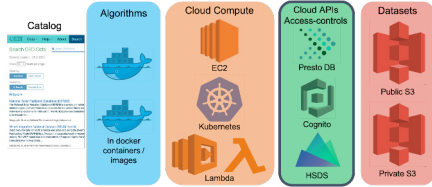


Cloud-based Framework for Evaluating and Disseminating Advanced Algorithms for Distributed Solar Integration and Related Data Sets

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Introduction



- Objective: Develop modular data repository and computing architecture with open-source datasets and baseline DER management algorithms
- Data: Open-source datasets including realistic sensor data streams from SCADA, AMI, inverters

How is AI/ML Used

❖ Distribution System State Estimation Problem

- A data-driven model that combines the analytical and artificial intelligence-based methods
- Physics-informed model that offers real-time state estimation

➤ Generalized state estimation formulation:

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathcal{L}(\mathbf{z}, \mathbf{h}) \\ \text{s.t.} \quad & \mathbf{h} = f(\mathbf{x}), \\ & g(\mathbf{x}) \leq 0, \end{aligned}$$

➤ Physics-informed autoencoders:



- The encoder provides a deterministic and approximated mapping from the measurements to the true states

➤ Design of two-part loss function

- WLS-based objective:

$$\mathcal{L}_1 = (\mathbf{z} - \mathbf{h})^T \cdot \mathbf{W} \cdot (\mathbf{z} - \mathbf{h})$$

- Violation of voltage magnitude limits:

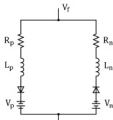
$$\mathcal{L}_2 = \rho \text{ReLU}(|\mathbf{V}| - V^{\max}) + \rho \text{ReLU}(V^{\min} - |\mathbf{V}|)$$

▪ Numerical Results

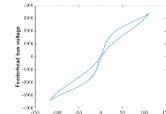
Method	c	Measurements	MAPE (%)			
			Hour 4	Hour 11	Hour 13	Hour 20
WLS	0.02	30%	1.545	1.243	1.239	1.988
Autoencoder			0.523	0.612	0.622	0.837
WLS	0.02	50%	1.059	0.977	0.971	1.507
Autoencoder			0.489	0.568	0.569	0.710
WLS	0	50%	0.493	0.882	0.878	0.937
Autoencoder			0.352	0.364	0.338	0.531

❖ High Impedance Fault Identification Problem

- Tractable piecewise approximation of the voltage-current (V-I) trajectory during HIF events.
- An explainable and efficient support vector machine approach for the identification of HIF locations.



HIF circuit model



Voltage-current trajectory

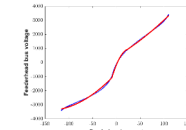
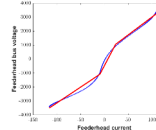
➤ Piecewise linear/quadratic regression for V-I trajectory:

Linear approximation

$$\begin{aligned} \min \quad & \sum_{i=1}^N \sum_{j=1}^N (s_{ij} I_i + y_{ij} - s_{ij} x_{ij} - V_j)^2 \\ \text{s.t.} \quad & y_{ij} \in \mathbb{R}, s_{ij} \in \mathbb{R}, y_{ij}, s_{ij} \in \mathbb{R} \quad (\text{variables}) \\ & y_{ij} \leq \kappa \leq \mathbb{R}, \quad \zeta = a, b, c, d. \end{aligned}$$

Quadratic approximation

$$\begin{aligned} \min \quad & \sum_{i=1}^N \sum_{j=1}^N (m_{ij} I_i^2 + n_{ij} I_i + y_{ij} - m_{ij} x_{ij}^2 - n_{ij} x_{ij} - V_j)^2 \\ \text{s.t.} \quad & y_{ij}, m_{ij}, n_{ij} \in \mathbb{R}, y_{ij}, m_{ij}, n_{ij} \in \mathbb{R} \quad (\text{variables}) \\ & y_{ij} \leq \kappa \leq \mathbb{R}, \quad \zeta = a, b, c, d, e, f, g. \end{aligned}$$



➤ Support vector machine approach:

- Support vector machine formulation:

$$\begin{aligned} \min \quad & \|\mathbf{w}\|^2 \\ \text{s.t.} \quad & y_i (\mathbf{w}^T \mathbf{x}_i - b) \geq 1, \forall i \end{aligned}$$

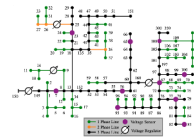
- The approximated function features (e.g., slope rates) are used as SVM inputs for HIF identification.

Linear model: $x_{\mathcal{L}} = \{s_1, s_2, s_3\}$

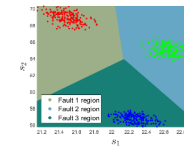
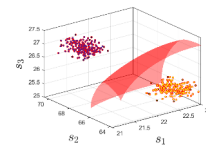
Quadratic model: $x_{\mathcal{Q}} = \{(m_1, n_1), (m_2, n_2), (m_3, n_3)\}$

▪ Numerical Results

- IEEE 123 node test feeder
- Varying operating conditions
- Samples collected at 20 kHz
- Data posted open-source [1]



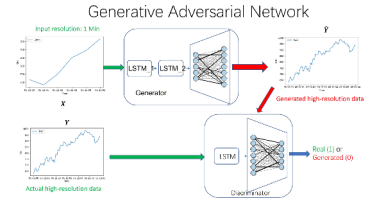
- Identification performance under different dimensional spaces:



❖ Synthetic Solar Irradiance Sequence Generation

- LSTM-based GAN [2] to generate high-resolution solar irradiance sequences from lower-resolution measurements.
- Multi-loss functions to accurately capture various temporal patterns of realistic solar irradiance data

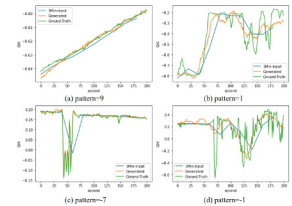
➤ GAN-based sequence-to-sequence generation:



➤ Neural network architecture

Case 1 (A)	Generator G (Layer Type, Feature Map)	Discriminator D (Layer Type, Feature Map)
Input	10 × 5	1 × 1
Layer 1	LSTMID, 10 × 256	LSTMID, 512
Layer 2	LSTMID, 512	Dense, 512
Layer 3	Dense, 1024	Dense, 256
Layer 4	Dense, 512	Dense, 64
Layer 5	Dense, r	Dense, 1
Output	r × 1	scalar ∈ [0, 1]

▪ Numerical Results



Challenges and Best Practices

- When machine learning models are utilized to handle different applications. It is important yet challenging to find the balance among accuracy, scalability and interpretability. This normally requires prior knowledge on the specific problem for constructing the most efficient learning architecture.

Key Takeaways and Future Work

- Future work includes developing novel and physics-informed machine learning algorithms for selected topics using the OEDI datasets.

References

- [1] Y. Dong, "Transient data library of solar grid integrated distributed system," <https://github.com/yuqingdong0/Transient-Data-for-OEDI/tree/main/Simulation%20Data>, 2023.
- [2] Z. Zhang and R. Yang, "High-resolution synthetic solar irradiance sequence generation: An LSTM-based generative adversarial network," in IEEE Power & Energy Society General Meeting (PESGM), 2023.