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Characterization of a method for transmission line parameters estimation with respect to PMU measurement error modeling

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Abstract – **The line parameters available to the System Operator can be quite different from actual values because of different reasons, such as aging, manufacturing tolerance, environmental conditions, etc. Proposals have been presented in literature to estimate line parameters and monitor their changes. Synchrophasor measurements from PMUs have appeared as a possible breakthrough for accurate estimation. A novel algorithm has been recently proposed to estimate line parameters in presence of realistic systematic errors in PMU-based measurement chains. This paper aims at characterizing the robustness of the algorithm with respect to possible mismatches of the models associated to PMU measurement errors. Systematic and random contributions are considered at different levels. Simulations on an IEEE test network help in investigating method robustness and possible limits.**

I. INTRODUCTION

When dealing with power system management, several applications are involved. Among others, state estimation [1], fault location methods [2], etc. In all these applications, network models play a fundamental role and line parameters are thus the basis of any further processing or evaluation. In practice, line parameter values can significantly differ from data available to Transmission System Operator (TSO) because manufacturing, installation or ageing introduce model mismatches that can result in Energy Management System issues. Measuring line parameters is thus a critical and challenging task, to which phasor measurements units (PMUs) can contribute significantly, since their outputs are direct, accurate and frequent measurements of voltage and current phasors synchronized to Coordinated Universal Time (UTC) and thus associated with an accurate time tag. TSOs have been installing PMUs in the last decade to build the so-called Wide Area Monitoring Systems (WAMSs), i.e., the new generation distributed monitoring infrastructures for power systems.

Even if promising, the PMU is only one element of the measurement chain, which includes also Instrument Transformers (ITs), and thus line parameter estimates are affected by measurement errors at different levels. In the literature, different approaches to PMU-based parameters estimation have been introduced recently. In [3], only the PMU error is considered for a single line estimation, while in [4] also ITs are considered, adopting an estimation method based on direct application of PMU current and voltage measurements available at both ends of the line at a given time instant. In [5] and [6], multiple time instants are considered, but IT errors are modeled as zero mean random noise, thus neglecting systematic errors.

When IT systematic errors are not fully compensated, which is a typical situation, line parameter estimation is strongly affected. In [7], calibrated transducers are used to propagate accuracy while estimating line parameters. In [8] systematic errors of current amplitudes and voltage phase angles are assumed negligible to simultaneously estimate line parameters and other systematic errors, while [9] focuses on the detection of uncalibrated ITs in a preliminary way.

In [10, 11], an algorithm to estimate simultaneously line parameters and systematic errors introduced by ITs was presented, dealing with multiple lines at the same time and with multiple operating conditions of the network. The method relies on the definition of a measurement model that considers both systematic and random measurement errors and on prior knowledge on line parameters, IT and PMU uncertainty. Considering the estimation framework, potential issues can arise when a mismatch between considered prior information and actual deviations occurs.

In this paper, the role of systematic and random errors in PMUs will be investigated. Indeed, PMU specifications do not allow tuning prior information on systematic and random errors in PMU measurement chain. For this reason, the impact of PMU systematic errors on line parameters estimation and their role in the compensation process of the entire measurement chain need to be assessed. Performance and robustness of the method [11] will be examined through simulation on the IEEE 14 bus test system.

II. ESTIMATION FRAMEWORK

In the following, the algorithm proposed in [10] and extended in [11] to address several load scenarios is briefly introduced with a focus on its assumptions and measure-

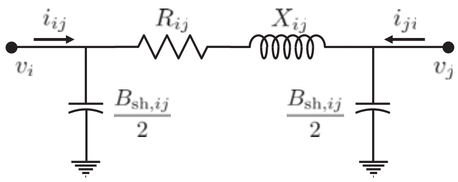

Fig. 1. π-model of a transmission line.

ment model. An equivalent single-phase model is considered (see [9]), which adopts a π-model for each line as that represented in Fig. 1. Fig. 1 also shows the considered measurements, since v_i, v_j, i_{ij} and i_{ji} are the synchronized phasor measurements (synchrophasors) of the start-node voltage of the line (node i), of the end-node voltage (node j), of the branch current from node i and of that from node j, respectively. The measurements are assumed available from two PMUs installed at both ends of the line and correspond to the same time instant $t = nT_{RR}$, which identifies the PMU generic timestamp (T_{RR} is the PMU reporting interval). From Fig. 1, it is clear that the line parameters to estimate are the line resistance R_{ij}, the line reactance X_{ij} and the shunt susceptance $B_{\text{sh},ij}$ (equally split into the two sides of the model).

The line parameter estimation algorithm is based on a set of equations, corresponding to different timestamps and involving the unknown line parameters and the measurement errors. In particular, the four measurements available for each timestamp and for each line allow writing two complex-valued equations: the first one expresses the voltage drop across the line; the second one derives from Kirchhoff's Current Law. In detail, the following two equations are considered:

$$v_i^R - v_j^R = (R_{ij} + jX_{ij}) \left(i_{ij}^R - j\frac{B_{\text{sh},ij}}{2} v_i^R \right) \quad (1)$$

$$i_{ij}^R + i_{ji}^R = j\frac{B_{\text{sh},ij}}{2}(v_i^R + v_j^R) \quad (2)$$

where superscript ^{R} indicates the reference value of the corresponding measured quantity. Equations (1) and (2) define thus constraints for the line parameters based on actual values of voltage and current phasors at a given time.

Since we are dealing with a measurement process, reference values can be rewritten as functions of measured synchrophasors, systematic and random errors as follows:

$$\begin{aligned} v_h^R &= \frac{v_h}{(1 + \xi_h^{\text{sys}} + \xi_h^{\text{rnd}})} e^{j(-\alpha_h^{\text{sys}} - \alpha_h^{\text{rnd}})} \\ &\approx V_h e^{j\varphi_h} \left(1 - \xi_h^{\text{sys}} - \xi_h^{\text{rnd}} - j\alpha_h^{\text{sys}} - j\alpha_h^{\text{rnd}}\right) \end{aligned} \quad (3)$$

$$\begin{aligned} i_{ij}^R &= \frac{i_{ij}}{(1 + \eta_{ij}^{\text{sys}} + \eta_{ij}^{\text{rnd}})} e^{j(-\psi_{ij}^{\text{sys}} - \psi_{ij}^{\text{rnd}})} \\ &\approx I_{ij} e^{j\theta_{ij}} \left(1 - \eta_{ij}^{\text{sys}} - \eta_{ij}^{\text{rnd}} - j\psi_{ij}^{\text{sys}} - j\psi_{ij}^{\text{rnd}}\right) \end{aligned} \quad (4)$$

where $h \in \{i, j\}$, V_h and I_{ij} are the measured voltage and current magnitudes, respectively, ξ_h and η_{ij} indicate the corresponding measurement errors, φ_h and θ_{ij} are the voltage and current phase angles measured by the PMUs, and α_h and ψ_{ij} are the corresponding errors. Superscripts $^{\text{sys}}$ and $^{\text{rnd}}$ are used to split the measurement errors in their systematic and random components. All the errors are $\ll 1$ (their absolute values) and the approximated expressions in (3) and (4) are obtained considering a first order approximation with respect to measurement errors and thus neglecting terms, even multivariate, with a degree > 1. An equation analogous to (4) can be written also for the other current in the opposite direction.

Systematic errors are unknown like the line parameters and thus multiple pairs of equations corresponding to different timestamps and possibly to different operating conditions of the network can be used to define a set of equations which is the basis for the estimation. In [10] and [11], systematic errors are attributed to ITs, i.e., to voltage transformers (VTs) and current transformers (CTs), while PMUs are considered as affected mainly by random errors.

To simplify the estimation task, (1) and (2) are further modified by considering line parameters as follows:

$$\begin{aligned} R_{ij} &= R_{ij}^0 (1 + \gamma_{ij}) \\ X_{ij} &= X_{ij}^0 (1 + \beta_{ij}) \\ B_{\text{sh},ij} &= B_{\text{sh},ij}^0 (1 + \delta_{ij}) \end{aligned} \quad (5)$$

where superscript ^{0} indicates the known values that are already available to the TSO, and γ_{ij}, β_{ij} and δ_{ij} are the unknown relative deviations from them, which represent the lack of knowledge.

Replacing then (3) and (4) into (1) and (2) and considering first order approximation ($|\gamma_{ij}|$, $|\beta_{ij}|$ and $|\delta_{ij}|$ are also $\ll 1$), a linear system of equations for branch (i, j) can be written as

$$\begin{aligned} \mathbf{b}_{ij} &= \mathbf{H}_{ij} \begin{bmatrix} \xi_i^{\text{sys}} \\ \alpha_i^{\text{sys}} \\ \xi_j^{\text{sys}} \\ \alpha_j^{\text{sys}} \\ \eta_{ij}^{\text{sys}} \\ \psi_{ij}^{\text{sys}} \\ \eta_{ji}^{\text{sys}} \\ \psi_{ji}^{\text{sys}} \\ \gamma_{ij} \\ \beta_{ij} \\ \delta_{ij} \end{bmatrix} + \mathbf{E}_{ij} \begin{bmatrix} \xi_i^{\text{rnd}} \\ \alpha_i^{\text{rnd}} \\ \xi_j^{\text{rnd}} \\ \alpha_j^{\text{rnd}} \\ \eta_{ij}^{\text{rnd}} \\ \psi_{ij}^{\text{rnd}} \\ \eta_{ji}^{\text{rnd}} \\ \psi_{ji}^{\text{rnd}} \end{bmatrix} \\ &= \mathbf{H}_{ij}\mathbf{x}_{ij} + \mathbf{E}_{ij}\mathbf{e}_{ij} = \mathbf{H}_{ij}\mathbf{x}_{ij} + \boldsymbol{\epsilon}_{ij} \end{aligned} \quad (6)$$

where $\mathbf{b}_{ij}$ is the real-valued vector of constant terms (representing equivalent measurements) derived from (1) and (2) when real and imaginary coordinates are considered. $\mathbf{b}_{ij}$ includes multiple sets of equivalent measurements corresponding to (1) and (2) for each considered timestamp. The unknowns are common to all the timestamps and thus

$\mathbf{x}_{ij}$ is the vector of unknown quantities, which are all the parameter deviations and systematic errors. Vector $\mathbf{e}_{ij}$ includes all the random errors, while $\mathbf{H}_{ij}$ and $\mathbf{E}_{ij}$ are the measurement matrix and the random error transformation matrix, respectively. The former links equivalent measurements in $\mathbf{b}_{ij}$ to $\mathbf{x}_{ij}$ and the latter computes the associated equivalent random errors (included in $\boldsymbol{\epsilon}_{ij}$) from $\mathbf{e}_{ij}$.

Using N_t timestamps and four equations for each timestamp, we have $4N_t$ equations for each branch. It is possible to consider also multiple branches (e.g. N_{br} branches) together in the same estimation process. In this case, for the same timestamp, we have all the voltage and current measurements of all the considered branches and thus we can define an augmented model with $4N_tN_{\text{br}}$ equations. Instead of the vector of the unknowns for a single branch, we have a vector $\mathbf{x}$ of N unknown quantities corresponding to all the parameter deviations of the lines ($3N_{\text{br}}$ unknowns if all the branches have the same model as in Fig. 1) and to all the systematic errors of the measured synchrophasors. Since joint branches share the same node voltage measurements, the number of systematic errors in $\mathbf{x}$ can be $< 8N_{\text{br}}$. In addition, prior knowledge on the unknowns can be considered, thus defining an overall model as follows:

$$\mathbf{b}_{\text{tot}} = \begin{bmatrix} \mathbf{b}_{i_1j_1} \\ \vdots \\ \mathbf{b}_{i_{N_{\text{br}}}j_{N_{\text{br}}}} \\ \mathbf{0}_{N\times 1} \end{bmatrix} = \begin{bmatrix} \mathbf{H} \\ \mathbf{I}_N \end{bmatrix} \mathbf{x} + \begin{bmatrix} \mathbf{E}\mathbf{e} \\ \mathbf{e}_{\text{prior}} \end{bmatrix} \tag{7}$$

$$= \mathbf{H}_{\text{tot}}\mathbf{x} + \boldsymbol{\epsilon}_{\text{tot}} \tag{8}$$

where $\mathbf{b}_{i_kj_k}$ includes the equivalent measurements of the kth considered branch ($k = 1, \ldots, N_{\text{br}}$), while $\mathbf{H}$ and $\mathbf{E}$ are the measurement and transformation matrices obtained considering all the branches and the corresponding equations like those in (6). Vector $\mathbf{e}$ is composed of the random errors for all the measured synchrophasors, $\mathbf{0}_{N\times 1}$ is the N-size zero vector and $\mathbf{I}_N$ is the N-size identity matrix. Prior values are given by $\mathbf{0}_{N\times 1}$ since they are all zeros (best assumption on deviations and systematic errors without further information) and $\mathbf{e}_{\text{prior}}$ includes the corresponding prior errors. Prior errors represent lack of knowledge and can thus be treated as random variables as discussed in Section III.

Starting from the model defined by (8), it is possible to estimate all the unknowns, i.e., to achieve an estimation of line parameters and systematic errors simultaneously for all the lines and measurement channels without requiring a preliminary calibration. A Weighted Least Squares (WLS) solution of (8) can be obtained by solving the following system:

$$(\mathbf{H}_{\text{tot}}^{\text{T}}\mathbf{W}_{\text{tot}}\mathbf{H}_{\text{tot}})\hat{\mathbf{x}} = \left(\mathbf{H}_{\text{tot}}^{\text{T}}\mathbf{W}_{\text{tot}}\right)\mathbf{b}_{\text{tot}} \tag{9}$$

where $\hat{}$ indicates the estimate and $\mathbf{W}_{\text{tot}}$ is the weighing matrix, which is the inverse of the covariance matrix of random vector $\boldsymbol{\epsilon}_{\text{tot}}$, indicated as $\boldsymbol{\Sigma}_{\boldsymbol{\epsilon}_{\text{tot}}}$ in the following.

III. MEASUREMENT ERRORS AND PRIOR INFORMATION

Considering prior information on the unknowns and random errors of PMU measurements as uncorrelated, it is possible to write:

$$\boldsymbol{\Sigma}_{\boldsymbol{\epsilon}_{tot}} = \begin{bmatrix} \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}} & \mathbf{0} \\ \mathbf{0} & \Sigma_{\mathbf{e}_{\text{prior}}} \end{bmatrix} \tag{10}$$

where symbol $\boldsymbol{\Sigma}$ represents a covariance matrix (of the vector reported in the subscript), $\boldsymbol{\epsilon} = \mathbf{E}\mathbf{e}$ and $\mathbf{0}$ stands for a zero matrix of suitable size. From the law of propagation of uncertainty it follows

$$\boldsymbol{\Sigma}_{\boldsymbol{\epsilon}} = \mathbf{E}\boldsymbol{\Sigma}_{\mathbf{e}}\mathbf{E}^{\text{T}}. \tag{11}$$

To define $\Sigma_{\mathbf{e}}$ we have to consider all the random errors $\xi_{i_k}^{\text{rnd}}, \alpha_{i_k}^{\text{rnd}}, \xi_{j_k}^{\text{rnd}}, \alpha_{j_k}^{\text{rnd}}, \eta_{i_kj_k}^{\text{rnd}}, \psi_{i_kj_k}^{\text{rnd}}, \eta_{j_ki_k}^{\text{rnd}}$ and $\psi_{j_ki_k}^{\text{rnd}}$ for all the considered branches (i_k, j_k). In [11], these errors were assumed uncorrelated and associated with PMU uncertainty. Thus $\Sigma_{\mathbf{e}}$ was diagonal and included all the square standard uncertainties derived from PMU specifications (e.g., using maximum magnitude and phase-angle errors from instrument datasheet and assuming uniform distributions). To define $\Sigma_{\mathbf{e}_{\text{prior}}}$, two different considerations can be made:

- Prior variances $\sigma^2_{\gamma_{i_kj_k}}$, $\sigma^2_{\beta_{i_kj_k}}$ and $\sigma^2_{\delta_{i_kj_k}}$ are assumed from general considerations on the uncertainty of line parameters (e.g. relying on the TSO experience). Line parameter deviations are assumed uncorrelated (if further information is available, it can be integrated seamlessly). A mismatch between actual uncertainty and assumed values can occur and in [12] such issue is thus deeply investigated.

- Systematic errors in the measurement chain are considered uncorrelated (also in this case, if any prior knowledge is available it can be integrated). As mentioned above, in [11], systematic errors were attributed mainly to ITs and thus the variance of each error was derived from the IT class specification.

The presented assumptions allow computing $\Sigma_{\mathbf{e}}$ and $\Sigma_{\mathbf{e}_{\text{prior}}}$ and thus solving (9), but they might lead to possible issues in the algorithm configuration. Indeed, the measurement error of PMUs can be actually composed of both systematic and random errors and this would result in a transfer of uncertainty from $\Sigma_{\mathbf{e}}$ representing random error only to $\Sigma_{\mathbf{e}_{\text{prior}}}$. However, the amount of each error contribution is difficult to predict. For this reason, in the next section, the problem of uncertainty model mismatch and the robustness of the method against it are investigated by considering different PMU uncertainty scenarios while keeping the base configuration of the method.

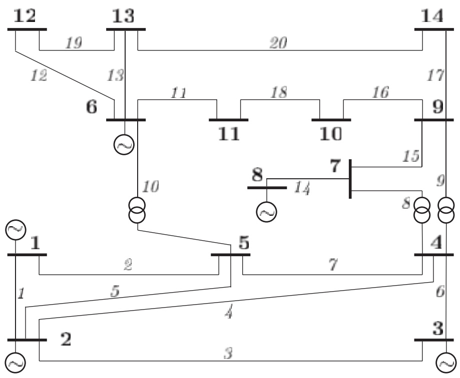

Fig. 2. IEEE 14 bus system with node and branch indices.

IV. TESTS AND RESULTS

A. *Test assumptions*

Tests have been performed via MATLAB simulations considering the IEEE 14 bus system (Fig. 2, [13]) and limiting the analysis to the first six branches (involving the first five buses). The algorithm is configured to work on all the branches simultaneously, considering $N_t = 100$ measurement timestamps for each estimation. In particular, 10 repeated measurements of the same load condition and 10 different load conditions (10 cases) are used for each test.

To assess the performance in each scenario, $N_{MC} = 10000$ Monte Carlo (MC) trials are used. In each trial, starting from a reference load condition, a powerflow is computed considering the actual line parameters to obtain the reference value of each measured quantity.

For each MC trial, the following conditions are considered:

1. The line parameters R_{ij}, X_{ij} and $B_{\text{sh},ij}$ are extracted from a uniform distribution with a maximum deviation of $\pm 15\,\%$ from R^0_{ij}, X^0_{ij} and $B^0_{\text{sh},ij}$, respectively (i.e., nominal values of the network).

2. All ITs are of Class 0.5 and thus maximum voltage and current magnitude errors are $0.5\,\%$, while maximum phase-angle displacements are 0.6 crad for VTs and 0.9 crad for CTs, respectively. Actual IT errors are extracted from uniform distributions.

3. The PMUs are compliant with the synchrophasor standard IEC/IEEE 60255-118-1:2018 [14]. Maximum errors for magnitudes (Δ_{mag}) and phase angles (Δ_{ang}) for both voltages and currents are assumed to vary from $\Delta_{\text{mag}} = 0.1\,\%$ and $\Delta_{\text{ang}} = 0.1$ crad (PMU accuracy A, in the following) to $\Delta_{\text{mag}} = 0.707\,\%$ and $\Delta_{\text{ang}} = 0.707$ crad (PMU accuracy B), depending on the test[1]. For each test, the values of Δ_{mag} and Δ_{ang} are numerically the same and are referred to as 'PMU accuracy' for the sake of brevity. In the different tests, percentage p ranging from $0\,\%$ to $75\,\%$ of systematic error has been associated with the PMU, for voltage and current measurements. This defines the maximum PMU systematic error of the measured quantity as follows:

$$\Delta^{\text{sys}}_{\text{mag}} = \frac{p}{100}\Delta_{\text{mag}} \tag{12}$$

$$\Delta^{\text{sys}}_{\text{ang}} = \frac{p}{100}\Delta_{\text{ang}} \tag{13}$$

PMU systematic errors are extracted from uniform distributions whose ranges are thus $\pm\Delta^{\text{sys}}_{\text{mag}}$ and $\pm\Delta^{\text{sys}}_{\text{ang}}$ for magnitudes and phase angles, respectively. PMU random errors are instead extracted from uniform distributions for each of the N_t timestamps in the trial and the considered maximum deviations are given by $\Delta^{\text{rnd}}_{\text{type}} = \Delta_{\text{type}} - \Delta^{\text{sys}}_{\text{type}}$, where type $\in \{\text{mag}, \text{ang}\}$.

4. The active and reactive power of loads and generators vary within $\pm 10\,\%$ (uniform distribution) of nominal value for all 10 cases in a trial.

In each MC trial, the systematic errors of the measurements are then the sum of two contributions, from IT and PMU.

B. *Systematic errors estimation and compensation*

To understand the impact of different values of p, we first focus on systematic error estimation. Figure 3 reports the average percent root mean square errors (RMSEs) of voltage magnitude systematic error estimation, i.e. the average on the nodes of the RMSE of ξ^{sys}_h ($h = 1, \ldots, 5$) estimates. This quantity represents also the root mean square residual compensation error and thus gives an idea of the capability to estimate the systematic component of the measurement chain. The results are obtained with PMU accuracy A and reported for different percentages of the PMU systematic error.

In Fig. 3, the RMSEs are compared with prior standard deviations, i.e., with the original standard uncertainty of ξ^{sys} (the generic node voltage magnitude systematic error), which is computed across all MC trials based on the extracted systematic errors and then averaged on the nodes. Prior values only slightly increase with p because, with $\Delta_{\text{mag}} = 0.1\,\%$, the additional contribution to systematic error brought by the PMU is much lower than IT contribution ($\sigma_{\xi^{\text{sys}}_h,\text{VT}} = 0.5/\sqrt{3}\,\%$). Average RMSE slightly decreases instead because PMU random errors decrease with higher p, thus confirming that, notwithstanding the mismatch in prior definition, the algorithm is still able to estimate the overall systematic error (which is reduced with respect to prior of about $49\,\%$, in absence of systematic error in PMU, and of about 52% when $p = 75\,\%$). Similar

[1]PMU accuracy B corresponds to about $1\,\%$ maximum total vector error (TVE) for synchrophasor measurement.

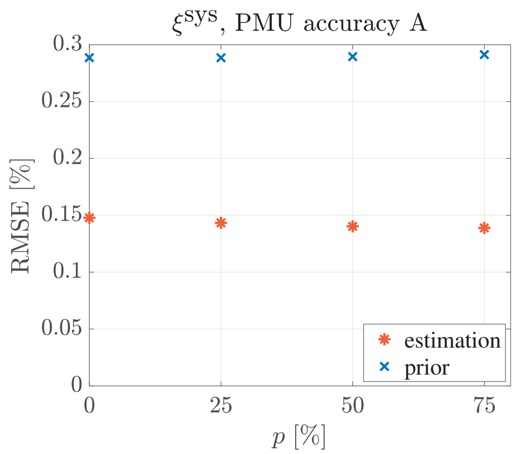

Fig. 3. Average RMSE of voltage synchrophasor magnitude estimation with a varying percentage of the PMU systematic error (PMU accuracy A).

considerations hold true also for voltage phase angles, and for current magnitudes and phase angles.

Figure 4 shows the same type of results obtained with PMU accuracy B. In this case, the contribution of PMU systematic errors is much larger, as proven by increasing prior values. Nevertheless, the algorithm is still able to reduce significantly the overall systematic error and the RMSE reduction with respect to prior is even larger with higher values of p, thanks to the reduced random contribution. In particular, the RMSE reduction is above 37% for $p = 0\,\%$, then it increases with p reaching the maximum improvement of about $44\,\%$ for $p = 75\,\%$.

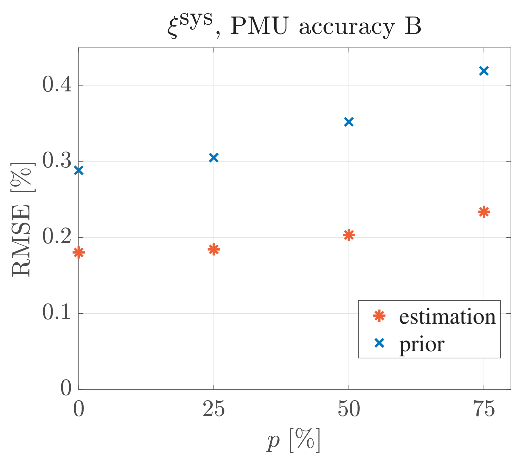

Fig. 4. Average RMSE of voltage synchrophasor magnitude estimation with a varying percentage of the PMU systematic error (PMU accuracy B).

C. *Line parameter estimation*

Previous results have shown that systematic errors in the measurement chain can be reduced significantly regardless of their origin and of possible lack of prior knowledge. However it is important to understand the effect of mismatch on the main target of the estimation, i.e., line parameters.

Figure 5 shows an example of the results on line parameters. Average percent RMSE values are reported for the estimates of γ_{i_k,j_k} ($k = 1, \ldots, 6$) when PMU accuracy and p vary. As a term of comparison, prior values are always the same and equal to $15/\sqrt{3} = 8.66\,\%$ (with slight variations when deviations are actually extracted during MC trials). The results are extremely interesting and need to be carefully interpreted. First of all, the estimation accuracy increases with PMU accuracy as expected. Second, the impact of p is not straightforward. For low PMU accuracies, as mentioned before, PMU systematic error doesn't affect significantly the overall systematic error and thus the main impact is given by the reduced random contribution (with increasing values of p). It is also important to remember that, since the overall systematic error is the sum of two uniform distributions and the PMU contribution changes with p, the resulting trapezoidal distributions of systematic errors can differ significantly. When PMU accuracy degrades, the contribution of systematic error becomes more relevant and comparable with IT contribution. For this reason, resistance estimation starts to degrade with higher p even if the random contribution is reduced (see PMU accuracy B). However the maximum RMSE increase is less than $6\,\%$ with $p = 75\,\%$ and worst PMU accuracy, thus confirming the robustness of the method also to measurement model tuning degradation (higher prior mismatch).

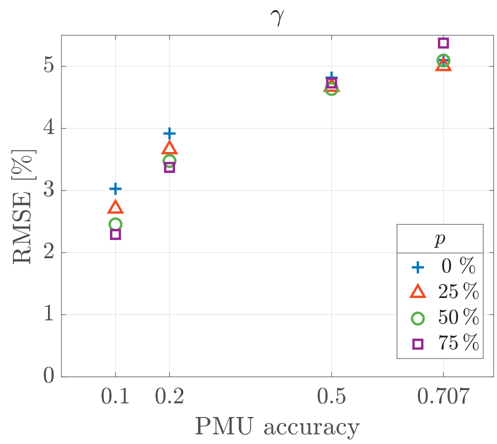

Fig. 5. Average RMSE of line resistance deviation with a varying percentage of the PMU systematic error and varying PMU accuracy.

V. CONCLUSIONS

In this paper, a recently proposed algorithm for transmission line parameters estimation relying on WAMS technology has been analyzed from the viewpoint of PMU measurement error model. Tests performed have shown that the systematic contribution of PMUs can be grasped by the estimation when highly accurate instruments are considered. When less accurate devices are used, the effect of additional systematic errors emerge. However, the impact of model mismatch is still low thus pointing to the algorithm robustness. These results are thus promising for method's applicability in real-word scenarios.

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