Climate Change AI

ICML 2021 Workshop
Tackling Climate Change with Machine Learning

CityU

DeepOPF-NGT: A Fast Unsupervised Learning Approach for Solving AC-OPF Problems without Ground Truth

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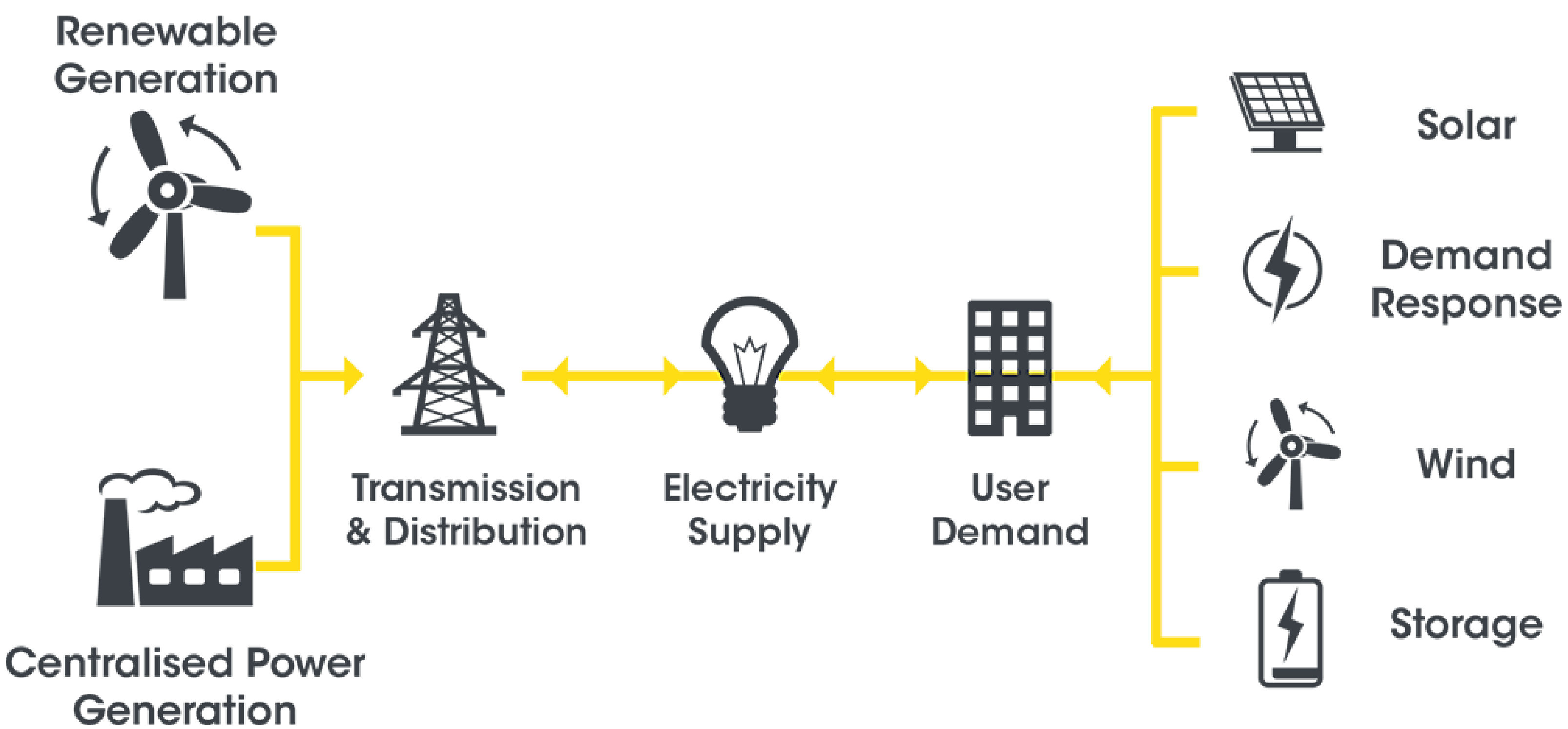
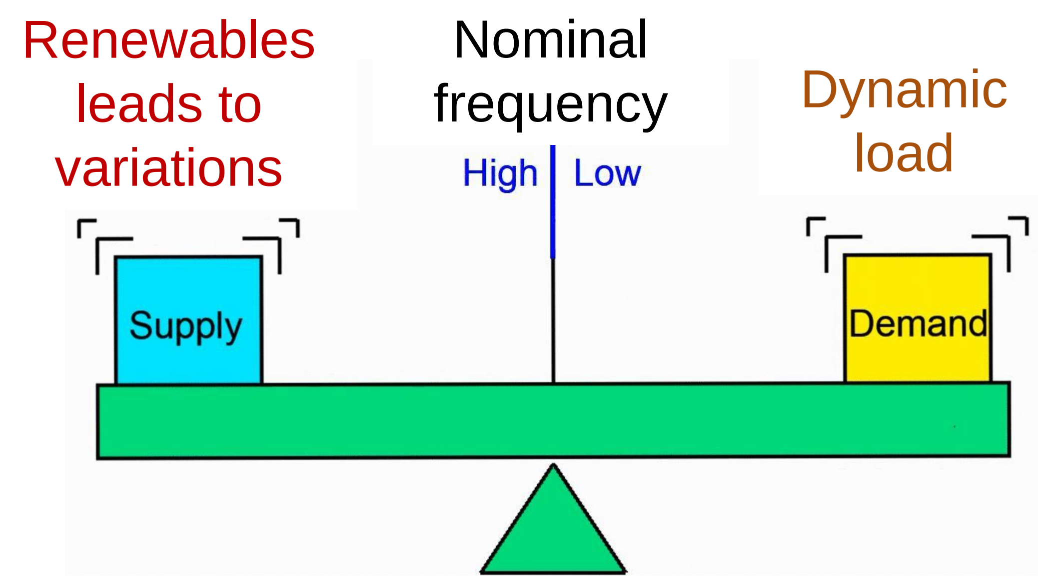
AC-OPF Needs to be Solved Faster

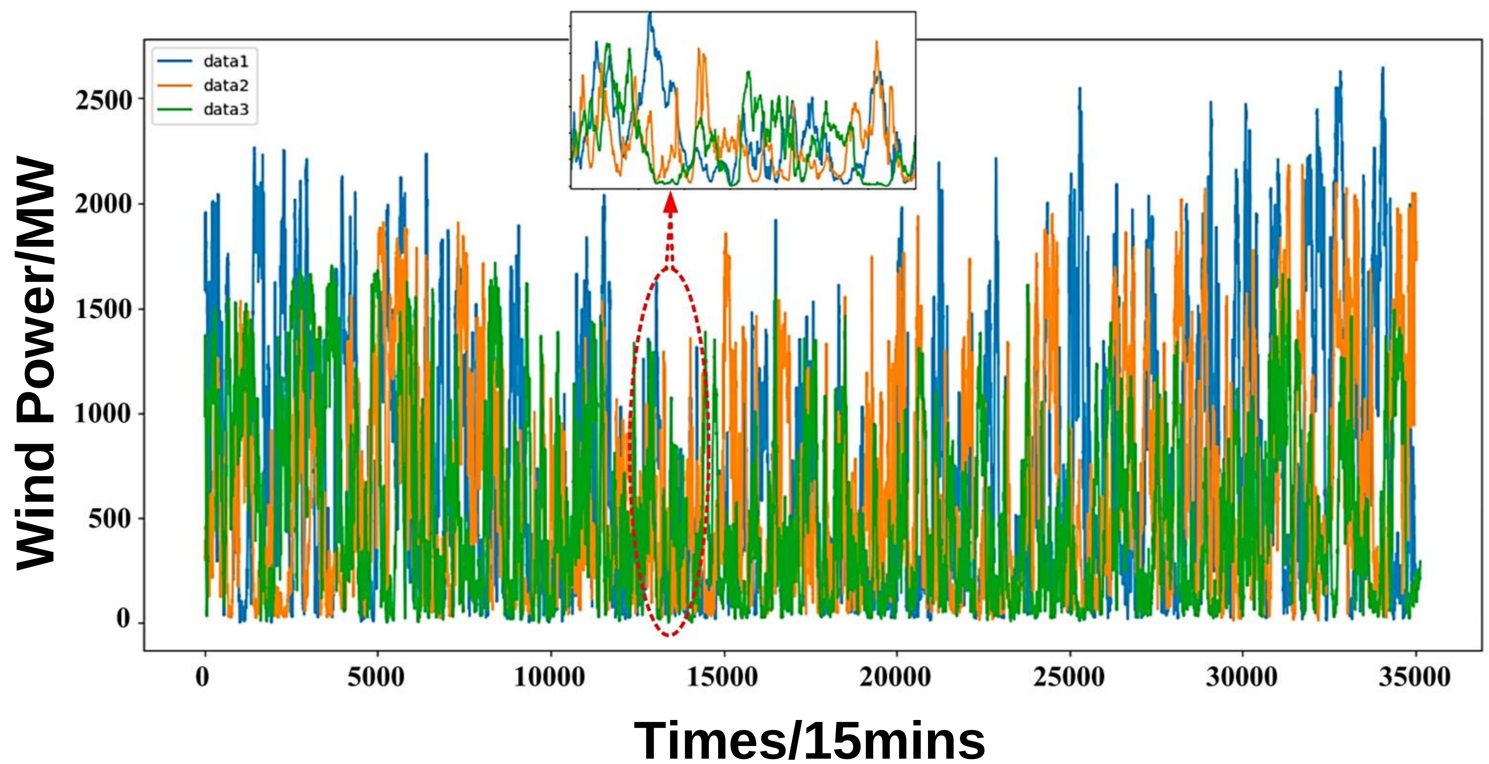


Source: http://northernutilities.co.uk/demand-side-response/



Source: https://www.rs.tus.ac.jp/j.kondoh/english.html

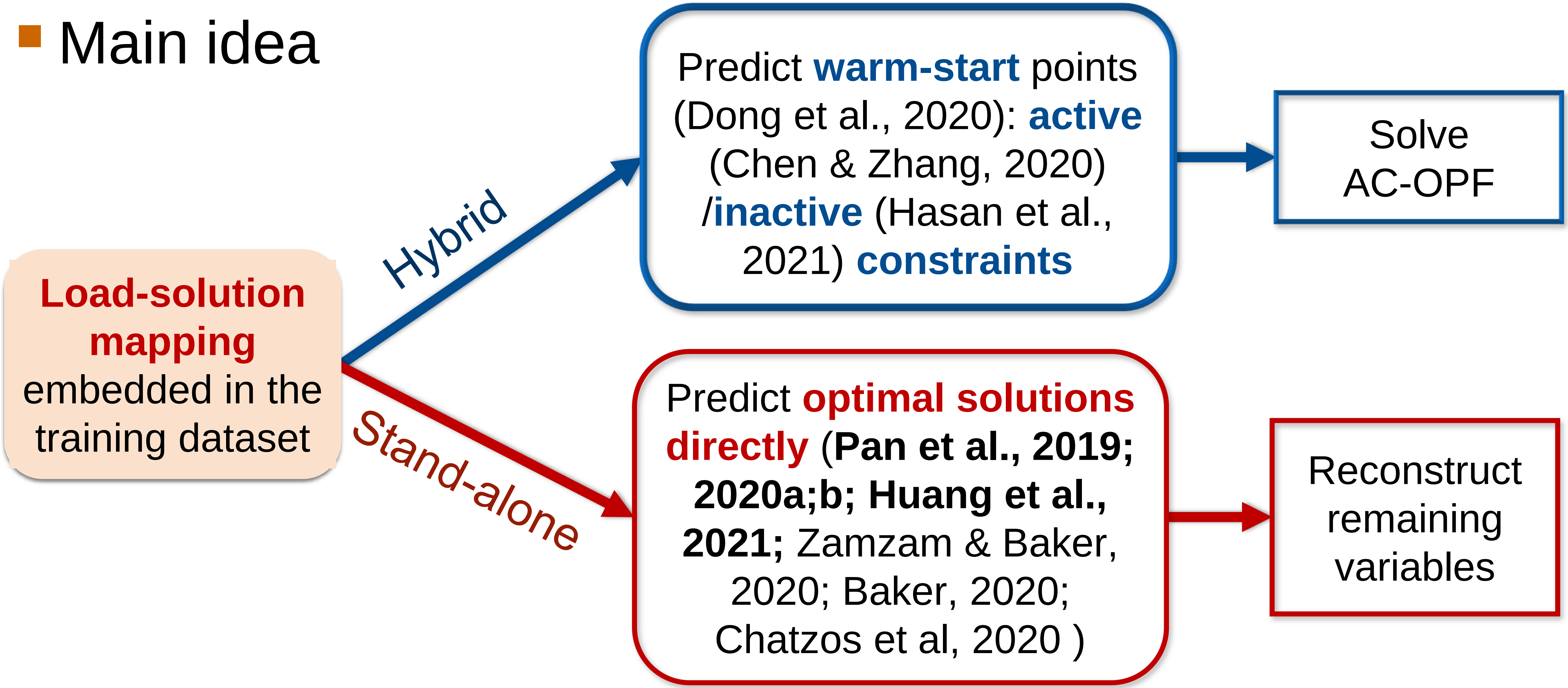
- **Real-time balance** between power **generation** and **load**
- Minimum cost with all physical constraints satisfied
- **Non-convexity**



Source: https://www.mdpi.com/2076-3417/9/6/1108

Supervised learning-based algorithm

- Main idea

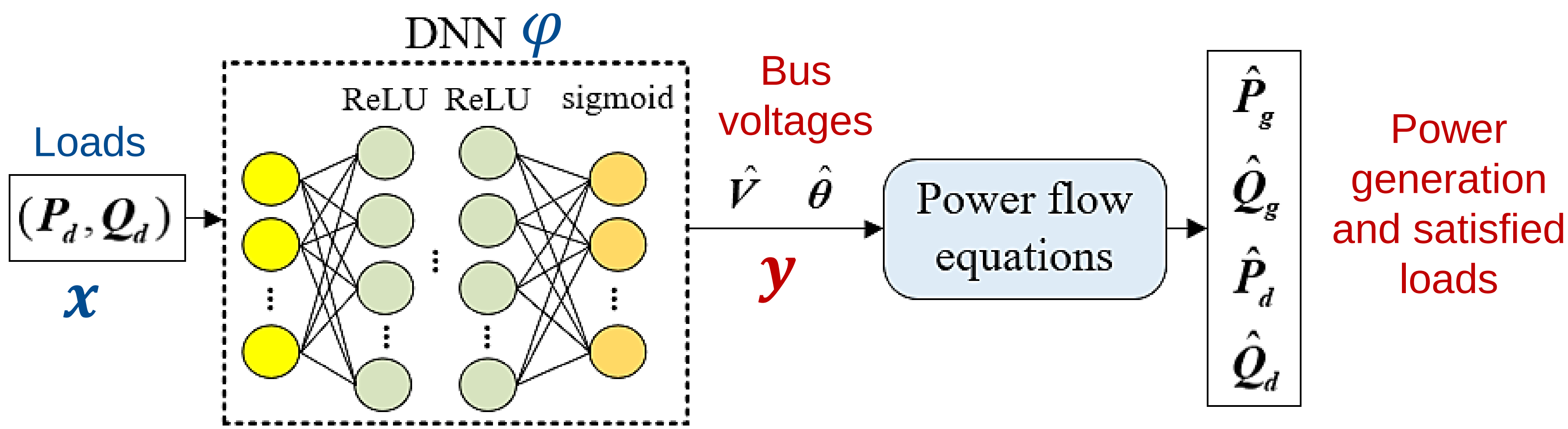


Limitations

- Computational expensive: a large training dataset
- Rely on **AC-OPF solvers** to generate the ground truth
  - Provide one of the locally optimal solutions
  - Samples may belong to different load-solution mappings

Unsupervised Learning Approach without Ground Truth

- DeepOPF-NGT



Mapping: $\boldsymbol{y} = \boldsymbol{F}(\boldsymbol{x}, \varphi)$

- Main idea: use **loss function** to guide the training of DNNs

$$L = k_{gen} \boxed{L_{gen}(\boldsymbol{x}, \varphi)} + \boxed{L_{cons}(\boldsymbol{x}, \varphi)} + k_d \boxed{L_d(\boldsymbol{x}, \varphi)}$$

No ground truth!

Generation cost (objective)

Penalty of constraints

Penalty of load deviations

- **DNN Training**: Gradient descent and Chain rule

$$\nabla_{\varphi} L = \nabla_{\boldsymbol{y}} L \cdot \nabla_{\varphi} \boldsymbol{y}$$

Case Study: IEEE 9-Bus System

- **Unsupervised** learning VS. **Supervised** learning

Metric	DeepOPF-NGT	DeepOPF-V
Optimality loss	<0.40	<0.10
$\eta_{\boldsymbol{V}}(\%)$	100.0	100.0
$\eta_{P_g}(\%)$	100.0	100.0
$\eta_{Q_g}(\%)$	100.0	100.0
$\eta_{S_l}(\%)$	100.0	100.0
$\eta_{\theta_l}(\%)$	100.0	100.0
$\eta_{P_d}(\%)$	99.3	99.8
$\eta_{Q_d}(\%)$	99.2	99.3
Speedup	Around X650	Around X610

Comparable performance

More than three orders of magnitude faster than MIPS !

W. Huang, X. Pan, and M. Chen, "DeepOPF-V: Solving AC-OPF Problem Efficiently," arXiv:2103.11793, *Power Engineering Letters*, under the second-round review.

Ongoing Work

- Large-scale system
- More efficient training algorithms
  - Learning to learn
  - • • •

Much to be explored!

Our On-Going Project

- DeepOPF: Deep Neural Networks for Optimal Power Flow
  - The **first** work in the literature applying neural networks to **directly** solve the optimal power flow (OPF) problem

Our recent works

1. X. Pan, T. Zhao, and M. Chen, “DeepOPF: Deep Neural Network for DC Optimal Power Flow”, in Proceedings of the 10th IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (IEEE SmartGridComm 2019), Beijing, China, October 21 - 24, 2019.
2. X. Pan, T. Zhao, M. Chen, and S. Zhang, “DeepOPF: A Deep Neural Network Approach for Security-Constrained DC Optimal Power Flow”, IEEE Transactions on Power Systems, vol. 36, issue 3, pp. 1725 - 1735, May 2021.
3. X. Pan, M. Chen, T. Zhao, and S. H. Low, “DeepOPF: A Feasibility-Optimized Deep Neural Network Approach for AC Optimal Power Flow Problems”, arXiv preprint arXiv:2007.01002, 2020.
4. T. Zhao, X. Pan, M. Chen, A. Venzke, and S. H. Low, “DeepOPF+: A Deep Neural Network Approach for DC Optimal Power Flow for Ensuring Feasibility”, in Proceedings of the 11th IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (IEEE SmartGridComm 2020), virtual conference, Nov. 11 - 13, 2020.
5. W. Huang, X. Pan, and M. Chen, “DeepOPF-V: Solving AC-OPF Problems Efficiently,” arXiv:2103.11793, Power Engineering Letters, under the secondround review.

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