDF; however, the PDF of<br>the real measurements in the distribution system is unknown.<br>This section discusses the performance of the proposed method<br>shows the hardware simulation in which two the real measurements in the distribution system is unknown.<br>
This section discusses the performance of the proposed method<br>
using the real measurements of the measuring equipment. Fig. 4. Hardway<br>
shows the hardware simu This section discusses the performance of the pr<br>using the real measurements of the measuring eq<br>shows the hardware simulation in which two t<br>line are deployed by measuring equipment<br>accuracies. The specific network topol In the real measurements of the measuring equipment. Fig. 4<br>
Transformer Current<br>
e are deployed by measuring equipment with different<br>
transformer Current<br>
currencies. The position extends that is used for<br>
the and Maxim shows the hardware simulation in which two terminals of the<br>
line are deployed by measuring equipment with different<br>
accuracies. The specific network topology of the hardware<br>
simulation is lustrated in Tables I and II.<br> From the are deployed by measuring equipment with different<br>
accuracies. The specific network topology of the hardware<br>
simulation is illustrated in Fig. 5. The equipment that is used for<br>
the hardware simulation is prese

L OF POWER AND ENERGY SYSTEMS<br>
is the smallest singular value of the expanded time references, but di<br>
measurements of bus 2 h<br>
the proposed algorithm, the line parameter<br>
is shown in Algorithm 1 and in the flow chart in<br> CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
where  $\sigma_{T+1}$  is the smallest singular value of the expanded time references, but different<br>
sample matrix  $[A, y_{PQ}]$ .<br>
To show the proposed algorithm, the line parameter that of time references, but different measuring accuracies. The<br>measurements of bus 2 have a lower measuring accuracy than<br>that of bus 1. Therefore, we randomly select one measurement<br>per second as one SCADA measurement per secon time references, but different measuring accuracies. The<br>measurements of bus 2 have a lower measuring accuracy than<br>that of bus 1. Therefore, we randomly select one measurement<br>per second as one SCADA measurement per secon time references, but different measuring accuracies. The<br>measurements of bus 2 have a lower measuring accuracy than<br>that of bus 1. Therefore, we randomly select one measurement<br>per second as one SCADA measurement per secon time references, but different measuring accuracies. The<br>measurements of bus 2 have a lower measuring accuracy than<br>that of bus 1. Therefore, we randomly select one measurement<br>per second as one SCADA measurement per secon time references, but different measuring accuracies. The<br>measurements of bus 2 have a lower measuring accuracy than<br>that of bus 1. Therefore, we randomly select one measurement<br>per second as one SCADA measurement per secon time references, but different measuring accuracies. The<br>measurements of bus 2 have a lower measuring accuracy than<br>that of bus 1. Therefore, we randomly select one measurement<br>per second as one SCADA measurement per secon time references, but different measuring ac<br>measurements of bus 2 have a lower measuring<br>that of bus 1. Therefore, we randomly select one<br>per second as one SCADA measurement per second<br>measurements of bus 1 and the SCADA m







JINPING SUN et al.: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PMU A<br>
SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>
THE MEASURENCE EQUIPMENT OF THE HARDWARE SIMULATION<br>
Name (or name in Fig. 5) Equipment SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>
THE MEASURNG EQUIPMENT OF THE HARDWARE SIMULATION<br>
Name (or name in Fig. 5) Equipment type<br>
Memory recorder HIOKI MR6000  $\text{mod}$  =0.1%<br>
Current sensor 2 FLUKE 308<br>
Current sensor THE MEASURING EQUIPMENT OF THE HARDWARE SIMULATION<br>
Memory recorder<br>
Memory recorder<br>
Memory recorder<br>
HOKI CT6862<br>
Current sensor 1<br>
HOKI CT6862<br>
Current sensor 1<br>
HOKI CT6862<br>
CHIVE 1308 (amplitude); 0.2° (phasor angle) THE MEASURING EQUIPMENT OF THE HARDWARE SIMULATION<br>
Memory recorder<br>
Measuring accuracy<br>
Measuring accuracy<br>
Measuring accuracy<br>
Current sensor 2<br>
EL **From 1,001** to 15,000. The PDF of the measurement data is the measurement sensor by the measurement sensor 2 FLUKE i306000 to the measurement sensor 2 FLUKE i306 to  $\frac{11\%}{40.9\%}$  (resistance):  $\frac{11\%}{40.9\%}$  (resi Memory recorder<br>
are the GMM PDF street assets in the constrained to be the GMM PDF when  $\frac{+0.1\%}{2}$ <br>
Current sensor 2<br>
Unity Collage sensor 2<br>
FLUKE i30s<br>
Current sensor 2<br>
FLUKE i30s<br>
Current sensor 2<br>
CHNT IDG4<br>
40.5 Current sensor 1<br>
Current sensor 2<br>
Current sensor 2<br>
Unit (DKIC COSE)<br>
Unit aloction of SCAL<br>
In this section, we identify the line parameters using 1) The number of SCAL<br>
Algorithm 1. The PDF of the measurement data is Collage sensor 2<br>
CHNT JDG4<br>
LEAT JDG4<br>
Digital electric bridge<br>
CCHNT JDG4<br>
Leading the Directric bridge<br>
CCHNT JDG4<br>
Algorithm 1. The PDF of the measurement data is assumed to to Section III, an unbiased estitive<br>
be a Digital electric bridge  $V4092A$   $\pm 0.3\%$  (resistance);  $\pm 0.3\%$  (induct<br>Algorithm 1. The PDF of the measurement data is assumed to to Section III, an unbiase<br>be a Gaussian PDF when  $K=1$ . In stage two of Algorithm 1, In this section, we identify the line parameters using 1) The number of Algorithm 1. The PDF of the measurement data is assumed to to Section III, an unk be a obtain 15,000 power-loss samples with PMU time stamps and samp gorithm 1. The PDF of the measurement data is assumed to to Section III, an unbiased<br>a Gaussian PDF when  $K=1$ . In stage two of Algorithm 1, we be given by the sample<br>tain 15,000 power-loss samples with PMU time stamps an be a Gaussian PDF when  $K=1$ . In stage two of Algorithm 1, we be given by the sample mean<br>obtain 15,000 power-loss samples with PMU time stamps and snapshots. When the number of<br>chronological correlations. However, the fi obtain 15,000 power-loss samples with PMU time stamps and<br>
shaphots. When the number of s<br>
follow the correct distribution and should be discarded [67]. original population. In this study<br>
fillence the results of the measu chronological correlations. However, the first sample may not distribution of the samples w<br>follow the correct distribution and should be discarded [67]. corriginal population. In this stu<br>Therefore, in this study, we choo

follow the correct distribution and should be discarded [67]. original population. In thi<br>Therefore, in this study, we choose the power-loss samples<br>from 1,001 to 15,000. The PDF of the measurement data is measurements, w Therefore, in this study, we choose the power-loss samples<br>from 1,001 to 15,000. The PDF of the measurement data is measurements, which m<br>assumed to be the GMM PDF when K is not one. In this GMM, detection and identificat from 1,001 to 15,000. The PDF of the measurement data is measurements, which may lead<br>assumed to be the GMM PDF when K is not one. In this GMM, detection and identification of lit<br>the PDF of the measurements contains thre assumed to be the GMM PDF when *K* is not one. In this GMM, detection and identification<br>the PDF of the measurements contains three Gaussian 2) The error of PMU a<br>components, and the power-loss samples from 1 to 100 in ea the PDF of the measurements contains three components, and the power-loss samples from 1 to Gaussian component are discarded. Then, there were loss samples are used to identify the line parameter As the time skew of the S Comparative<br> *B.* Comparative Experiment<br>
B. Comparative Experiment<br>  $B = \frac{1}{2}$ <br> *B.* Comparative Experiment<br> *B.* Comparative Experiment<br> *B.* Comparative Experiment<br> *B.* Comparative Experiment<br>
B. Comparative Experime



Experiment<br>
Samples<br>
Samples<br>
Number of the SCADA measurement value of the branch is the of VC4092A. The measuring accuracions<br>
Publis the measurement value of this line. Because<br>
Publis 11.2 150.051.62 1100<br>
To make a co fiftieth time stamp of the PMU measurements in the Samples<br>
PMU **comparation**  $\frac{1}{12}$  is the measured value of WC4<br>
Population  $\frac{1}{12}$  is the same as  $\frac{1}{15000}$ <br>  $\frac{1}{15000$ At one end of the line, there are 300 PMU measurements (the Polydiation 11 (2 (50 (51152 (1100) (115000) real value of this line. Because the parameter is close to one.<br>
For make a comparison, the tests are also performed under the parameter is close to one.<br>
condition that the de Fig. 6. Measurements of the estable properties of the actual distribution in the actual distribution is<br>
Fig. 6. Measurements of comparison, the tests are also performed under the parameter is close to one.<br>
Condition tha Fig. 6. Measurements of comparative experiment<br>
To make a comparation, the tests are also performed under the<br>
condition that the delay of the SCADA measurement is III lists the impedance parameter<br>
condition that the del Fig. 6. Measurements of comparative experiment<br>To make a comparison, the tests are also performed under the<br>condition that the delay of the SCADA measurement is<br>neglected, i.e., the SCADA measurements obtained match with<br> Fo make a comparison, the tests are also performed under the condition that the delay of the SCADA measurement is neglected, i.e., the SCADA measurements obtained match with the closest PMU measurements. In Fig. 6, for ea glected, i.e., the SCADA measurements obtained match with<br>
voltage. In this study,<br>
closest PMU measurements. In Fig. 6, for each second, the<br>
method proposed in this study,<br>
be stamp of the SCADA measurements in the can the closest PMU measurements. In Fig. 6, for each second, the MATLAB 2018b install<br>time stamp of the SCADA measurement is the same as the 2.60 GHz and 2.59 GHz<br>fiftieth time stamp of the PMU measurements in the CPU. The r First the stamp of the SCADA measurement is the same as the 2.60 GHz and 2.59 GHz fiftieth time stamp of the PMU measurements in the CPU. The results of comparative experiment, i.e., the green  $txl$  is the same as t50. ide Fiftieth time stamp of the PMU measurements in the C1<br>fiftieth time stamp of the PMU measurements in the C1<br>comparative experiment, i.e., the green  $tx1$  is the same as 150. id<br>At one end of the line, there are 300 PMU mea

INE PARAMETERS WITH PMU AND UNSYNCHRONIZED<br>  $\frac{1}{2}$ <br>  $\frac{1}{2}$ <br> F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED<br>
THE HARDWARE SIMULATION<br>
Measuring accuracy<br>  $+1\%$ <br>  $+6\%$  (amplitude); 0.2° (phasor angle)<br>  $+1\%$ <br>  $+9\%$  (100mV/A<br>  $+0.5\%$ <br>
3% (resistance);  $\pm 0.3\%$  (inductance)<br>
1) F LINE PARAMETERS WITH PMU AND UNSYNCHRONIZED<br>
FIE HARDWARE SIMULATION<br>
Measuring accuracy<br>  $\frac{\pm 0.1\%}{\pm 0.5\%}$  (amplitude); 0.2° (phasor angle)<br>  $\frac{2\sqrt{50A}}{\pm 1000}$ <br>  $\frac{3\%}{\pm 0.5\%}$  (resistance):  $\pm 0.3\%$  (indu FLINE PARAMETERS WITH PMU AND UNSYNCHRONIZED<br>
FIE HARDWARE SIMULATION<br>
Measuring accuracy<br>
Measuring accuracy<br>
Measuring accuracy<br>
196% (amplitude); 0.2° (phasor angle)<br>
2V/50A<br>
196% (resistance): ±0.3% (inductance)<br>
380/0 ET<br>
HE HARDWARE SIMULATION<br>
Measuring accuracy<br>  $\frac{10.1\%}{2.00}$ <br>  $\frac{100 \text{m}}{100}$ <br>  $\frac{100 \text{m}}{100}$ <br>  $\frac{100 \text{m}}{100}$ <br>  $\frac{3\%}{1000}$ <br>  $\frac{3\%}{1000}$ <br>  $\frac{3\%}{1000}$ <br>  $\frac{3\%}{1000}$ <br>  $\frac{3\%}{1000}$ <br>  $\frac{3\%}{1000}$ original population. In this study, 300 SCADA measurements EXECTED Manuform CHE EXABIVARE SIMULATION<br>  $\frac{100}{20}$  (amplittel); 0.2° (phasor angle)<br>  $\frac{100 \text{mV/A}}{100 \text{mV/A}}$ <br>  $\frac{100 \text{mV/A}}{100 \text{mV/A}}$ <br>  $\frac{3\% \text{(resistance)} \pm 0.3\% \text{(inductance)}}{380/100 \text{V}}$ <br>
1) The number of SCADA sample m Measuring accuracy<br>  $+0.1\%$ <br>  $+0.1\%$ <br>  $+0.5\%$ <br>  $+1.6\%$ <br>  $+0.5\%$ <br>  $\frac{+0.1\%}{+0.1\%}$ <br>  $\frac{+0.1\%}{+0.5\%}$ <br>  $\frac{+0.5\%}{+0.5\%}$  (resistance):  $\frac{+0.3\%}{+0.3\%}$  (inductance)  $\frac{+0.3\%}{-0.3\%}$  (resistance):  $\frac{+0.3\%}{-0.3\%}$  (inductance)  $\frac{+0.3\%}{-0.3\%}$  (now the sample measureme  $^{6}$  (amplitude); 0.2° (phasor angle) 2V/50A<br>  $\pm 1\%$  100mV/A<br>  $\pm 0.5\%$  100mV/A<br>
(resistance);  $\pm 0.3\%$  (inductance) 380/100V<br>
1) The number of SCADA sample measurements: according<br>
Section III, an unbiased estimato <sup>21.7</sup><br>
<sup>2036</sup> (resistance):  $\pm 0.3\%$  (inductance)<br>
<sup>39%</sup> (resistance):  $\pm 0.3\%$  (inductance)<br>
1) The number of SCADA sample measurements: according<br>
to Section III, an unbiased estimator of the population mean can<br>
b <sup>3%</sup> (resistance):  $\pm 0.3\%$  (inductance)  $\rightarrow$ <br>
1) The number of SCADA sample measurements: according<br>
to Section III, an unbiased estimator of the population mean can<br>
be given by the sample mean in the abundant measure 1) The number of SCADA sample measurements: according<br>to Section III, an unbiased estimator of the population mean can<br>be given by the sample mean in the abundant measurement<br>snapshots. When the number of samples is large to Section III, an unbiased estimator of the population mean can<br>be given by the sample mean in the abundant measurement<br>snapshots. When the number of samples is large, the probability<br>distribution of the samples will be v be given by the sample mean in the abundant measurement<br>snapshots. When the number of samples is large, the probability<br>distribution of the samples will be very close to that of the<br>original population. In this study, 300

apshots. When the number of samples is large, the probability<br>tribution of the samples will be very close to that of the<br>ginal population. In this study, 300 SCADA measurements<br>e used as the samples of the population of 15 distribution of the samples will be very close to that of the original population. In this study, 300 SCADA measurements are used as the samples of the population of 15,000 PMU measurements, which may lead to errors but ca

original population. In this study, 300 SCADA measurements<br>are used as the samples of the population of 15,000 PMU<br>measurements, which may lead to errors but can realize the<br>detection and identification of line parameters. are used as the samples of the population of 15,000 PMU<br>measurements, which may lead to errors but can realize the<br>detection and identification of line parameters.<br>2) The error of PMU and SCADA measurements: the PMU<br>and SC measurements, which may lead to errors but can realize the detection and identification of line parameters.<br>
2) The error of PMU and SCADA measurements: the PMU and SCADA measurements are provided by measuring equipment th detection and identification of line parameters.<br>
2) The error of PMU and SCADA measurements: the PMU<br>
and SCADA measurements are provided by measuring<br>
equipment that possesses inherent measuring accuracy. When<br>
the measu 2) The error of PMU and SCADA measurements: the PMU<br>and SCADA measurements are provided by measuring<br>equipment that possesses inherent measuring accuracy. When<br>the measurements at both ends of the line have the same exact and SCADA measurements are provided<br>equipment that possesses inherent measuring a<br>the measurements at both ends of the line have<br>time stamps, the deviation of the estimated line<br>be brought about by the related measurement uipment that possesses inherent measuring accuracy. When<br>
reasurements at both ends of the line have the same exact<br>
ne stamps, the deviation of the estimated line parameter may<br>
brought about by the related measurements.<br> the measurements at both ends of the line have the same exact<br>time stamps, the deviation of the estimated line parameter may<br>be brought about by the related measurements.<br>3) The choice of the base power and base voltage: time stamps, the deviation of the estimated line parameter may<br>be brought about by the related measurements.<br>3) The choice of the base power and base voltage: when the<br>resistance value, in p.u., is approximately one, Equa be brought about by the related measurements.<br>3) The choice of the base power and base voltage: when the resistance value, in p.u., is approximately one, Equation (6) is used. However, the real value of the impedance is u

3) The choice of the base power and base voltage: when the resistance value, in p.u., is approximately one, Equation (6) is used. However, the real value of the impedance is unknown. The impedance value, in p.u., can be a resistance value, in p.u., is approximately one, Equation (6) is<br>used. However, the real value of the impedance is unknown.<br>The impedance value, in p.u., can be approximately one, rather<br>than exactly equal to one, using th used. However, the real value of the impedance is unknown.<br>The impedance value, in p.u., can be approximately one, rather<br>than exactly equal to one, using the appropriate choice of base<br>power and base voltage. Therefore, The impedance value, in p.u., can be approximately one, rather<br>than exactly equal to one, using the appropriate choice of base<br>power and base voltage. Therefore, the standard deviation of<br>the power loss in the proposed al than exactly equal to one, using the appropriate choice of base<br>power and base voltage. Therefore, the standard deviation of<br>the power loss in the proposed algorithm deviates from the true<br>standard deviation.<br>In this study power and base voltage. Therefore, the standard deviation of<br>the power loss in the proposed algorithm deviates from the true<br>standard deviation.<br>In this study, the real values of impedance are the measured<br>resistance and i the power loss in the proposed algorithm deviates from the true<br>standard deviation.<br>In this study, the real values of impedance are the measured<br>resistance and inductance based on a digital electric bridge, i.e.,<br>VC4092A. standard deviation.<br>
In this study, the real values of impedance are the measured<br>
resistance and inductance based on a digital electric bridge, i.e.,<br>
VC4092A. The measuring accuracy of the VC4092A for the<br>
resistance and In this study, the real values of impedance are the measured resistance and inductance based on a digital electric bridge, i.e., VC4092A. The measuring accuracy of the VC4092A for the resistance and inductance is  $\pm 0.3\$ resistance and inductance based on a digital electric bridge, i.e.,<br>VC4092A. The measuring accuracy of the VC4092A for the<br>resistance and inductance is  $\pm 0.3\%$  in Table I, which shows that<br>the measured value of VC4092A VC4092A. The measuring accuracy of the VC4092A for the resistance and inductance is  $\pm 0.3\%$  in Table I, which shows that the measured value of VC4092A can be believed. The initial value of the branch is known, but may resistance and inductance is  $\pm 0.3\%$  in Table I, which shows that<br>the measured value of VC4092A can be believed. The initial<br>value of the branch is known, but may have an error with the<br>real value of this line. Because the measured value of VC4092A can be believed. The initial value of the branch is known, but may have an error with the real value of this line. Because some real line parameters are unknown in the actual distribution netw value of the branch is known, but may have an error with the<br>real value of this line. Because some real line parameters are<br>unknown in the actual distribution network, we adjust the base<br>power and base voltage such that th real value of this line. Because some real line parameters are unknown in the actual distribution network, we adjust the base power and base voltage such that the p.u. value of the initial parameter is close to one. The in unknown in the actual distribution network, we adjust<br>power and base voltage such that the p.u. value of th<br>parameter is close to one. The initial values of 1<br>parameters are within a 20% error from their real value<br>III lis wer and base voltage such that the p.u. value of the initial<br>rameter is close to one. The initial values of the line<br>rameters are within a 20% error from their real values. Table<br>lists the impedance parameters, base power, parameter is close to one. The initial values of the line<br>parameters are within a 20% error from their real values. Table<br>III lists the impedance parameters, base power, and base<br>voltage. In this study, the proposed method parameters are within a 20% error from their real values. Table<br>III lists the impedance parameters, base power, and base<br>voltage. In this study, the proposed method is analyzed using<br>MATLAB 2018b installed on a computer wi III lists the impedance parameters, base power, and base<br>voltage. In this study, the proposed method is analyzed using<br>MATLAB 2018b installed on a computer with 8 GB of RAM,<br>2.60 GHz and 2.59 GHz processors, and an Intel C voltage. In this study, the proposed method is analyzed using MATLAB 2018b installed on a computer with 8 GB of RAM, 2.60 GHz and 2.59 GHz processors, and an Intel Core i7-9750H CPU. The results of the line parameter detec

MATLAB 2018b installed on a computer with 8 GB of RAM, 2.60 GHz and 2.59 GHz processors, and an Intel Core i7-9750H CPU. The results of the line parameter detection and identification for five consecutive times are shown 2.60 GHz and 2.59 GHz processors, and an Intel Core i7-9750H CPU. The results of the line parameter detection and identification for five consecutive times are shown in Tables IV, V, and VI. We determine this threshold (0.

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CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>measured impedance of VC4092A. The average errors of the chro CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>measured impedance of VC4092A. The average errors of the chronological correlations from<br>line parameter identification of the hardware simulation by the time stamps and a power-lo<br>c CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
measured impedance of VC4092A. The average errors of the chronological correlations from<br>
line parameter identification of the hardware simulation by the time stamps and a power-l csee JoURNAL OF POWER AND ENERGY SYSTEMS<br>measured impedance of VC4092A. The average errors of the<br>line parameter identification of the hardware simulation by the<br>comparative experiment are 25.3233% and 20.6801% in Table<br>v CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
measured impedance of VC4092A. The average errors of the<br>
line parameter identification of the hardware simulation by the<br>
time stamps and a power-<br>
comparative experiment are 25.3 csee JOURNAL OF POWER AND ENERGY SYSTEMS<br>
measured impedance of VC4092A. The average errors of the chronological correlations from line<br>
parameter identification of the hardware simulation by the time stamps and a power-lo CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
measured impedance of VC4092A. The average errors of the<br>
line parameter identification of the hardware simulation by the imme stamps and a power-<br>
comparative experiment are  $25.$ CSEE JOURNAL OF POWER AND ENERGY SYSTEMS<br>
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measured impedance of VC4092A. The average errors of the chronological correlations from<br>
line parameter identification of the hardware simulation by the time stamps and a power-l measured impedance of VC4092A. The average errors of the chronological correlations f<br>line parameter identification of the hardware simulation by the time stamps and a power<br>comparative experiment are 25.3233% and 20.6801% measured impedance of VC4092A. The average errors of the chronological correlations from in<br>line parameter identification of the hardware simulation by the time stamps and a power-los<br>comparative experiment are 25.3233% an measured impedance of VC4092A. The average errors of the chronological correlations from<br>line parameter identification of the hardware simulation by the time stamps and a power-lc<br>comparative experiment are 25.3233% and 2 line parameter identification of the hardware simulation by the time stamps and a power-loomparative experiment are 25.3233% and 20.6801% in Table parameter identification is realized by the proposed method are -2.3084% a comparative experiment are 25.3233% and 20.6801% in Table parameter identification is real<br>V, and 21.9467% and 15.9152% in Table VI. However, those and PMU current measurement<br>by the proposed method are -2.3084% and -1.100 V, and 21.9467% and 15.9152% in Table VI. However, those and PMU current measure<br>by the proposed method are -2.3084% and -1.1009% in Table V, this study are as follows:<br>and -3.7267% and -0.5621% in Table VI. It is clear f by the proposed method are -2.3084% and -1.1009% in<br>
and -3.7267% and -0.5621% in Table VI. It is clear fr<br>
data that the maximal error of the proposed method (3.<br>
is smaller than the minimal error of the comparative exp<br> error of the comparative experiment<br>
rence is more than 10%. The line the m<br>
the proposed method is close to the role in<br>
ed on a digital electric bridge. 2)<br>
ian and GMM distributions, it is proposed<br>
nethronized issue o impedance based on a digital electric bridge. 2) A<br>
in both Gaussian and GMM distributions, it is propose<br>
at for an unsynchronized issue of the PMU and magnitu<br>
reasurements, the line parameter can be detected by paramet Initial values of impedance (p.u.)  $\mu$ <sub>j×0.8</sub> 1+j×0.8 1 assessing the power (VA) and the error of the line Therefore, in both Gaussian and GMM distributions, it is proposed PPII is the subseted that for an unsynchronized issue of the PMU and magnitude measurement<br>SCADA measurements, the line parameter can be detected by parame



distribution grids. Because the proposed method is a Base power (VA)<br>
Base voltage (V) and a state of the measurements based on the condition<br>
Distribution PPII-1 PPII-2 PPII-3 PPII-4 PPII-5 at the prior time stamp and<br>
Caussian 2.1522 2.1907 2.2954 2.0197 1.5622 at to model Base voltage (V)<br>
TABLE IV<br>
DETECTION RESULTS OF HARDWARE SIMULATION<br>
Distribution PPII-1 PPII-2 PPII-4 PPII-5 PPI-4 IS and the prior time stamp are<br>
Gaussian 2.1522 2.1907 2.2954 2.0197 1.5622<br>
(SMM 4.5543 6.5463 6.1470 **EXECTION RESULTS OF HARDWARE SIMULATION** is used to model the chronologica<br>
This tribution PPII-1 PPIL-2 PPIL-3 PPII-4 PPIL-5<br>
Caussian 2.1522 2.1907 2.954 2.0197 1.5622 EMM 4.5543 6.3463 6.1470 4.3911 6.6003 used to mode The samples and SCADA measurements as the population. This the proof GAUSSIAN DISTRIBUTION of the power-loss P<br>
SMM 4.5543 6.5463 6.1470 4.3911 6.6003 used to model the correlation b<br>
This paper presents a data-based metho  $\begin{tabular}{c|c|c|c} \hline Gaussian & 2.1522 & 2.1907 & 2.2954 & 2.0197 & 1.5622 & Furthermore, the power-lo  
\nGMM & 4.5543 & 6.5463 & 6.1470 & 4.3911 & 6.6003 & used to model the correlati  
\nVII. CONCLUSION & time stamps. \\ \hline & VII. CONCLUSION & 4) The power loss sam  
\ndetection and identification where PMU measurements have measurements and power-exact time stamps and SCADA measurements do not in  
\ndata-driven method, the PDFs obtained from the data do not Gaussian and GMM district  
\nread to be known previously. For the time skew of the PMU that when SCADA measurements  
\nand SCADA$ **GMM** 4.5543 6.5463 6.1470 4.3911 6.6003 used to model the correlation be<br>
VII. CONCLUSION time stamps.<br>
This paper presents a data-based method for line parameter<br>
the power-loss samples start time stamps and SCADA measu listribution grids. Because the propos-<br>lata-driven method, the PDFs obtained freed to be known previously. For the time<br>md SCADA measurements, we take SCAD<br>he samples and PMU measurements as tl<br>tudy derives a PPII to dete Is. Because the proposed method is a based of<br>
od, the PDFs obtained from the data do not Gaussia<br>
in previously. For the time skew of the PMU that wh<br>
surements, we take SCADA measurements as measur<br>
PMU measurements as

chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with<br>time stamps and a power-loss chronological PDF<br>parameter identification is realized by the power-loss s<br>and PMU current measurements. The primary conclus<br>this study are ronological correlations from a power-loss PDF with PMU<br>ne stamps and a power-loss chronological PDF. Line<br>rameter identification is realized by the power-loss samples<br>d PMU current measurements. The primary conclusions of chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu ronological correlations from a power-loss PDF with PMU<br>ne stamps and a power-loss chronological PDF. Line<br>rameter identification is realized by the power-loss samples<br>d PMU current measurements. The primary conclusions of

chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu chronological correlations from a power-loss PDF with PMU<br>time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclu time stamps and a power-loss chronological PDF. Line<br>parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclusions of<br>this study are as follows:<br>1) The time skew of th parameter identification is realized by the power-loss samples<br>and PMU current measurements. The primary conclusions of<br>this study are as follows:<br>1) The time skew of the PMU and SCADA measurements for<br>the line parameter d and PMU current measurements. The primary conclusions of<br>this study are as follows:<br>1) The time skew of the PMU and SCADA measurements for<br>the line parameter detection and identification is solved using<br>probabilistic appro this study are as follows:<br>
1) The time skew of the PMU and SCADA measurements for<br>
the line parameter detection and identification is solved using<br>
probabilistic approaches. Both the probability distribution of<br>
the measu comparisons. 2) Example 1: Inne parameter detection and identification is solved using<br>
2) babilistic approaches. Both the probability distribution of<br>
2) eneasurements and the sampling algorithm play a crucial<br>
2) A PPII is proposed t probabilistic approaches. Both the probability distribution of<br>the measurements and the sampling algorithm play a crucial<br>role in realizing the line parameter detection and identification.<br>2) A PPII is proposed to detect t the measurements and the sampling algorithm play a crucial<br>role in realizing the line parameter detection and identification.<br>2) A PPII is proposed to detect the line parameter. The<br>proposed PPII is the sum of the relative role in realizing the line parameter detection and identification.<br>
2) A PPII is proposed to detect the line parameter. The<br>
proposed PPII is the sum of the relative errors of the voltage<br>
magnitude measurement means, deri

3) A power-loss chronological PDF and a power-loss PDF with PMU time stamps are derived based on the conditional Furthermore, the power-loss PDF with the PMU time stamps is used to model the correlation between the power loss and PMU 2) A PPII is proposed to detect the line parameter. The proposed PPII is the sum of the relative errors of the voltage magnitude measurement means, derived from the PDF parameters of the measurements and line parameters. proposed PPII is the sum of the relative errors of the voltage<br>magnitude measurement means, derived from the PDF<br>parameters of the measurements and line parameters. A PPII is<br>derived based on the measurement-based method ( magnitude measurement means, derived from the PDF<br>parameters of the measurements and line parameters. A PPII is<br>derived based on the measurement-based method (i.e., the<br>data-driven method). The detection of the accuracy of parameters of the measurements and line parameters. A PPII is<br>derived based on the measurement-based method (i.e., the<br>data-driven method). The detection of the accuracy of the line<br>parameter depends on the PPII and thresh derived based on the measurement-based method (i.e., the<br>data-driven method). The detection of the accuracy of the line<br>parameter depends on the PPII and threshold over many<br>comparisons.<br>3) A power-loss chronological PDF a data-driven method). The detection of the a<br>parameter depends on the PPII and three<br>comparisons. 3) A power-loss chronological PDF and<br>with PMU time stamps are derived based<br>probability and nonparametric KDE, which<br>of the rameter depends on the PPII and threshold over many<br>mparisons.<br>3) A power-loss chronological PDF and a power-loss PDF<br>th PMU time stamps are derived based on the conditional<br>bability and nonparametric KDE, which provides t comparisons.<br>
3) A power-loss chronological PDF and a power-loss PDF<br>
with PMU time stamps are derived based on the conditional<br>
probability and nonparametric KDE, which provides the PDF<br>
of the measurements based on the m 3) A power-loss chronological PDF and a power-loss PDF<br>with PMU time stamps are derived based on the conditional<br>probability and nonparametric KDE, which provides the PDF<br>of the measurements based on the measurements-base with PMU time stamps are derived based on the conditional<br>probability and nonparametric KDE, which provides the PDF<br>of the measurements based on the measurements-based method,<br>i.e., the data-driven method. The power-loss c

probability and nonparametric KDE, which provides the PDF<br>of the measurements based on the measurements-based method,<br>i.e., the data-driven method. The power-loss chronological PDF<br>is used to model the chronological correl of the measurements based on the measurements-based method,<br>i.e., the data-driven method. The power-loss chronological PDF<br>is used to model the chronological correlation of the power loss<br>at the prior time stamp and the fo i.e., the data-driven method. The power-loss chronological PDF<br>is used to model the chronological correlation of the power loss<br>at the prior time stamp and the following time stamp.<br>Furthermore, the power-loss PDF with the is used to model the chronological correlation of the power loss<br>at the prior time stamp and the following time stamp.<br>Furthermore, the power-loss PDF with the PMU time stamps is<br>used to model the correlation between the p at the prior time stamp and the following time stamp.<br>Furthermore, the power-loss PDF with the PMU time stamps is<br>used to model the correlation between the power loss and PMU<br>time stamps.<br>4) The power-loss samples are samp Furthermore, the power-loss PDF with the PMU time<br>used to model the correlation between the power loss<br>time stamps.<br>4) The power-loss samples are sampled from two<br>the power loss by the MH algorithm. Using the PM<br>measuremen ter the power loss by the MH algo<br>
ve measurements and power-loss s:<br>
in and chronological correlations,<br>
a based on the data-driven and n<br>
ot Gaussian and GMM distribution<br>
flul that when SCADA measurements<br>
as measureme



	exact time stamps and SCADA measurements do not in						and chronological correlations, we identify line parameters
distribution grids. Because the proposed method is a				based on the data-driven and model-driven methods. For the			
	data-driven method, the PDFs obtained from the data do not						Gaussian and GMM distributions, hardware simulations show
	need to be known previously. For the time skew of the PMU						that when SCADA measurements do not match with PMU
	and SCADA measurements, we take SCADA measurements as						measurements, the incorrect line parameter can be detected and
	the samples and PMU measurements as the population. This						the identification errors of the line parameters are between
	study derives a PPII to detect the line parameters. We generate			$-3.7267\%$ and $-0.5621\%$ .			
	samples of the power loss with PMU time stamps and						
			<b>TABLE V</b>				
	<b>IDENTIFICATION OF HARDWARE SIMULATION FOR GAUSSIAN DISTRIBUTION</b>						
Method type	Estimated impedance	Test 1	Test 2	Test 3	Test 4	Test 5	Average value
		$1.0876 + j \times 0.$	$1.1018+j\times 0.$	$1.1532 + j \times 0$ .	$1.0684+j\times 0.$	$1.0500 + j \times 0$ .	$1.0922 + j \times 0.8881$
Identification of	Estimated values of impedance (p.u.)	8908	8883	8790	8756	9068	
proposed method	Relative errors of resistance $(\% )$	$-2.7207$	$-1.4476$	3.1473	$-4.4373$	$-6.0836$	$-2.3084$
	Relative errors of reactance (%)	$-0.8031$	$-1.0776$	$-2.1137$	$-2.4894$	0.9795	$-1.1009$
Identification of	Estimated values of impedance (p.u.)	$1.3801+j\times1$ .	$1.4140+j\times1$ .	$1.4132+j\times1$ .	$1.4447 + j \times 1$ .	$1.3536+j\times1$ .	$1.4011+j \times 1.0837$
comparative	Relative errors of resistance $(\% )$	0871 23.4432	0781 26.4744	0660 26.4004	1052 29.2251	0821 21.0736	25.3233
experiment	Relative errors of reactance (%)	21.0630	20.0514	18.7069	23.0732	20.5060	20.6801
			<b>TABLE VI</b>				
			IDENTIFICATION OF HARDWARE SIMULATION FOR GMM DISTRIBUTION				
Method type	Estimated impedance	Test 1	Test 2	Test 3	Test 4	Test 5	Average value
Identification of proposed method		$1.1084 + j \times 0.$	$1.0277 + j \times 0$ .	$1.0180+j\times 0.$	$1.1189 + j \times 0$ .	$1.0654+j\times 0.$	$1.0677 + j \times 0.8949$
	Estimated values of impedance (p.u.)	8702	8855	8985	9210	8994	
	Relative errors of resistance $(\% )$	$-0.0558$	$-7.3336$	$-8.2044$	0.8926	$-3.9323$	$-3.7267$
	Relative errors of reactance $(\%)$	$-3.3082$	$-1.6094$	$-0.1646$	2.3335	$-0.0620$	$-0.5621$
Identification of comparative experiment	Estimated values of impedance (p.u.)	$1.3816+j\times1$ .	$1.3252+j\times1$ .	$1.3427+j\times1$ .	$1.3762 + j \times 1$	$1.3363+j\times1$ .	$1.3524+j \times 1.0432$
		0415	0508	0551	0249	0439	
	Relative errors of resistance (%) Relative errors of reactance (%)	24.5762	19.4949	21.0760	24.0893	20.4969	21.9467
		15.7204	16.7588	17.2283	13.8765	15.9920	15.9152

JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE<br>SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>The detection method presented here has its limitations: first, [13] J.<br>if the errors of the line parameters The detection method presented here has its limitations: first,<br>The detection method presented here has its limitations: first, [13] J. Zhu, and A. Abur, "Improvember the errors of the line parameters are too small, we ca JINPING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PM<br>SCADA MEASUREMENTS IN DISTRIBUTION GRIDS<br>
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if the errors of the line p PING SUN *et al.*: DATA-DRIVEN DETECTION AND IDENTIFICATION OF LINE PARAMETERS WITH PMU A<br>
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Mostlemguish b t detect the incorrect line parameters of the small errors.<br>
Such decoted decetion method to<br>
tect errors that result from the resistance and reactance, it<br>
and correct errors that result from the resistance and reactance Second, despite the ability of the proposed detection method to<br>
detect rems threshince and reactance, it and oceracine of branch part cannot detect whether the error is brought about by resistance<br>
or reactance. Neverthe

detect errors that result from the resistance and reactance, 1<br>cannot detect whether the error is brought about by resistance<br>or reactance. Nevertheless, the results of the hardware<br>simulations are credible, and the detect

# ACKNOWLEDGMENT

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