DPMU for Harmonic State Estimation

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Outline

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2. Methodology
   - Estimating Measurement Matrix
   - SBL-based State Estimator
3. Simulation Results
   - Test systems
   - Results

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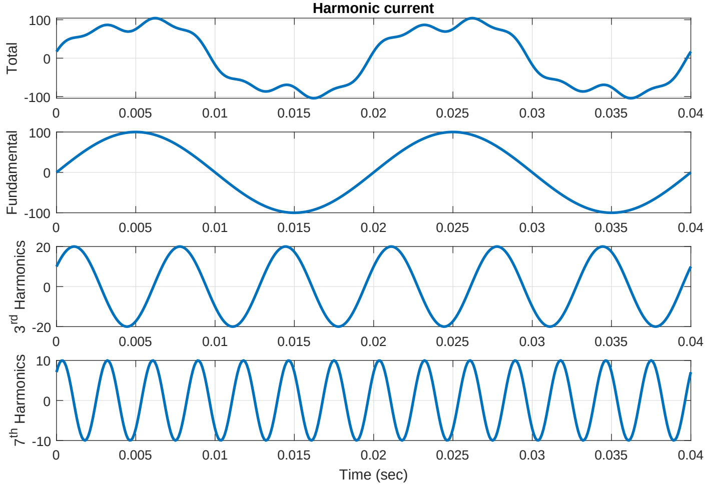
Background

The growing adoption of power electronic devices and large non-linear loads has increased *harmonic-related* power quality problems.



Harmonic State estimation (HSE)

- Locate the harmonic sources;
- Estimate harmonic voltage distribution.

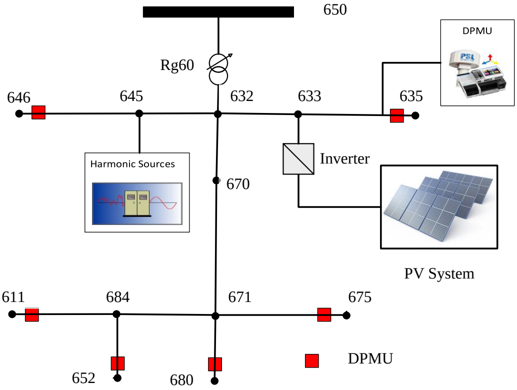
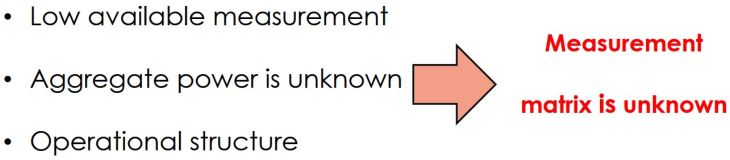


Figure: Diagram of HSE in distribution systems.

Harmonic State estimation (HSE)

We consider the harmonic state estimation problem in distribution system. The main difficulties include:

- unbalanced phases and phase coupling;
- Measurement matrix is unknown.



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Component Model

We use time-invariant harmonic models to represent all the components in distribution networks except for the loads.

- **Lines:** multiphase coupled equivalent π model;
- **Transformer:** the constant short-circuit impedance model;
- **Voltage regulators:** the short-circuit impedance model ;
- **Supply sources:** the Thevenin model;
- **PV system:** Norton model.

Nonlinear loads that produce harmonics are modelled as current injecting sources with time-varying impedance.

Load Model

The impedance of a load, denoted by $y_\ell(h)$, is computed as,

$$y_\ell(h) = y_\ell^p(h) + y_\ell^s(h), \tag{1}$$

$$y_\ell^p(h) = \frac{(1-c)P}{V_n^2} - j\frac{(1-c)hQ}{V_n^2}, \tag{2}$$

$$y_\ell^s(h) = \left[\frac{V_n^2 P}{c(P^2+Q^2)} + j\frac{hV_n^2 Q}{c(P^2+Q^2)}\right]^{-1}, \tag{3}$$

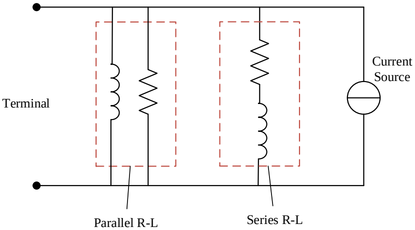

Figure: The utilized load model for harmonic analysis.

Formulation

HSE aims to estimate state variables x from DPMU measurements z with measurement noise ξ:

$$z(h) = \Phi(h)x(h) + \xi(h), \tag{4}$$

with

$$z(h) = \begin{bmatrix} V(h) \\ I^{\text{line}}(h) \end{bmatrix}, \quad \Phi(h) = \begin{bmatrix} S_1[Y^{\text{H}}(h)]^{-1} \\ S_2 Y^{\text{B}}(h)[Y^{\text{H}}(h)]^{-1} \end{bmatrix}. \tag{5}$$

where $x(h) \in \mathbb{C}^{\mathfrak{n}\times 1}$, $z(h) \in \mathbb{C}^{2\mathfrak{m}\times 1}$, $2\mathfrak{m} \leq \mathfrak{n}$.
Matrices S_1 and S_2 encode the locations of DPMUs. $Y^{\text{B}}(h)$ and $Y^{\text{H}}(h)$ are the branch admittance matrix and harmonic admittance matrix, respectively.

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Contribution

Our contribution are twofold:

- We propose a data-driven approach to HSE which copes with the unknown measurement matrix leveraging data from smart meters.
- We propose an SBL-based estimator for networks that are not fully observable to locate the harmonic sources, and to estimate the voltages using considerably fewer DPMUs than distribution nodes.

Outline

Framework

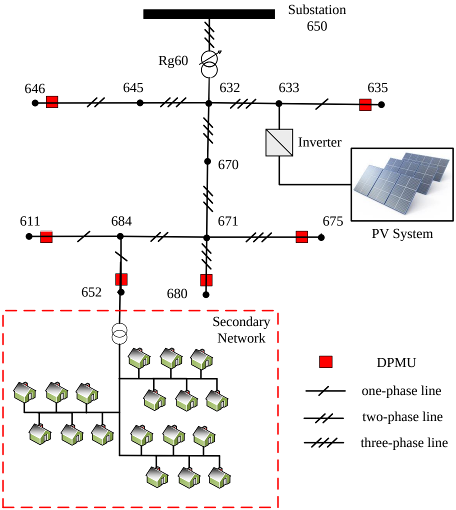

Figure: A typical distribution network.

Framework

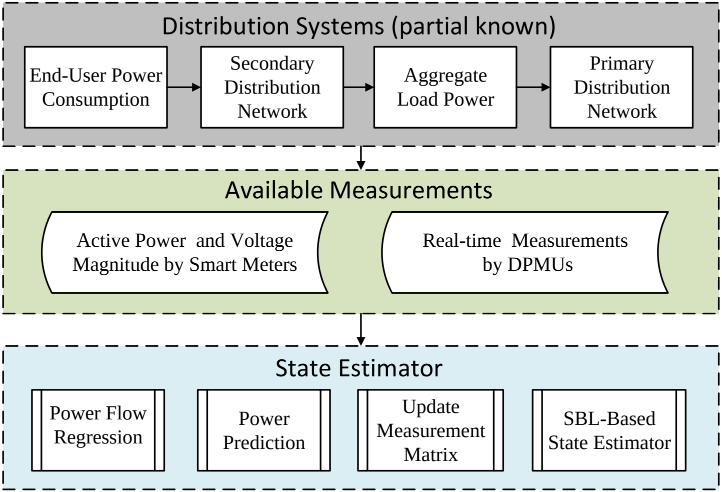

Figure: The overall framework for HSE in distribution networks.

Power Flow Regression

The first step is to infer the relationship between power flow in primary nodes and the demands of downstream customers measured by smart meters. This requires measuring the real and reactive power at each primary node for a relatively short time. We assume that this data is available.

$$\Upsilon = \Psi\Theta \tag{6}$$

where

$$\Upsilon = \begin{bmatrix} P^1 & Q^1 \\ \vdots & \vdots \\ P^{t_s} & Q^{t_s} \end{bmatrix}, \Psi = \begin{bmatrix} p^1 & v^1 & {v^1}^2 \\ \vdots & \vdots & \vdots \\ p^{t_s} & v^{t_s} & {v^{t_s}}^2 \end{bmatrix},$$

${v^{t_s}}^2$ represents the square of its element and Θ is the coefficient matrix.

The least squares method is utilized to solve this problem.

Demand Prediction

Since the refreshing rate of smart meter is much slower than that of DPMU, it is necessary to predict the power consumption based on the historical power. we employ the LSTM network to predict the power and then update the measurement matrix.

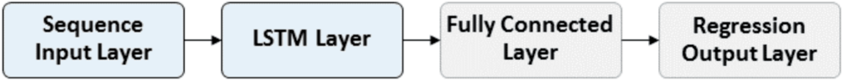

Figure: The architecture of LSTM network (Source: **MATLAB** 2018).

Estimating Measurement Matrix

One can compute the admittance matrix in real-time as follows:

$$
\begin{aligned}
\widehat{Y}^{\mathrm{H}^t}(h) &= Y^{\mathrm{H}^0}(h) + \Delta Y^{0\to t}(h) \\
\Delta Y^{0\to t}(h) &= f(\widehat{P}^t, \widehat{Q}^t, \widetilde{P}^0, \widetilde{Q}^0) \\
\widehat{P}^t &= [\widehat{P}_1^t, \cdots, \widehat{P}_{n_b}^t]^\top \\
\widehat{Q}^t &= [\widehat{Q}_1^t, \cdots, \widehat{Q}_{n_b}^t]^\top
\end{aligned} \tag{7}
$$

where $f(\cdot)$ is a function that returns the changes in the load admittance values according to the load model in Eqs. (1) (2) (3).

Outline

SBL-based Estimator

The likelihood is

$$p(z|x) \sim \mathcal{N}(\Phi x, \lambda I). \tag{8}$$

We introduce Gaussian prior for x to induce the sparsity,

$$p(x) = \prod_{i=1}^{n} p(x_k) \sim \prod_{i=1}^{n} \mathcal{N}(0, \gamma_i). \tag{9}$$

SBL-based Estimator

The posterior of x is

$$p(x|z) = \frac{p(z|x;\lambda)p(x;\gamma)}{\int p(z|x;\lambda)p(x;\gamma)dx} \sim \mathcal{N}(\mu_x, \Sigma_x), \tag{10}$$

with

$$\Sigma_x = (\Gamma^{-1} + \lambda^{-1}\Phi^T\Phi)^{-1}, \quad \Gamma = \mathrm{diag}(\gamma),$$
$$\mu_x = \lambda^{-1}\Sigma_x\Phi^T z.$$

The Bayes estimator of x is

$$\widehat{x} = (\lambda\Gamma_{\mathrm{MP}}^{-1} + \Phi^T\Phi)^{-1}\Phi^T y = \Gamma_{\mathrm{MP}}\Phi^T(\lambda I + \Phi\Gamma_{\mathrm{MP}}\Phi^T)^{-1}z. \tag{11}$$

SBL-based Estimator

The hyperparameter γ is optimized through type-2 maximum likelihood as

$$\gamma = \arg\max_{\gamma \geq 0} \int p(z|x;\lambda)p(x;\gamma)dx.$$

Taking $-2\ln(\cdot)$ transformation yields

$$L(\gamma) = \ln\det(\lambda I + \Phi\Gamma\Phi^T) + z^T(\lambda I + \Phi\Gamma\Phi^T)^{-1}z, \tag{12}$$

where the second term is data dependent. Note that

$$\begin{aligned} z^T(\lambda I + \Phi\Gamma\Phi^T)^{-1}z &= \lambda^{-1}z^T(z - \Phi\mu_x) \\ &= \lambda^{-1}\|z - \Phi\mu_x\|_2^2 + \mu_x^T\Gamma^{-1}\mu_x \\ &= \min_x \lambda^{-1}\|z - \Phi x\|_2^2 + x^T\Gamma^{-1}x. \end{aligned} \tag{13}$$

SBL-based Estimator

Substitute Eq. (13) into Eq. (12) yielding

$$L(z,\gamma) = \ln\det(\lambda I + \Phi\Gamma\Phi^T) + \lambda^{-1}\|z - \Phi x\|_2^2 + z^T\Gamma^{-1}z. \tag{14}$$

Observe that this is a convex-concave problem. We solve it following the convex concave programming idea.

SBL-based Estimator

By virtue of the sparsity of harmonic sources, the injecting harmonic currents are calculated as,

$$\hat{x}^{(k)} = \arg\min_{x} \frac{1}{2}\|z - \hat{\Phi}x\|_2^2 + \lambda \sum_{i=1}^{\mathfrak{n}} u_i^{(k)}|x_i|, \tag{15}$$

$$\gamma_i^{(k)} = \hat{x}_i^{(k)}/u_i^{(k)}, \tag{16}$$

$$u_i^{(k+1)} = [\hat{\Phi}_{\cdot i}^{\top}(\lambda I + \hat{\Phi}\Gamma^{(k)}\hat{\Phi}^{\top})^{-1}\hat{\Phi}_{\cdot i}]^{\frac{1}{2}}. \tag{17}$$

The re-weighting parameter u_i promotes the sparsity of x, and the weight parameter λ trades off sparsity for estimation error.

Outline

Test Feeder

- We test the proposed HSE framework on the modified IEEE 13-bus feeder under light and heavy loading conditions.
- We use real load data from ADRES data set and real harmonic spectrum from Power Stand Lab.

Table: The proposed harmonic state estimator and four baselines.

Cases	B1	B2	B3	B4	B5
Observed Data	$z(h)$				
Measurement Matrix	$\widehat{\Phi}$	$\widetilde{\Phi}$	$\bar{\Phi}$	$\check{\Phi}$	Φ
Regression	Yes	Yes	No	No	No
Prediction	Yes	No	No	Yes	No

Metrics

Three metrics, i.e., the identification error $\epsilon_x(h,i)$, the localization failure rate (LFR), and the normalized root-mean-square error (nRMSE), are utilized for evaluating HSE.

$$\epsilon_x(h,i) := \frac{|x_i^{es}(h) - x_i^{tr}(h)|}{\|x^{tr}(h)\|_2}\ , \tag{18}$$

$$\mathrm{LFR} := \frac{m}{N} \times 100\% \tag{19}$$

$$\mathrm{nRMSE_{IM}} := \sqrt{\frac{\sum_{i=1}^{\mathfrak{n}} \left(|x_i^{tr}| - |x_i^{es}|\right)^2}{\|x^{tr}\|_2}}, \tag{20}$$

$$\mathrm{nRMSE_{VM}} := \sqrt{\frac{\sum_{i=1}^{n_b} \left(|V_i^{tr}| - |V_i^{es}|\right)^2}{\|V^{tr}\|_2}}. \tag{21}$$

Outline

Prediction Results

- The regression error (nRMSE) is less than 1%, and the prediction error is about 11.90% and 10.16% under lighting and heavy two conditions.

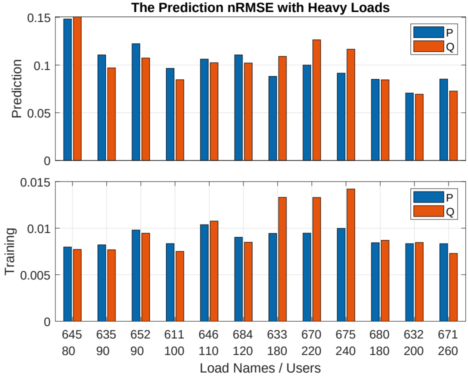

Figure: The training and prediction nRMSE of an hour ahead along buses under heavy loading condition.

Load only

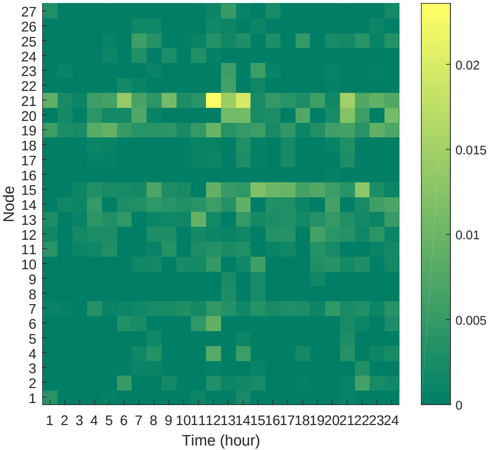

Figure: The maximum identification error among all harmonic orders at different nodes for each hour of the day under the light loading condition.

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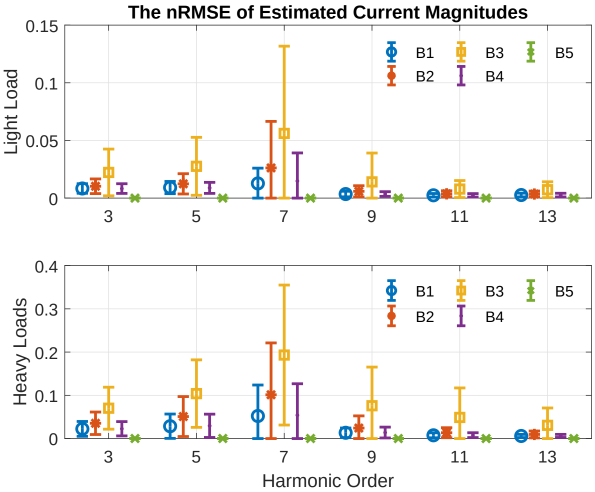

Figure: Comparison of nRMSE_{IM} for five cases under light and heavy operating conditions.

Load only

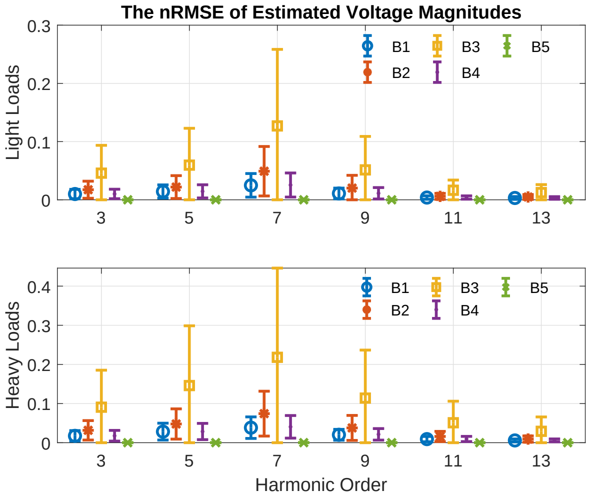

Figure: Comparison of $\mathrm{nRMSE}_{\mathrm{VM}}$ for five cases under light and heavy operating conditions.

Load only

Results:

The simulation result shows that the proposed SBL-based estimator can accurately estimate the voltage distribution and reliably locate the harmonic sources.

- The hourly maximum identification error among all orders is 2.36% which is attained for the peak hour, 12:00pm.
- the nRMSE_{IM} of our approach improves by 71.27% and 73.31% compared to B3 benchmark under light and heavy operating conditions, respectively.
- The proposed method has a smaller nRMSE_{VM} and a lower LFR than B2 and B3 benchmarks.

PV Systems is not harmonic sources

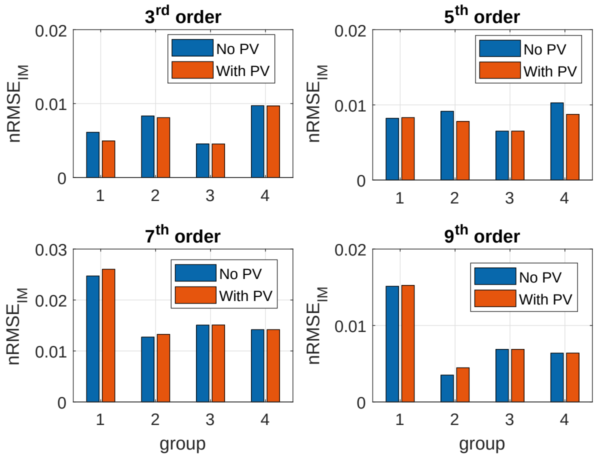

Figure: Comparing the $nRMSE_{IM}$ for harmonic orders $3, 5, 7, 9$ when a grid-connected PV system is installed and when there are only loads.

PV Systems is harmonic sources

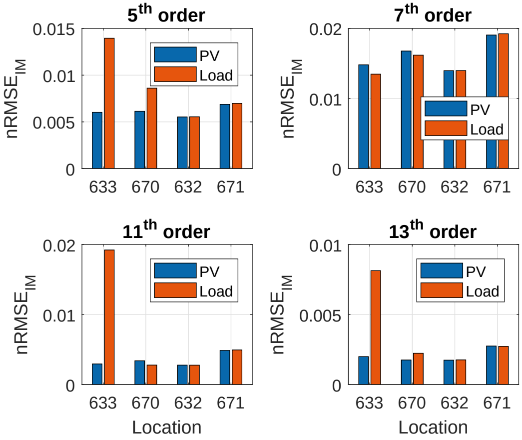

Figure: Comparing the $\mathrm{nRMSE_{IM}}$ for harmonic orders $5, 7, 11, 13$ when harmonic sources are located at buses that are not equipped with a DPMU.

Summary

- The proposed data-driven approach for updating the measurement matrix enhances the estimation performance.
- The proposed SBL-based estimator can locate the harmonic sources accurately using a small number of DPMUs.
- PV systems do not have a negative impact on the proposed estimator.

References

W. Zhou, O. Ardakanian, H.-T. Zhang and Y. Yuan, "Bayesian Learning-Based Harmonic State Estimation in Distribution Systems with Smart Meter and DPMU Data." IEEE Transactions on Smart Grid (2019).

Thanks! Any questions?

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