Impact of Forecasting Error on Predictive Estimation

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- Distribution System Transformation
- Proactive Operation
- Predictive State Estimation 1: Matrix Completion
- Predictive State Estimation 2: Multi-kernel Learning
- Conclusion
- Acknowledgement

Distribution system energy management at multi-level

- Individual control targets
- Temporal and spatial complexity
- High dimension of controllability

Smart inverters

Building energy management systems

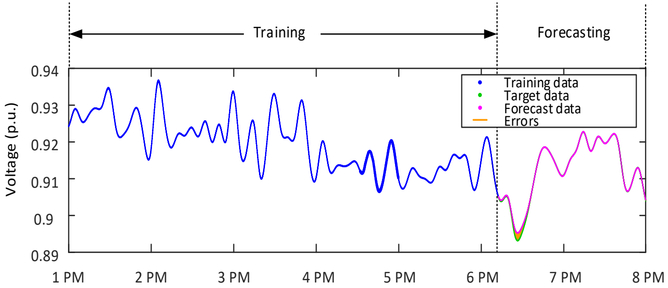
Battery energy management systems

Home energy management systems

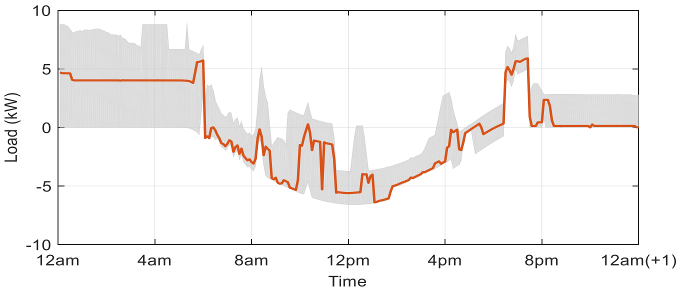
Aggregators

Microgrids

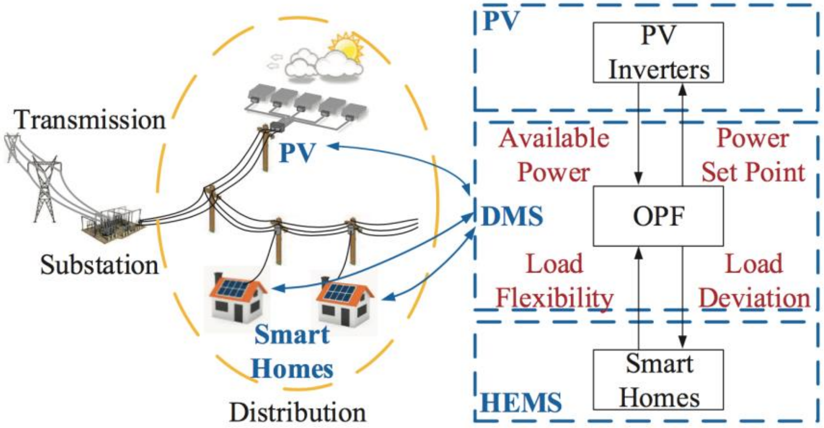
Proactive distribution system dispatch using PSE



If we can predict the system states



Individual system can be predispatches within its constraints.



$$\min_{P^{\phi}_{S,m},Q^{\phi}_{S,m},P^{\phi}_{L,k}} \sum_{i\in\mathcal{N}}\sum_{\phi\in\mathcal{P}_i} \omega^{\phi}_i \cdot s^{\phi}_i + \omega_L \cdot \sum_{k\in\mathcal{N}_L}\sum_{\phi\in\mathcal{P}_{L,k}} \left(\frac{P^{\phi}_{L,k}-\widetilde{P}^{\phi}_{L,k}}{\widetilde{P}^{\phi}_{L,k}}\right)^2$$

Dynamically determined by the forecasted voltages

s.t.

$$P^{\phi}_{G,i} + P^{\phi}_{S,i} - P^{\phi}_{L,i} = \Re\{V^{\phi}_i \cdot (I^{\phi}_i)^*\}$$
$$Q^{\phi}_{G,i} + Q^{\phi}_{S,i} - Q^{\phi}_{L,i} = \Im\{V^{\phi}_i \cdot (I^{\phi}_i)^*\}$$

Power balance

$$\underline{V}^{\phi}_i - s^{\phi}_i \le |V^{\phi}_i| \le \overline{V}^{\phi}_i + s^{\phi}_i,\; s^{\phi}_i \ge 0$$

Voltage constraints

$$0 \le P^{\phi}_{S,m} \le \overline{P}^{\phi}_{S,m}$$
$$P^{\phi^2}_{S,m} + Q^{\phi^2}_{S,m} \le S^{\phi^2}_m$$

PV plant

$$\underline{P}^{\phi}_{L,k} \le P^{\phi}_{L,k} \le \overline{P}^{\phi}_{L,k}$$
$$Q^{\phi}_{L,k} = \sqrt{\frac{1}{\eta^{\phi^2}_{L,k}} - 1} \cdot P^{\phi}_{L,k}$$

HEMS

Predictive State Estimation 2: Multi-kernel Learning

- Multi-Kernel Learning
  - Vector-valued function $\mathbf{f} : \mathcal{X} \to \mathcal{Z}$

$$\mathcal{H}_{\mathbf{K}} := \left\{ \mathbf{f}(x) = \sum_{p=1}^{\infty} \mathbf{K}(\mathbf{x}_p, \mathbf{x})\mathbf{a}_p,\ \mathbf{x}_p \in \mathcal{X}, \mathbf{a}_p \in \mathbb{R}^D \right\}$$

  - Regularized least-squares problem

$$\widehat{\mathbf{f}} := \arg\min_{\mathbf{f} \in \mathcal{H}_{\mathbf{K}}} \sum_{c=1}^{D} \frac{1}{L} \sum_{n=1}^{L} \left(f_c(\mathbf{x}_n) - (\mathbf{z}_n)_c \right)^2 + \lambda \|\mathbf{f}\|_{\mathbf{K}}^2$$

  - Solution

$$\widehat{\mathbf{f}}(\mathbf{x}) = \sum_{n=1}^{L} \mathbf{K}(\mathbf{x}_n, \mathbf{x})\mathbf{a}_n^*$$

$$\mathbf{a}^* = \left(\mathbf{K}(\mathbf{X}, \mathbf{X}) + \lambda L \mathbf{I} \right)^{-1} \mathbf{z}$$

Predictive State Estimation 2: Clustering

- Clustering Method
  - Clustering buses according to the electric distance
  - Linear approximation of voltage magnitudes

$$\rho_{i\ell} = \sum_{j=1}^{N} \sum_{k=1}^{3} \left(r^{Y}_{(i\ell),(jk)} p^{Y}_{jk} + b^{Y}_{(i\ell),(jk)} q^{Y}_{jk} \right) + w_{i\ell}$$

  - Similarity metric

$$\alpha^{p,Y}_{(i\ell),(jk)} := \frac{\partial \rho_{i\ell} / \partial p^{Y}_{jk}}{\partial \rho_{jk} / \partial p^{Y}_{jk}} = \frac{r^{Y}_{(i\ell),(jk)}}{r^{Y}_{(jk),(jk)}}$$

$$\alpha^{q,Y}_{(i\ell),(jk)} := \frac{\partial \rho_{i\ell} / \partial q^{Y}_{jk}}{\partial \rho_{jk} / \partial q^{Y}_{jk}} = \frac{b^{Y}_{(i\ell),(jk)}}{b^{Y}_{(jk),(jk)}}$$

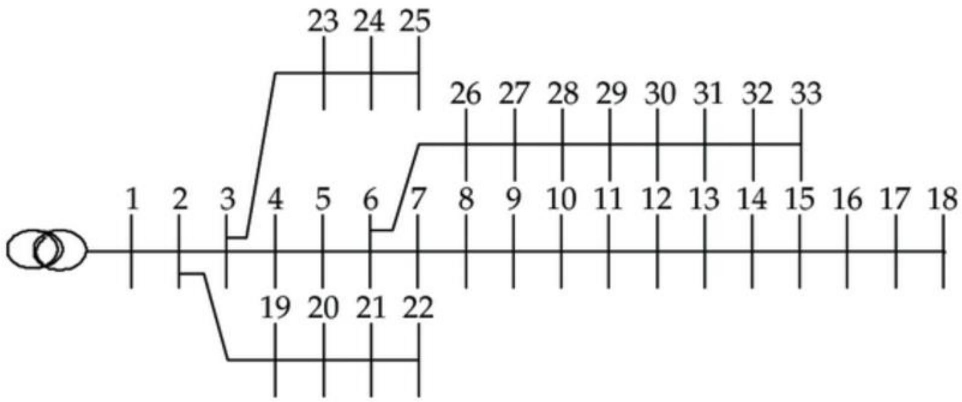
  - Distance

$$\alpha_{(i\ell),(jk)} := \left\| \left(\alpha^{p,Y}_{(i\ell),(jk)}, \alpha^{q,Y}_{(i\ell),(jk)} \right) \right\|_2$$

$$d_{(i\ell),(jk)} := \left\| \left(\alpha_{(i\ell),(jk)}, \alpha_{(jk),(i\ell)} \right) \right\|_2$$

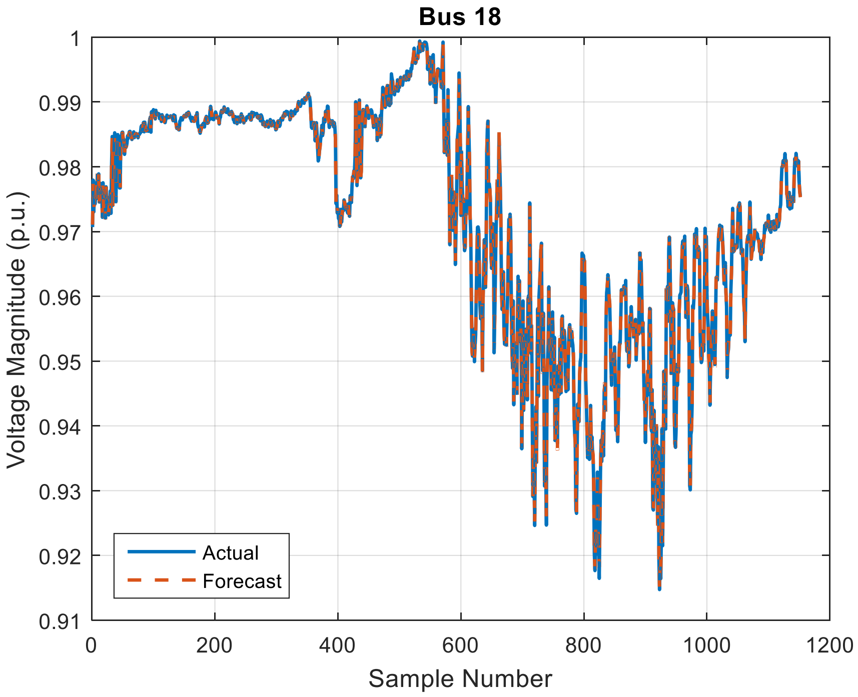
Simulations

- IEEE 33-bus system
- One PV system at bus 7
- Solar forecasting error
- Load forecasting error
- Kernel learning for PSE

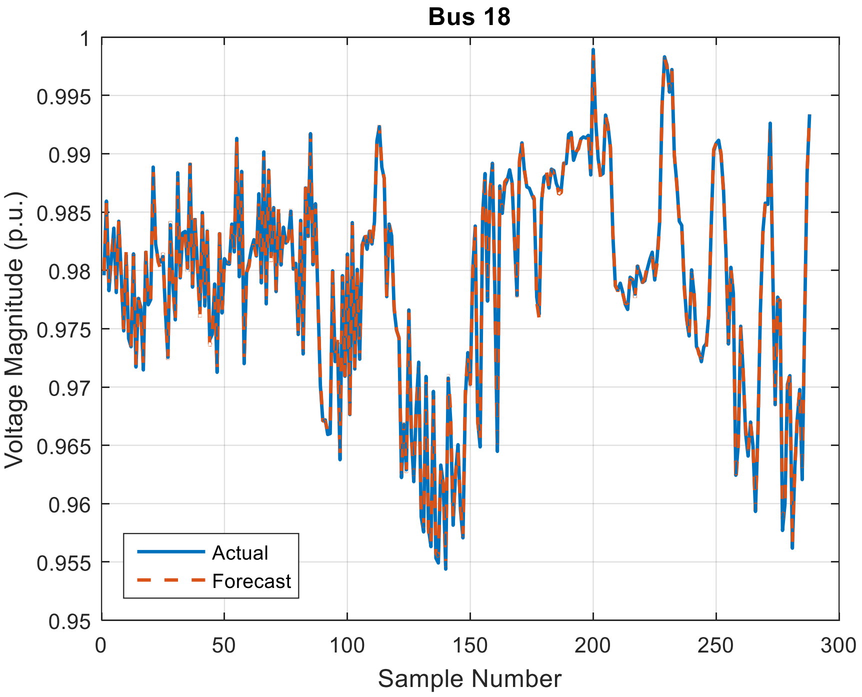


PSE w/o Forecast Error

Training Set

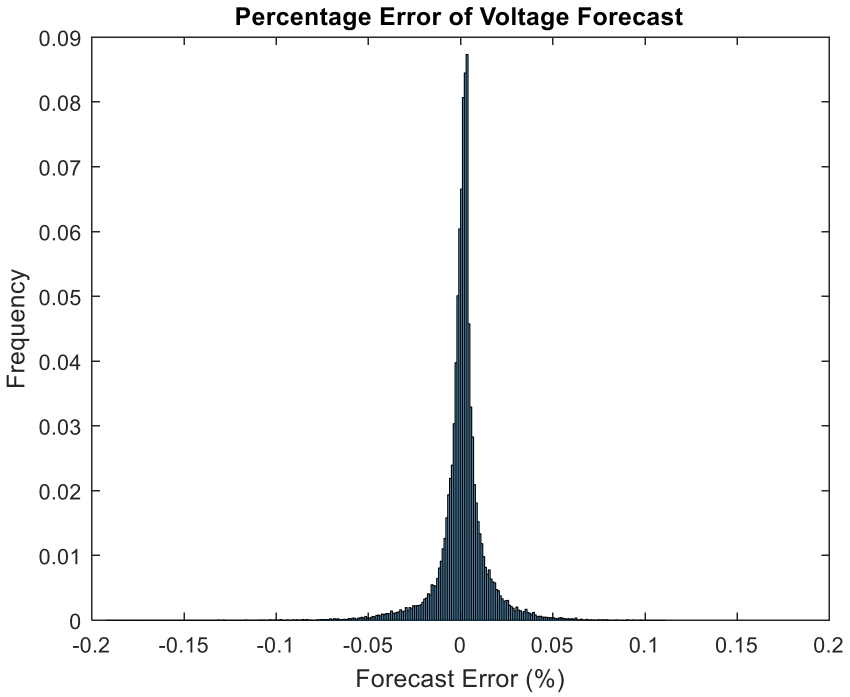


Testing Set

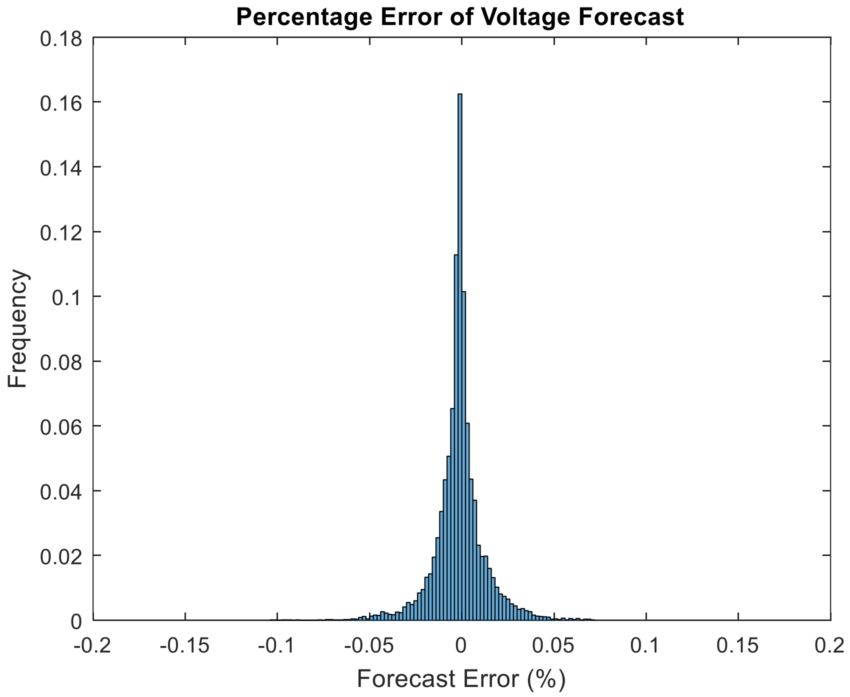


PSE w/o Forecast Error

Training Set



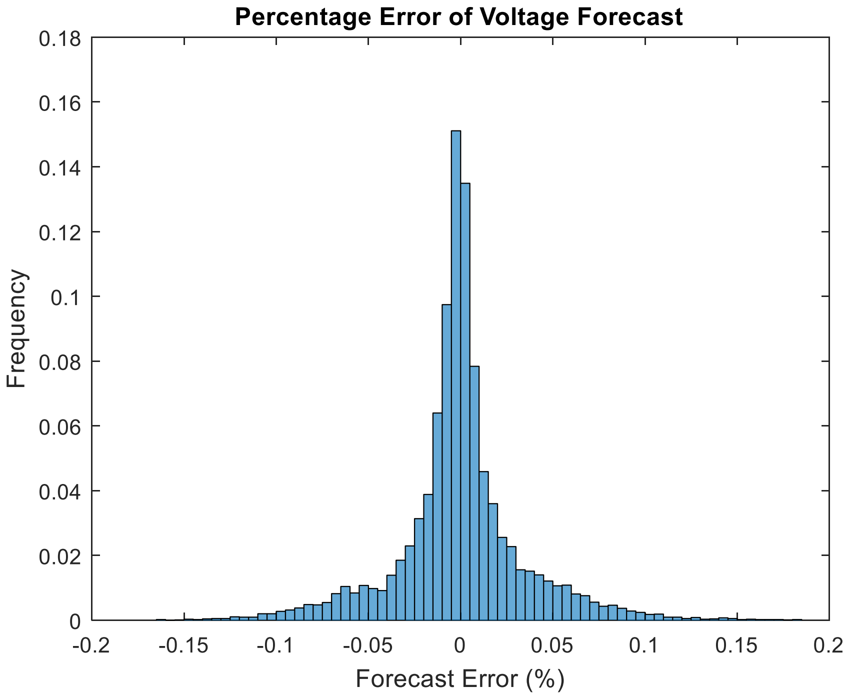
Testing Set



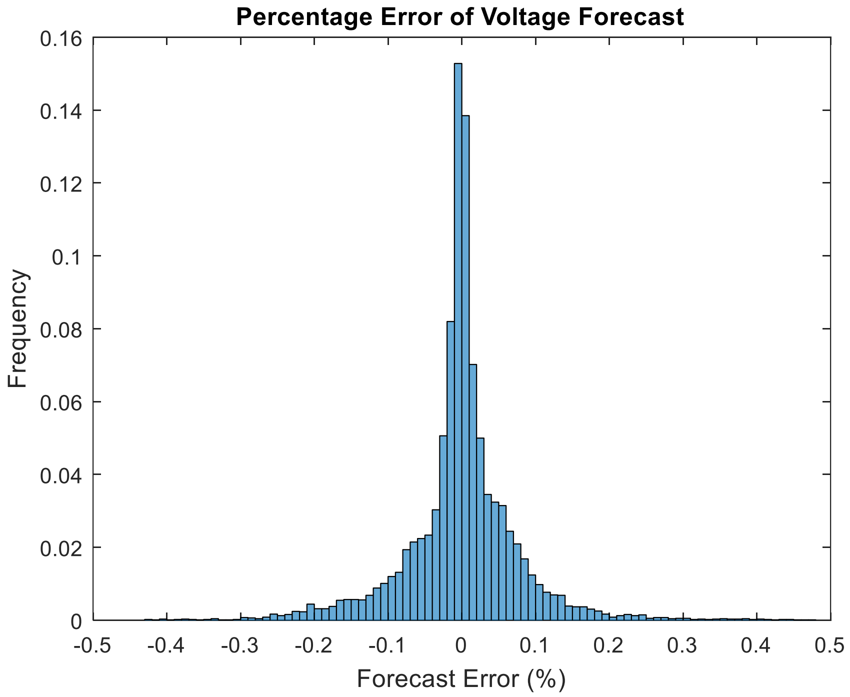
Forecast Error – Gaussian Distribution

$$\mathcal{N}(0, 5\%)$$

With Forecast Error of PV

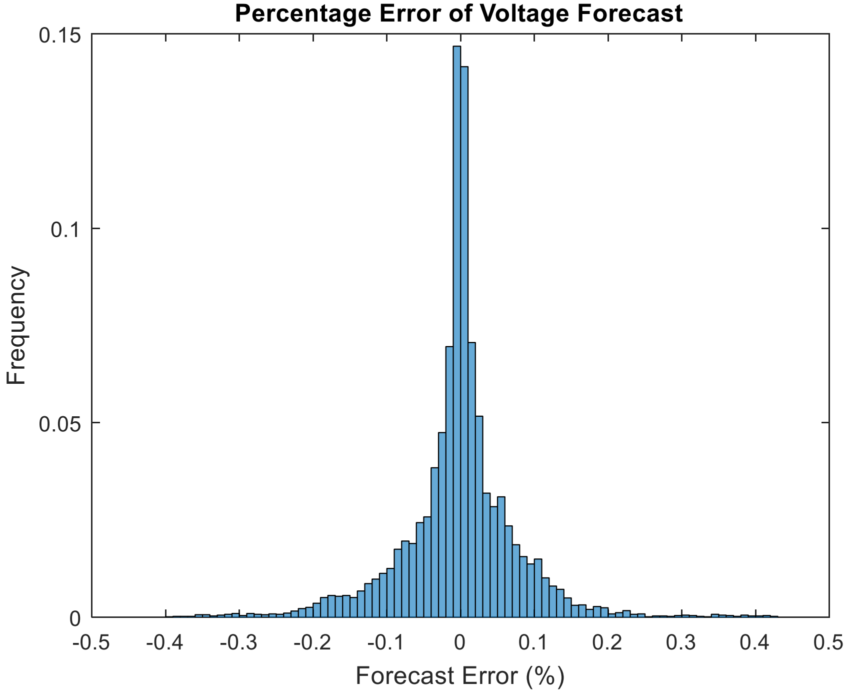


With Forecast Error of PV and Load

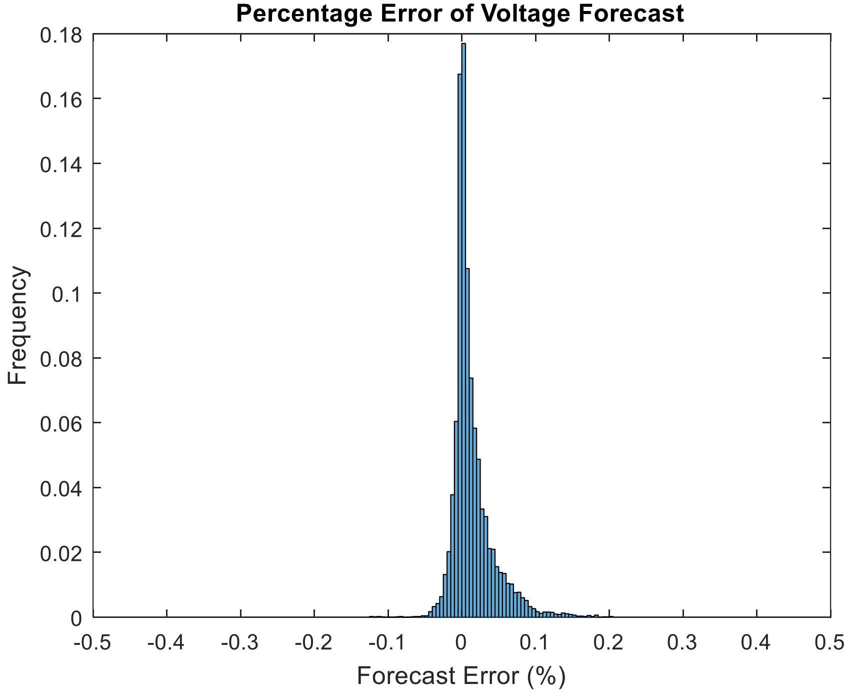


Forecast Error Distribution – Error within $\pm 10\%$

Beta Distribution

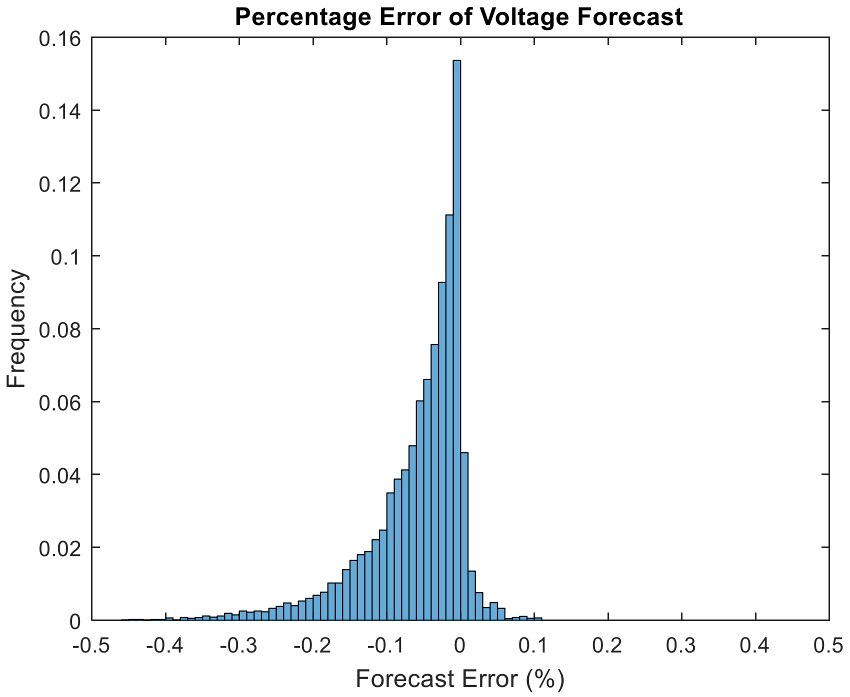


Gamma Distribution

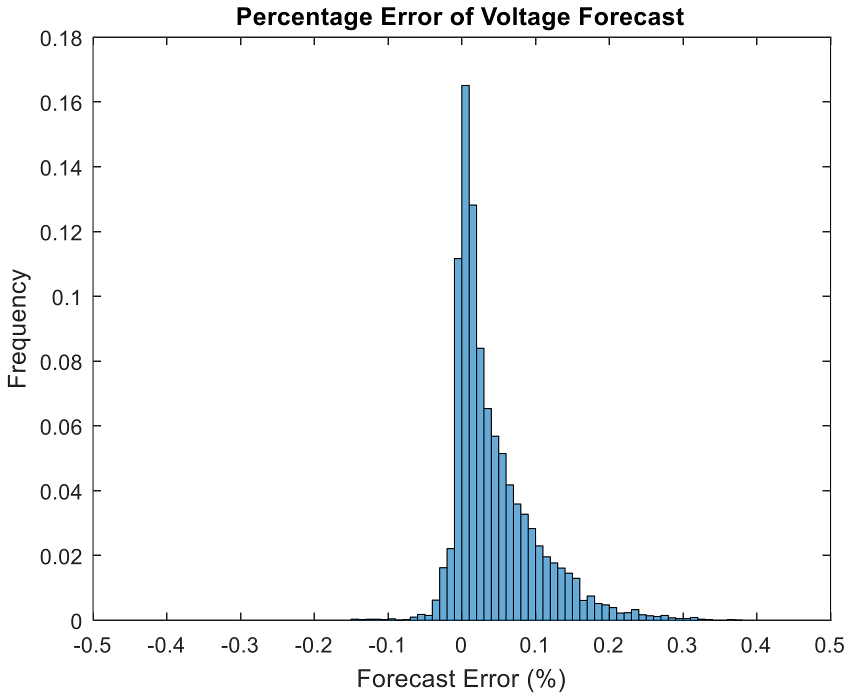


Forecast Error Distribution – Error within ±10%

Rayleigh Distribution

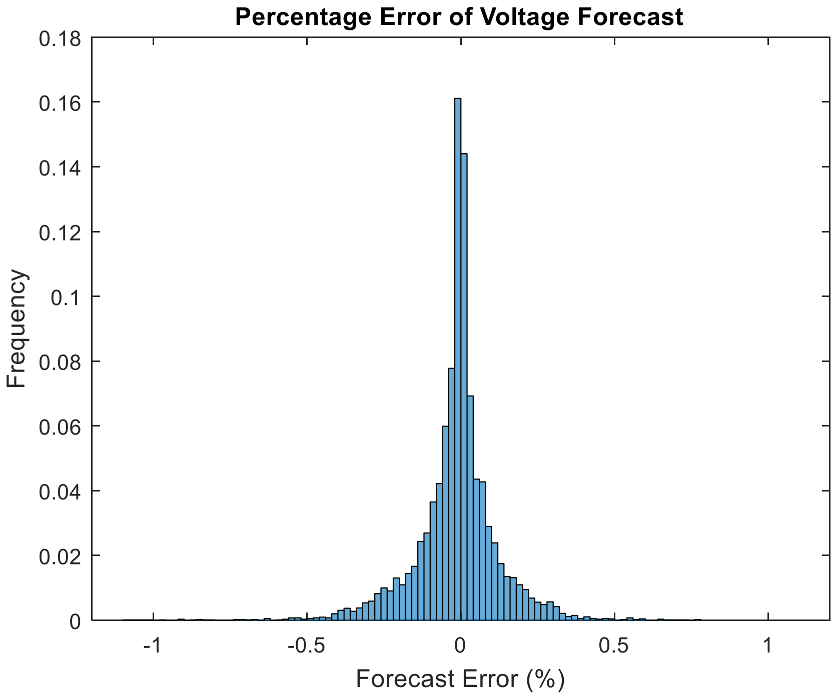


Weibull Distribution

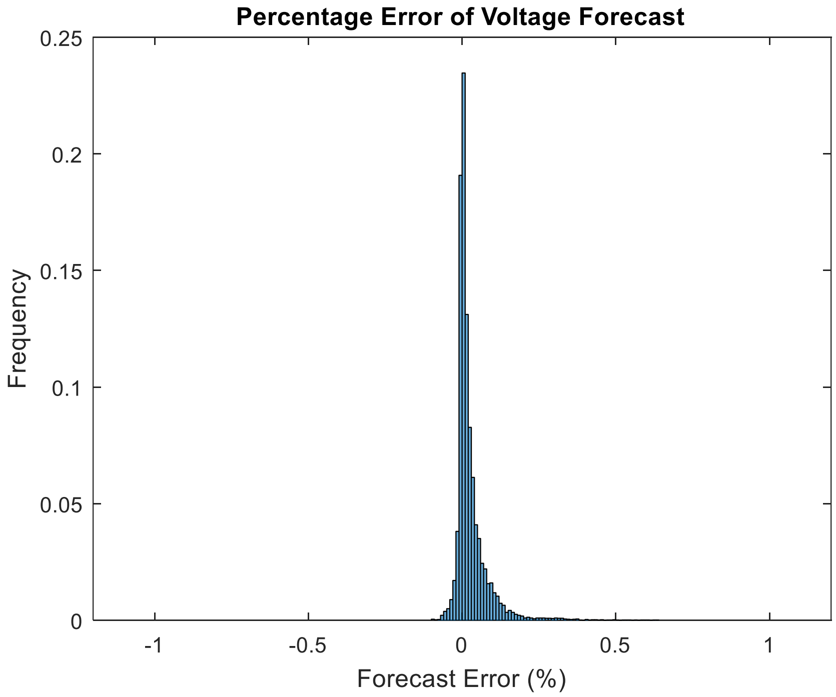


Forecast Error Distribution – Error within ±20%

Beta Distribution

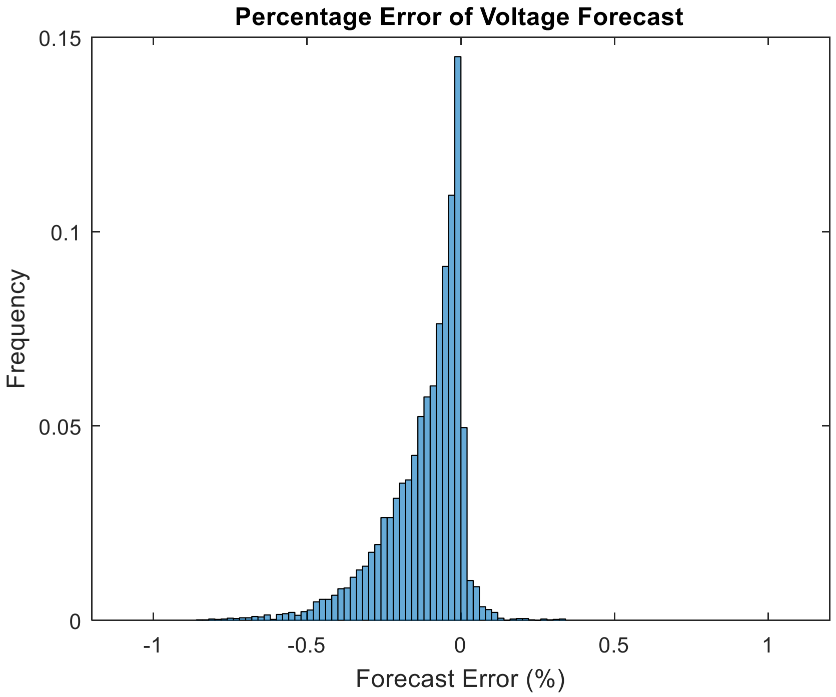


Gamma Distribution

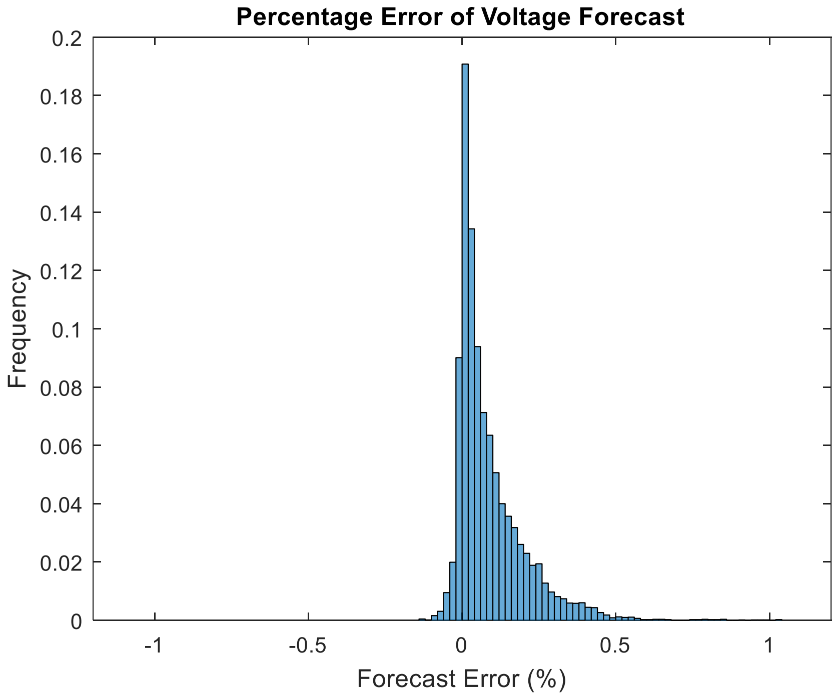


Forecast Error Distribution – Error within $\pm 20\%$

Rayleigh Distribution



Weibull Distribution



Conclusion

- Testing results demonstrated the PSE method is robust against forecasting errors

- Forecasting error distribution is directly correlated to PSE error distribution

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Thank you

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