State estimation of low voltage distribution network with integrated customer-owned PV and storage unit

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1 Introduction

Motivation:
There is increased penetration of customer-owned low carbon technology devices in modern power networks including DGs like photovoltaics (PVs) and Energy Storage Units (ESUs). As a result, there is a change in the net demand profiles of customers connected to these networks. Consequently, researchers and utility engineers now have particular interests in understanding these new load profiles especially in the low voltage (LV) networks.

Contributions:

a. Integrating PVs and energy storage units in the statistical models of customer load profiles.
b. Implemented state estimation of a LV network with customers having hybrid rooftop PVs and ESUs.
c. Conducted comparative evaluation of the network performances under different scenarios of load profiles: with PVs integrated but without ESUs, ESUs alone, and with hybrid systems (combination of PVs and ESUs).

2 Gaussian Mixture Model

Gaussian mixture model is a superposition solution from several Gaussian mixtures (GM). The probability density function of GMM is (1).

$$GMM_{pdf} = \sum_{i=1}^{I} \pi_i . G_{pdf} = \sum_{i=1}^{I} \pi_i . G(\mu_i, \sigma_i^2) \qquad (1)$$

Each cluster has a specific mean (μ), variance (σ) and weight (π), called GMM parameters. Expectation-Maximization (EM) algorithm was used to obtain GMM parameters using log-likelihood optimization.

3 WLS State Estimation Overview

The WLS is formulated as an optimization problem aimed to minimize the square of the measurement error e.

$$\min_x F = \frac{1}{2}\left(z - h(x)\right)^T R_{ii}^{-1}\left(z - h(x)\right) \qquad (2)$$

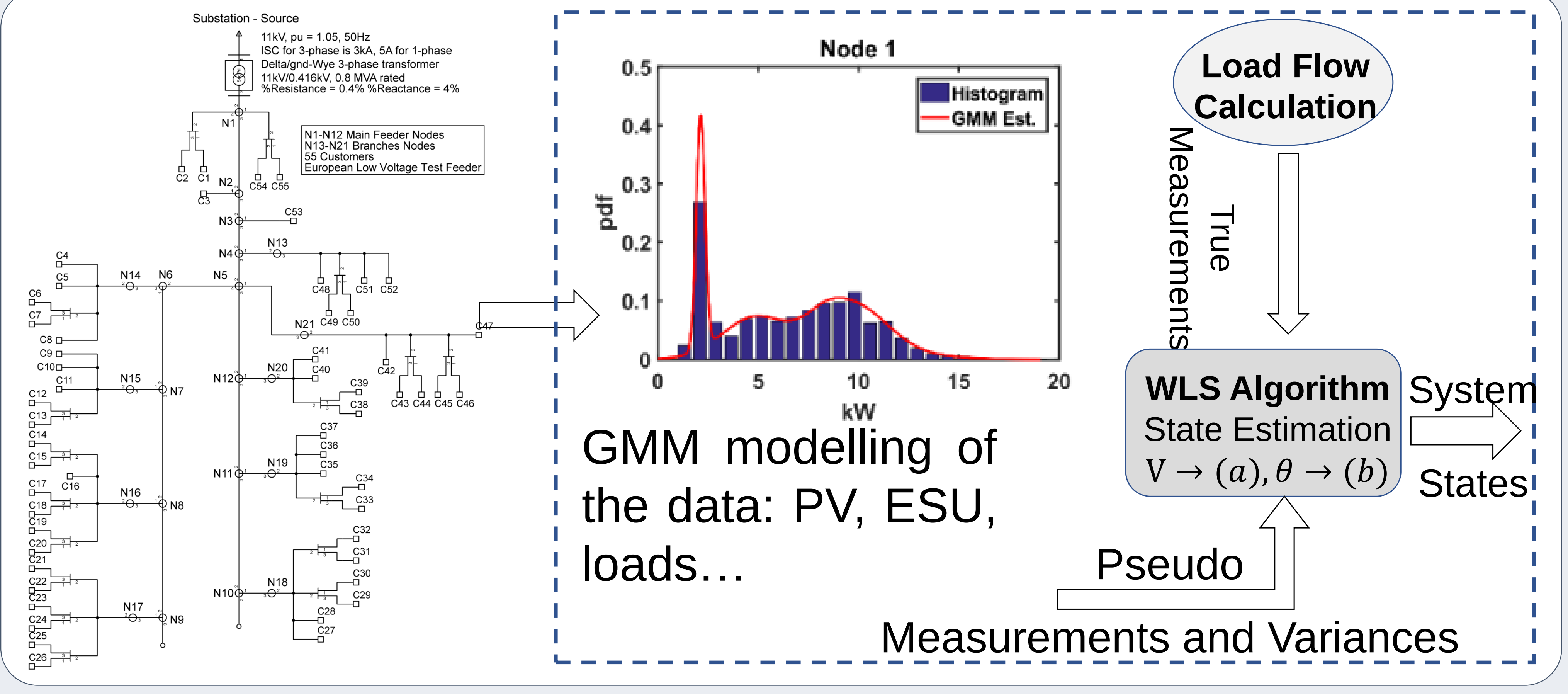
$$z = h(x) + e \qquad (3)$$

$$R_{ii} = diag[\sigma_1{}^2, \sigma_2{}^2, \dots \sigma_n{}^2] \qquad (4)$$

where: z = measurement vector, x = state vector,
R_{ii} = covariance matrix and F is the cost function.

This problem is reformulated and solved using Newton iterative technique.

4 Framework



GMM modelling of the data: PV, ESU, loads…

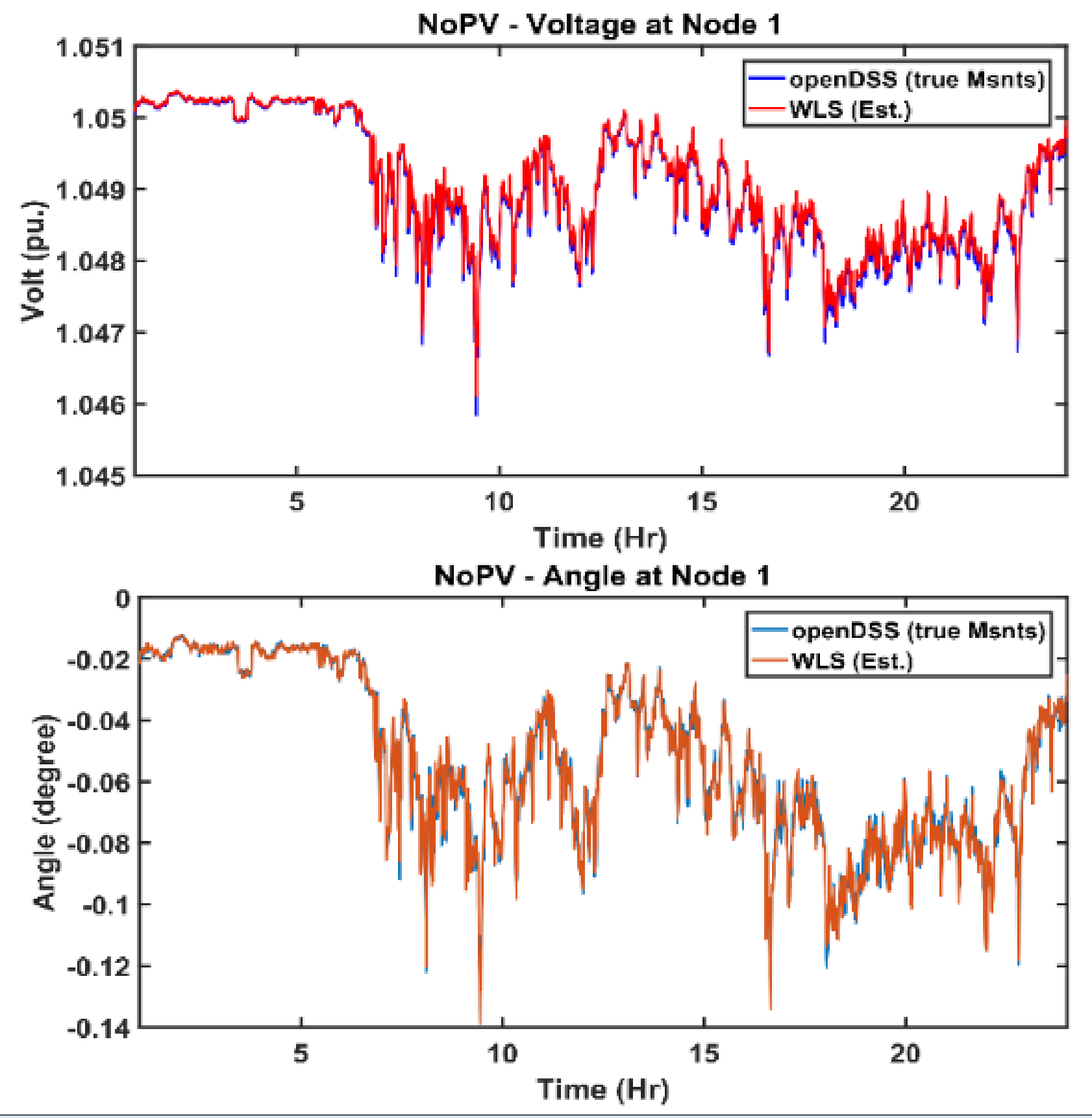
5 State estimation Results

The error on the voltage states of the network

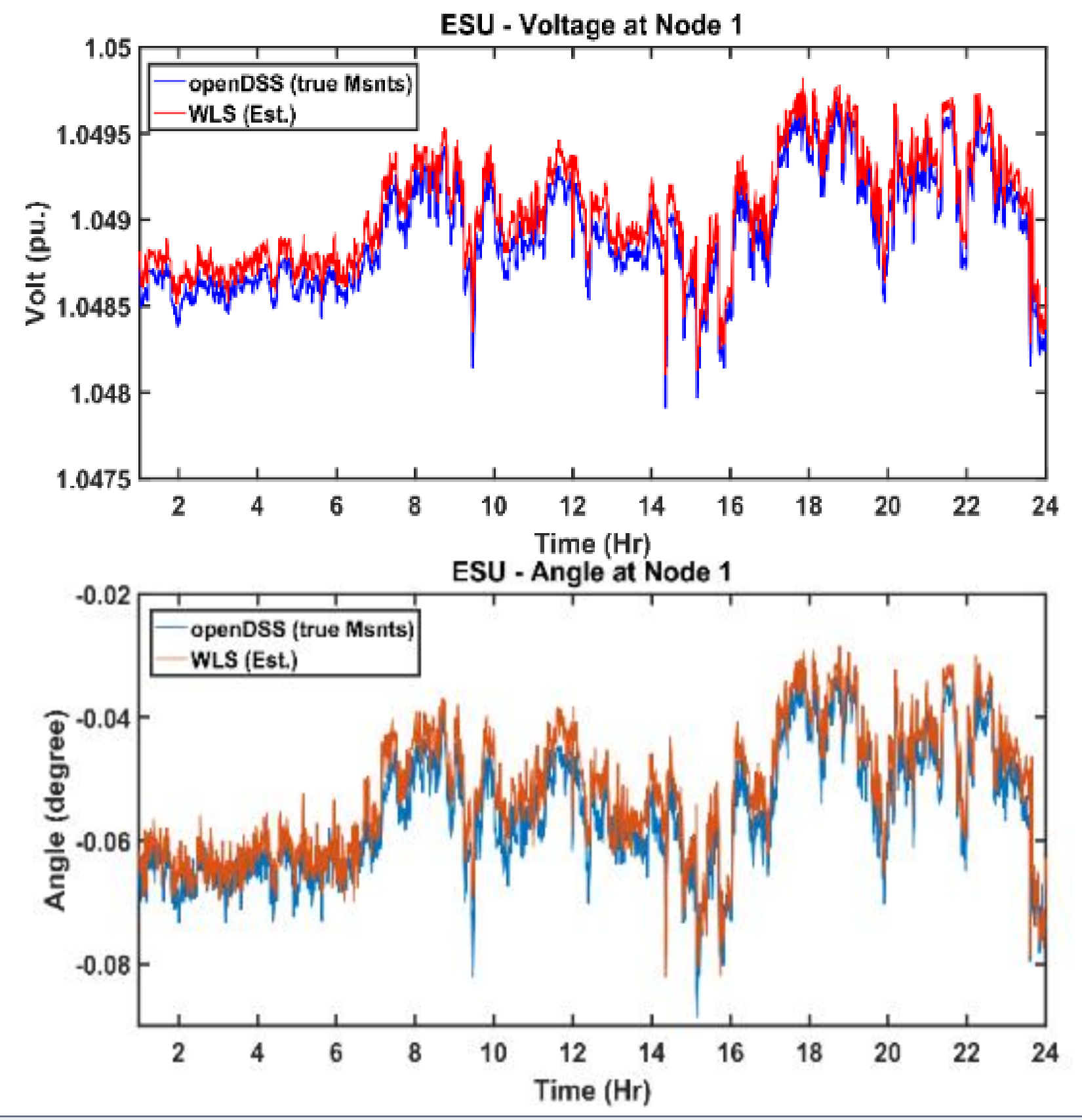
	Without PV/ESU	With ESU
AAE(%)	0.005747	0.012203
RMSE (pu)	0.000073	0.000130

	With PV on-grid	With PV and ESU
AAE (%)	0.007739	0.002265
RMSE (pu)	0.000111	0.000036

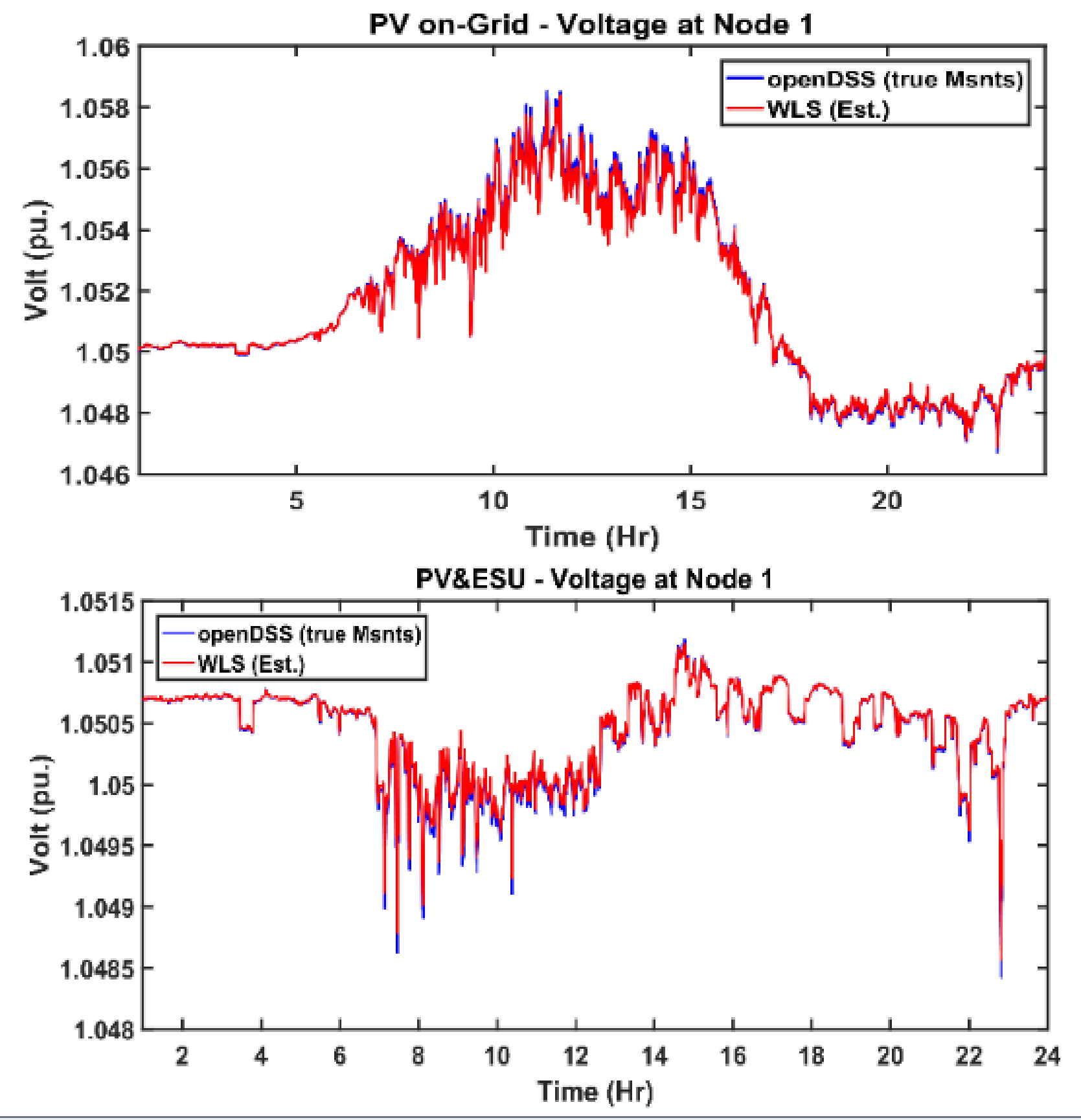
No PVs/ESUs: voltage and angle



ESU only: voltage and angle



PV only and hybrid PV&ESU: voltage



6 Conclusion

- The network without DGs experienced voltage drop during peak hours (in the morning and evening).
- Integrating PV resulted in voltage rise around midday due to excess PV power generation been exported to the grid. Such case revealed the need for PV power curtailment or ESUs installation to avoid voltage exceeding the standard limits.
- Integrating ESUs acted as a demand shifter, the demand is shifted from high load periods to low load periods.
- Integrating PV and ESU reduced the voltage drop during peak hours. However, voltage rise occurred when the ESUs were fully charged and PV generation was still higher than the demand.

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