Calibrated Maximum Ratio Combining for Fusion-Based Distribution System State Estimation

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***Abstract*—Advanced Metering Infrastructure (AMI) data enables the development of data-driven techniques for distribution system state estimation (DSSE), thereby improving system monitoring and reliability. However, AMI measurements are noisy and only a subset of meters can be polled in near real time, creating significant challenges for state estimation under low observability. Unobservable AMI data can be reconstructed by various methods, such as low-rank matrix completion, sparsity-based DSSE, historical-profile-based pseudo-measurements, and forecasting-aided state estimation (FASE). However, each model may exhibit bias and varying uncertainty depending on data quality and network conditions, resulting in suboptimal state estimates. To address this limitation, we propose a data-driven framework that explicitly fuses the outputs of two complementary state estimation methods to enhance accuracy. The proposed framework consists of three components. First, a Bayesian Weighted Least Squares (BWLS) estimator utilizes forecasted pseudo-measurements for state estimation. Second, Variational Bayesian Matrix Completion (VBMC) exploits spatio-temporal correlations in observed AMI data to estimate the system state. Finally, a calibrated Maximum Ratio Combining (MRC) scheme fuses the VBMC and BWLS estimates according to their standard deviations and estimated biases. Simulation results on a 210-bus real-world distribution feeder demonstrate that the proposed calibrated MRC fusion reduces the estimation error by 94%.**

***Index Terms*—Advanced metering infrastructure, load forecasting, maximum ratio combining, state estimation.**

I. Introduction

Advanced Metering Infrastructure (AMI) has recently expanded beyond its initial applications in billing and load research to support real-time situational awareness of power distribution systems. AMI meters provide electricity consumption data at the customer and transformer levels, enabling the development of data-driven techniques for distribution system state estimation (DSSE) and operational decision-making. These capabilities are increasingly important as modern distribution grids become more complex due to the growth of rooftop solar generation, electric vehicles, energy storage, and greater consumer engagement. However, AMI measurements are noisy and only a subset of meters can be polled in near real time due to communication and data-processing bottlenecks. As a result, utilities typically observe only a sparse subset of customers at each polling instant, creating a persistent low-observability challenge in which the full network state cannot be directly inferred from raw AMI data.

Under these conditions, enhancing DSSE requires reconstructing unobservable quantities by exploiting spatial and temporal correlations together with prior information. Probabilistic low-rank matrix completion methods reconstruct missing AMI entries by modeling the measurement matrix as approximately low rank and inferring unobserved values from the observed ones [1]. Forecasting-aided state estimation (FASE) models use historical AMI data to predict future demand, thereby generating pseudo-measurements of active and reactive power for DSSE. Each pathway has distinct advantages: matrix completion leverages redundancy across customers and time, whereas forecasting captures temporal dynamics and multi-seasonal patterns. However, each model may exhibit bias and varying uncertainty depending on data quality, missing-data patterns, and network conditions. Accordingly, relying on a single estimator can lead to suboptimal state estimates.

To address this limitation, we propose a data-driven framework that fuses outputs from two complementary state estimation methods to improve accuracy under low observability. The framework consists of three components. First, a FASE module uses a machine-learning-based load forecaster to reconstruct unobservable data. Specifically, the Seasonal–Periodic Decomposition Network (SPDNet) is trained on historical AMI data to predict short-term active and reactive power with their timestamp-wise standard deviations [2]. These forecasts are then converted into pseudo-measurements and injected into a Bayesian Weighted Least Squares (BWLS) estimator, which enforces the AC power-flow model and produces a physics-based voltage estimate. In parallel, Variational Bayesian Matrix Completion (VBMC), a probabilistic matrix-completion method, is applied directly to the partially observed AMI load matrix to reconstruct the missing data by exploiting spatio-temporal correlations and low-rank structure. The reconstructed data by VBMC provide an alternative set of pseudo-measurements to estimate the system state in a fully probabilistic manner [3]. Finally, a calibrated Maximum Ratio Combining (MRC) framework fuses the VBMC- and BWLS-based state estimates by weighting each estimator according to its standard deviation and empirically estimated bias, thereby enhancing accuracy and robustness under low observability. The contributions of this study can be summarized as follows:

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- We propose a data-driven state estimation framework that fuses a forecasting-aided state estimator with a probabilistic estimator to improve performance of state estimation under low observability.
- We introduce a calibrated Maximum Ratio Combining fusion scheme that merges state estimates using their uncertainty and bias characteristics.
- Using a 210-bus real-world distribution feeder with sparse AMI availability, we show that the proposed calibrated Maximum Ratio Combining fusion reduces the state estimation error by 94%.

A. Related Work

1) Forecasting-Aided State Estimation: Beyond classical DSSE, where missing measurements are compensated using historical-data-based pseudo-measurements, several recent studies exploit forecasting models to generate pseudo-measurements. A multi-layer perceptron neural network is utilized in [4] to model active/reactive power and their standard deviation profiles, and showed that the resulting pseudo-measurements can be reliably injected into DSSE. In [5] a WaveNet-LSTM forecaster is developed to model nonconventional loads. Monte Carlo dropout is used to quantify forecast uncertainty, and the resulting pseudo-measurements are injected into an adaptive-smoothing FASE for unbalanced three-phase feeders. The authors of [6] propose a FASE scheme in which GRformer-based short-term load forecasts are converted into bus pseudo-measurements and combined with a Kalman filter, improving the accuracy and robustness of state estimation in active distribution networks.

2) Sparsity-Based DSSE: To reduce dependence on dense pseudo-measurements, sparsity-based methods exploit the underlying correlation structure of measurements and system states to enable state estimation with limited data. Compressive sensing (CS) approaches, introduced in [7], demonstrated that voltage states could be accurately estimated from only 50% of measurements by exploiting spatio-temporal correlations in distribution systems through wavelet-domain sparsity. Matrix completion methods [1] extend this paradigm by treating missing data as unknown entries of an incomplete low-rank matrix and recovering them through nuclear-norm minimization. Tensor completion frameworks [3] incorporate spatio-temporal correlations by modeling AMI and branch measurements as a 3-way state tensor and performing low-rank tensor recovery with power flow constraints. However, these sparsity-based DSSE methods rely on strong low-rank assumptions, may be sensitive to model mismatch and bad data [1].

3) Machine Learning-Based DSSE: In recent years, machine learning techniques have been explored to improve DSSE by capturing nonlinear dependencies among measurements and system states. Deep neural networks have been used to approximate state estimators [8]. Graph neural networks (GNNs) [9] extend this paradigm by incorporating network topology as graph structures, modeling state estimation as node-level prediction problems. A hybrid learning–optimization approach is proposed in [10], where a neural network is trained to provide high-quality initial states for Gauss–Newton, significantly improving convergence and accuracy. However, these estimators require large amounts of training data, are not easily adaptable to network changes, can be biased, and do not provide confidence bounds on the estimates.

II. Background

A. Forecasting-Aided State Estimation

In the FASE framework, unobservable data are reconstructed by a forecasting module that supplies pseudo-measurements. In this study, we employ the SPDNet to forecast these unobservable quantities for the next 24 hours using available historical data.

1) SPDNet: SPDNet is a deep learning framework tailored to capture temporal characteristics of electricity demand, achieving state-of-the-art forecasting accuracy and computational efficiency. SPDNet comprises three main components. First, the Seasonal-Trend Decomposition Module (STDM) applies 1D convolutions to decompose input load data into trend, seasonal, and residual components. Second, the Periodical Decomposition Module (PDM) uses Fast Fourier Transform to identify dominant periods and reshapes the data into 2D representations. These periodical representations are then processed through three parallel branches: 1D convolutional layers to capture short-term variations, a 2D convolutional branch to model intra- and inter-period correlations, and a Transformer-encoder to learn long-range temporal dependencies. Finally, an aggregation layer combines the PDM and STDM outputs to forecast active and reactive power. In addition, the forecast uncertainty at each timestamp is quantified by calculating the sample standard deviation of prediction errors across all test days for that specific time of day [11]. These forecasted values along with their uncertainties are then used as pseudo-measurements in the BWLS-based state estimation [2].

2) Bayesian Weighted Least Squares: BWLS is used as the physics-based component of the FASE framework. At each estimation instant, all unknown bus-voltage angles and magnitudes are stacked into the state vector $\mathbf{x}$. The real-time AMI measurements and SPDNet-based pseudo-measurements of active and reactive power are collected in the vector $\mathbf{z}$ and modeled as

$$\mathbf{z} = \mathbf{h}(\mathbf{x}) + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(\mathbf{0}, R), \tag{1}$$

where $\mathbf{h}(\mathbf{x})$ denotes the nonlinear AC power-flow model and $R = \mathrm{diag}(\sigma_1^2, \ldots, \sigma_m^2)$ encodes the variances of the measurements and forecasts. Under this Gaussian likelihood and a non-informative prior on $\mathbf{x}$, the posterior mean is obtained by solving the weighted least-squares problem

$$\hat{\mathbf{x}}_{\mathrm{FASE}} = \arg\min_{\mathbf{x}} \tfrac{1}{2}(\mathbf{z} - \mathbf{h}(\mathbf{x}))^\top R^{-1}(\mathbf{z} - \mathbf{h}(\mathbf{x})). \tag{2}$$

This optimization is solved iteratively using a Gauss–Newton scheme, yielding the estimated state vector

$$\hat{\mathbf{x}}_{\mathrm{FASE}} = \begin{bmatrix} \hat{\boldsymbol{\delta}}_{\mathrm{FASE}} \\ \hat{\mathbf{v}}_{\mathrm{FASE}} \end{bmatrix}, \qquad \boldsymbol{\sigma}_{\mathbf{x},\mathrm{FASE}} = \begin{bmatrix} \boldsymbol{\sigma}_{\delta,\mathrm{FASE}} \\ \boldsymbol{\sigma}_{v,\mathrm{FASE}} \end{bmatrix},$$

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where $\hat{\boldsymbol{\delta}}_{\text{FASE}}$ and $\hat{\mathbf{v}}_{\text{FASE}}$ are the estimated voltage angles and magnitudes, and $\boldsymbol{\sigma}_{\delta,\text{FASE}}$, $\boldsymbol{\sigma}_{v,\text{FASE}}$ are their corresponding standard deviation vectors derived from the approximate posterior covariance [1].

B. *Variational Bayesian Matrix Completion*

VBMC is used as a data-driven benchmark that reconstructs the unobservable AMI data using a low-rank probabilistic matrix-factorization model. The partially observed AMI data are arranged into a matrix $\mathbf{Z}$, with observed entries indexed by Ω, and modeled as

$$z_{ij} = x_{ij} + \varepsilon_{ij}, \qquad \varepsilon_{ij} \sim \mathcal{N}(0, \sigma_{ij}^2),\ (i,j) \in \Omega, \quad (3)$$

where $\mathbf{X} = [x_{ij}]$ is the low-rank latent matrix to be inferred. The posterior mean $\hat{\mathbf{X}}_{\text{VBMC}}$ can be calculated as

$$\hat{\mathbf{X}}_{\text{VBMC}} = \arg\min_{\mathbf{X}} \sum_{(i,j)\in\Omega} \frac{(z_{ij} - x_{ij})^2}{2\sigma_{ij}^2} + \mathcal{R}_{\text{VB}}(\mathbf{X}), \quad (4)$$

where $\mathcal{R}_{\text{VB}}(\mathbf{X})$ denotes the Bayesian regularization induced by the latent-factor priors. By solving VBMC, the corresponding state estimates and their standard deviations are obtained as

$$\hat{\mathbf{x}}_{\text{VBMC}} = \begin{bmatrix} \hat{\boldsymbol{\delta}}_{\text{VBMC}} \\ \hat{\mathbf{v}}_{\text{VBMC}} \end{bmatrix}, \qquad \boldsymbol{\sigma}_{\mathbf{x},\text{VBMC}} = \begin{bmatrix} \boldsymbol{\sigma}_{\delta,\text{VBMC}} \\ \boldsymbol{\sigma}_{v,\text{VBMC}} \end{bmatrix},$$

where $\hat{\boldsymbol{\delta}}_{\text{VBMC}}$ and $\hat{\mathbf{v}}_{\text{VBMC}}$ are the estimated voltage angles and magnitudes, and $\boldsymbol{\sigma}_{\delta,\text{VBMC}}$ and $\boldsymbol{\sigma}_{v,\text{VBMC}}$ are their corresponding standard deviations. Uncertainty is estimated from the inverse Gauss–Newton Hessian, which provides an approximation of the posterior covariance under the Gaussian measurement model [1]. The FASE and VBMC estimates are then fused through a calibrated MRC scheme.

III. Methodology

The proposed framework fuses the outputs of the FASE and VBMC to obtain a more accurate and robust state.

A. *Classical Maximum Ratio Combining*

Let x_1 and x_2 denote two independent unbiased estimates of the true state x_{true}, obtained from FASE and VBMC, respectively. Their error models are

$$x_1 = x_{\text{true}} + e_1, \qquad x_2 = x_{\text{true}} + e_2, \quad (5)$$

where the random errors satisfy

$$\begin{aligned} \mathbb{E}[e_1] &= 0, & \mathbb{E}[e_2] &= 0, \\ \operatorname{Var}(e_1) &= \sigma_1^2, & \operatorname{Var}(e_2) &= \sigma_2^2, \\ \operatorname{Cov}(e_1, e_2) &= 0. \end{aligned}$$

We seek a linear fused estimate

$$x_f = w_1 x_1 + w_2 x_2, \qquad \text{s.t. } w_1 + w_2 = 1, \quad (6)$$

where the weights minimize the mean-squared error of x_f. Because the errors are zero-mean and uncorrelated, mean-squared error of x_f can be written as

$$J(w_1, w_2) = \mathbb{E}\big[(x_f - x_{\text{true}})^2\big] = w_1^2\sigma_1^2 + w_2^2\sigma_2^2. \quad (7)$$

To minimize (7) under $w_1 + w_2 = 1$, we form the Lagrangian

$$\mathcal{L}(w_1, w_2, \lambda) = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + \lambda(w_1 + w_2 - 1), \quad (8)$$

and set the derivatives to zero:

$$\frac{\partial \mathcal{L}}{\partial w_1} = 2w_1\sigma_1^2 + \lambda = 0, \qquad \frac{\partial \mathcal{L}}{\partial w_2} = 2w_2\sigma_2^2 + \lambda = 0. \quad (9)$$

Eliminating λ yields

$$\frac{w_1}{w_2} = \frac{\sigma_2^2}{\sigma_1^2}. \quad (10)$$

Together with $w_1 + w_2 = 1$, this gives the closed-form MRC weights

$$w_1 = \frac{1/\sigma_1^2}{1/\sigma_1^2 + 1/\sigma_2^2}, \qquad w_2 = \frac{1/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2}. \quad (11)$$

Substituting (11) into (6) gives the final fused estimate

$$x_f = \frac{1/\sigma_1^2}{1/\sigma_1^2 + 1/\sigma_2^2}\, x_1 + \frac{1/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2}\, x_2. \quad (12)$$

B. *Calibrated Maximum Ratio Combining*

Unlike classical MRC, which assumes unbiased estimators, the FASE- and VBMC-based estimates may exhibit systematic bias at certain buses. To address this limitation, we introduce a calibration step prior to fusion that explicitly accounts for both bias and variance.

1) Bias Correction: Each estimator is modeled using an affine bias representation:

$$x_i = a_i x_{\text{true}} + b_i + e_i, \qquad i = 1, 2, \quad (13)$$

where a_i and b_i capture multiplicative and additive bias, and e_i is zero-mean noise. The observable subset of AMI measurements (where true values are available) is used to estimate the bias parameters by least squares:

$$\begin{bmatrix} a_i \\ b_i \end{bmatrix} = \arg\min_{a,b} \left\| x_{\text{true}} - (a x_i + b) \right\|_2^2, \qquad i = 1, 2. \quad (14)$$

The bias-corrected estimates are then obtained as

$$\widehat{x}_i = a_i x_i + b_i, \qquad i = 1, 2. \quad (15)$$

After calibration, the residual error for each estimator is:

$$r_i = \widehat{x}_i - x_{\text{true}} = \mu_i + \varepsilon_i, \quad (16)$$

where $\mu_i = \mathbb{E}[r_i]$ is the residual bias and $\sigma_i^2 = \operatorname{Var}(\varepsilon_i)$ is the residual variance, both estimated from the calibration data. The mean-squared error of each estimator is quantified by the sum of residual bias and residual variance as

$$\mu_i^2 + \sigma_i^2, \qquad i = 1, 2. \quad (17)$$

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2) Bias-Aware Fusion Rule: Similar to classical MRC, we seek a linear fusion

$$x_f = w_1 \widehat{x}_1 + w_2 \widehat{x}_2, \qquad \text{s.t. } w_1 + w_2 = 1, \tag{18}$$

that minimizes the mean-squared error of x_f,

$$J = \mathbb{E}\big[(x_f - x_{\text{true}})^2\big].$$

Using the Lagrangian multiplier method and replacing variances with the total error $\mu_i^2 + \sigma_i^2$ of each estimator, the optimal calibrated weights are obtained as

$$w_i = \frac{1/(\mu_i^2 + \sigma_i^2)}{1/(\mu_1^2 + \sigma_1^2) + 1/(\mu_2^2 + \sigma_2^2)}, \qquad i = 1, 2. \tag{19}$$

3) Final Fused Estimate: With the calibrated weights, the final fused estimate is

$$x_f = w_1(a_1 x_1 + b_1) + w_2(a_2 x_2 + b_2). \tag{20}$$

Therefore, calibrated MRC generalizes classical MRC by incorporating both bias and variance into the fusion weights.

IV. Results

A. Case Study

The proposed framework is evaluated on a real-world, mixed-phase 210-bus distribution feeder. AMI meters record 15-minute demand from October 25, 2020, to March 10, 2024. At each estimation instant, only 20% of AMI meters are polled in near real time, while full logs are retrieved every 24 hours. Therefore, 80% of AMI data are unobservable and must be inferred via forecasting-based pseudo-measurements and matrix-completion mechanisms within the DSSE framework. The simulations are performed on a 12-core x86-64 CPU using MATLAB R2021a in CPU-only mode. The proposed pipeline requires approximately 3 s per snapshot, with memory usage dominated by approximately 56 MB, confirming its practical computational feasibility.

B. Load Demand Forecasting

In the FASE framework, unobservable AMI data are reconstructed using SPDNet-based load forecasts that serve as pseudo-measurements. The SPDNet model is trained on 70% of the AMI data, validated on 10%, and tested on the remaining 20%. The prediction horizon is 24 hours ahead, and forecasts are updated at each estimation instant. In addition, Fig. 1 shows the histogram of forecast errors for load 10 at 16:00 on July 8, 2023, over the test set. The error distribution is approximately zero-mean with a standard deviation of 0.293 kW. Following this procedure for all loads and timestamps, the empirical standard deviations are used as timestamp-wise uncertainty levels and inserted as the corresponding pseudo-measurement variances in the BWLS covariance matrix.

C. State Estimation Performance

This section evaluates the DSSE performance of the BWLS, VBMC, and fused estimators on the 210-bus feeder. Fig. 2 shows the per-unit phase-A voltage magnitude across all buses at 16:00 on July 8, 2023, including the true profile, the BWLS and VBMC estimates, and their fusion using classical MRC. For this snapshot, the BWLS estimator achieves $\text{MAE} = 0.00217$ and $\text{RMSE} = 0.00352$, while VBMC yields $\text{MAE} = 0.00356$ and $\text{RMSE} = 0.00415$. The classical MRC fusion slightly improves the RMSE to 0.00343 with the same MAE as BWLS. However, at several buses BWLS and VBMC outperform the fused estimate, indicating suboptimal behavior of classical MRC. This can be attributed to the fact that BWLS and VBMC exhibit systematic bias at different subsets of buses, whereas classical MRC assumes unbiased estimators.

To mitigate these biases, the calibrated MRC scheme is applied using the observable subset of AMI data (20% of buses). Fig. 3 presents the corresponding results for calibrated MRC for the same time instant as Fig. 2. For this snapshot, the calibrated MRC achieves $\text{MAE} = 0.00012$ and $\text{RMSE} = 0.00015$, which corresponds to approximately a 94% reduction in MAE and a 93% reduction in RMSE compared to the classical MRC estimates. To examine robustness, the calibrated MRC is evaluated under varying observability levels (5–50%) and data noise up to 5%, with the results summarized in Table I. The calibrated MRC remains highly accurate across all cases, exhibiting only mild degradation under higher noise, which confirms the robustness of the proposed bias-aware fusion scheme. To further validate the robustness of the proposed approach, Fig. 4 shows the average phase-A voltage magnitude MAE across all buses over a full 24-hour period. The calibrated MRC consistently outperforms both BWLS and VBMC estimators throughout the day. The substantial error reduction achieved by calibrated MRC demonstrates the effectiveness of bias-aware fusion for improving state estimation accuracy in low-observable distribution systems.

V. Conclusion

This paper presents a data-driven framework that fuses the outputs of two complementary DSSE models to improve

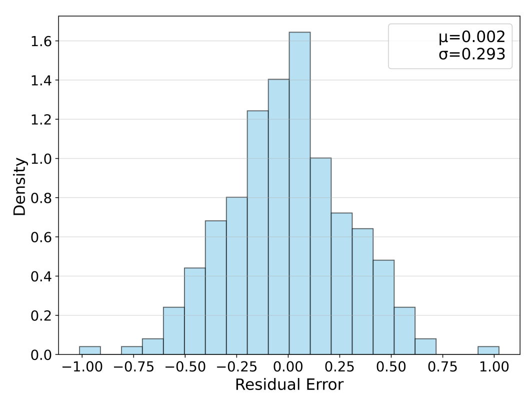

Fig. 1. Histogram of SPDNet forecast errors for load 10 at 16:00 over the test set.

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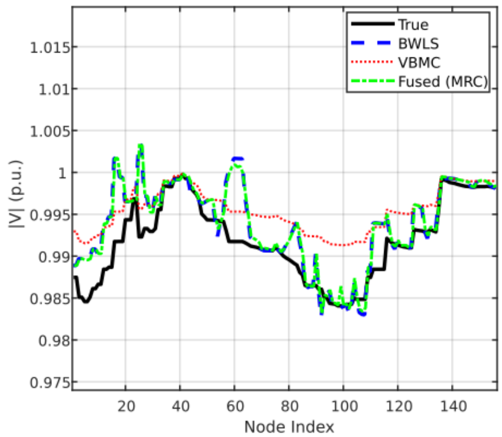

Fig. 2. Phase-A voltage magnitude across all buses using classical MRC.

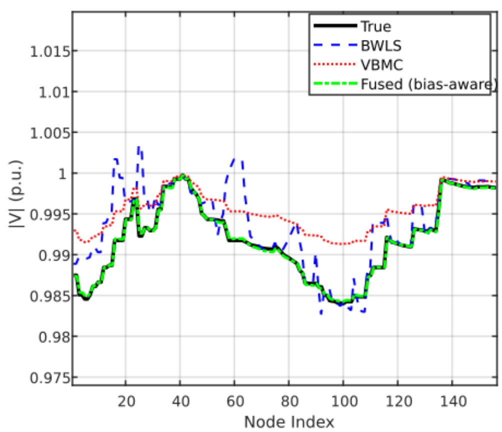

Fig. 3. Phase-A voltage magnitude across all buses using calibrated MRC.

TABLE I
ROBUSTNESS OF BIAS-AWARE MRC UNDER VARYING DATA OBSERVABILITY AND NOISE LEVELS.

Observability (%)	Data Noise (%)	MAE (p.u.)	RMSE (p.u.)
5	0	0.00007	0.00010
5	2	0.00030	0.00051
5	5	0.00447	0.00788
10	0	0.00005	0.00008
10	2	0.00039	0.00057
10	5	0.00081	0.00133
20	0	0.00005	0.00010
20	2	0.00019	0.00040
20	5	0.00055	0.00111
30	0	0.00004	0.00007
30	2	0.00015	0.00035
30	5	0.00041	0.00077
50	0	0.00003	0.00007
50	2	0.00009	0.00025
50	5	0.00025	0.00058

accuracy under low observability. The approach combines a forecasting-aided state estimator, based on SPDNet and BWLS, with a probabilistic VBMC-based estimator. However, BWLS-based and VBMC-based estimates may exhibit bias and varying uncertainty depending on data quality and network conditions, resulting in suboptimal state estimates. To address

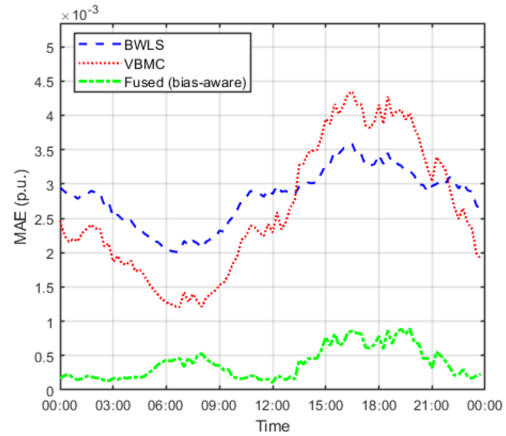

Fig. 4. Average phase-A voltage magnitude MAE over 24 hours.

this limitation, we developed a calibrated MRC scheme that explicitly accounts for both systematic bias and variance by estimating affine correction parameters from observable AMI data. Simulation results on a 210-bus real-world distribution feeder with 80% unobservable data demonstrate that the calibrated MRC fusion achieves up to a 94% reduction in state estimation error. These results highlight the effectiveness of bias-aware fusion for improving state estimation accuracy under low observability.

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