Data-Driven Optimal Solver for Coordinating a Sustainable and Stable Power Grid

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Power Grid and Optimal Power Flow

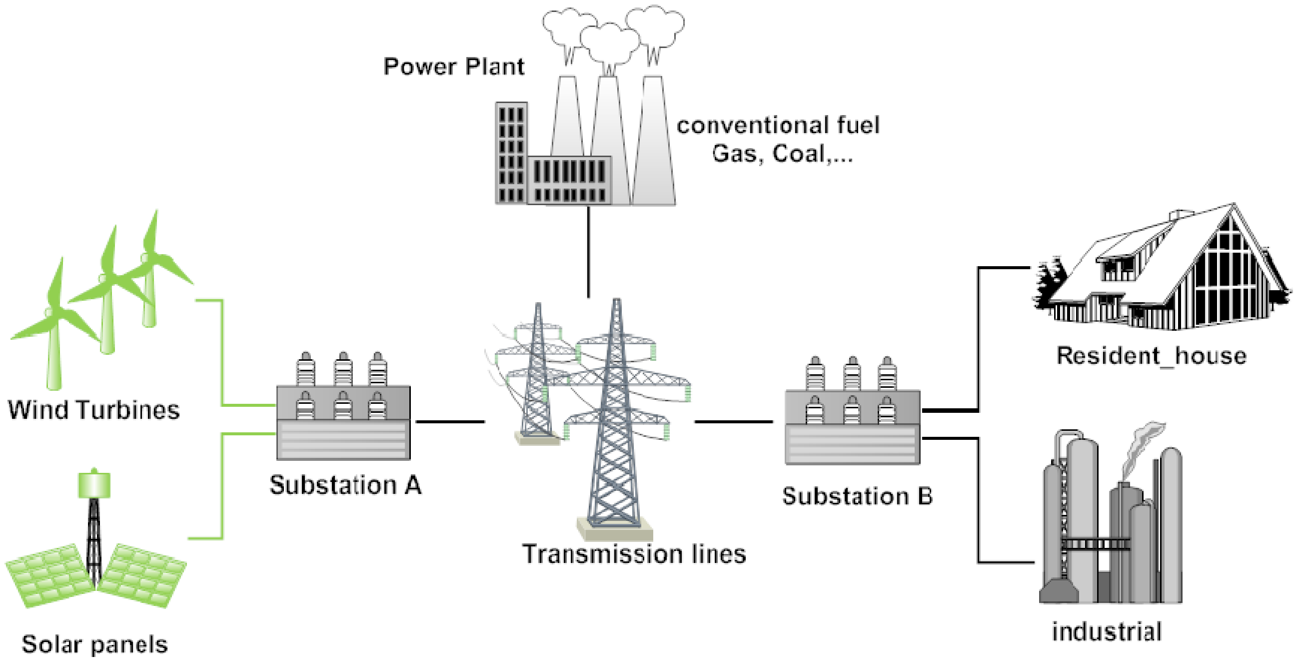

Figure 1. The Structure of AC Power Grid with Sustainable Resources[2]

Energy-related CO_2 emission grew to 36.3Gt in 2021, the highest record in history, 6% increase from 2020[1].

Transition from traditional fossil fuel driven grid to smart grid with increasing proportion of sustainable resources.

Core problem of power grids: supply meets demand, and reduce carbon footprint.

- Optimal Power Flow: feasibility and optimality.

Formulation of OPF

$$\min_{P_g^{gen}} \sum_{g \in \mathbb{G}} C_g(P_g^{gen})$$

- ✓ Quadratic Cost Function
- ✓ Traditional vs sustainable fuels
- ✓ Reaction to stochasticity

$$s.t.\ P_i^{gen} - P_i^{load} = \sum_{k=1}^{N} |V_i V_k Y_{ik}| cos(\phi_i - \phi_k - \theta_{ik})\, \forall i \in \mathbb{N}$$

$$Q_i^{gen} - Q_i^{load} = \sum_{k=1}^{N} |V_i V_k Y_{ik}| sin(\phi_i - \phi_k - \theta_{ik})\, \forall i \in \mathbb{N}$$

- ✓ Power flow constraints
- ✓ Guaranteeing power balance
- ✓ Renewable resources close to demand

$$\underline{P}_g^{gen} \leq P_g^{gen} \leq \overline{P}_g^{gen}, \forall g \in \mathbb{G}$$

$$\underline{Q}_g^{gen} \leq Q_g^{gen} \leq \overline{Q}_g^{gen}, \forall g \in \mathbb{G}$$

- ✓ Power generation capacity constraints
- ✓ Stability of generators

$$\underline{|V|} \leq |V_i| \leq \overline{|V|}, \forall i \in \mathbb{N}$$

$$\underline{\phi} \leq \phi_i \leq \overline{\phi}, \forall i \in \mathbb{N}$$

- ✓ Voltage constraints at each node
- ✓ Guaranteeing voltage stability

Assumptions and Resources

Papers	Techniques	Considering Renewable Resources	Optimal / Feasible Dataset	Aid from Traditional OPF Solver
Our proposal	GAN	Yes	Feasible	No
[3]-[7]	MLP, GNN, CNN	No	Optimal	Yes
[8][9]	MLP, Reinforcement Learning	yes	Optimal	Yes
[10]	MLP, Implicit Layers	No	Optimal	No

Proposed Generative Model

- Conditional GAN(*model G&D*): two players game enabling model G to learn the real data distribution

- *Physics-guided penalty:* power flow equation and branch limits violation loss

- Norm of Jacobian matrix as penalty for continuous condition

- Feasibility score: prediction of violation of the constraints

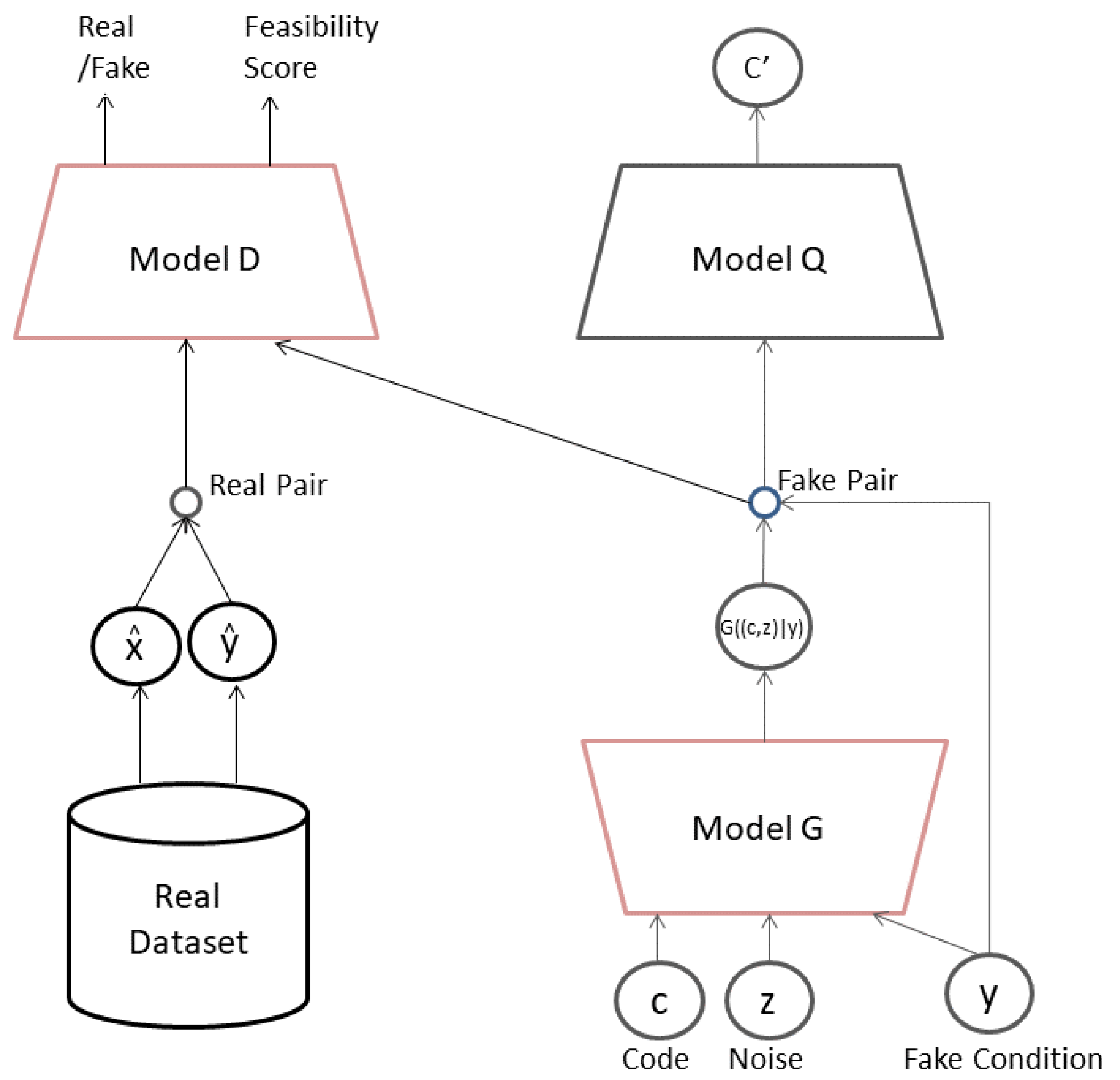

Figure 2. The Architecture of Proposed Generative Model

Proposed Generative Model

- Representation extraction by *model G&Q*
- Latent code c is a one-dimensional variable
- Maximizing the mutual information between c and G(c,z|y)
- The most salient feature of dataset being encoded into code c

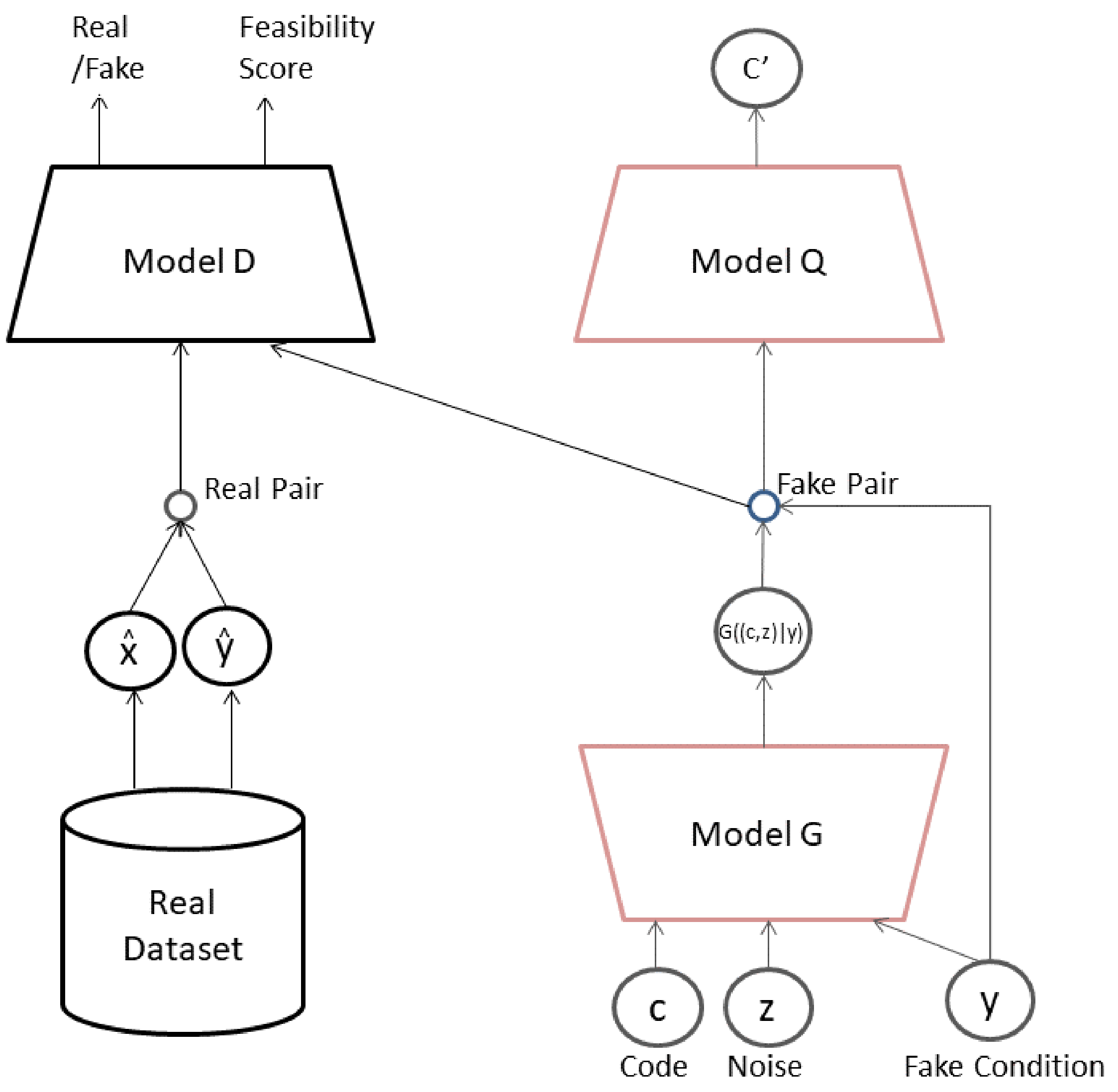

Figure 2. The Architecture of Proposed Generative Model

Optimization via Proposed Generative Model

- Changing the value of latent code c causes linear-like changes of x's cost
- The distribution P(x|y) covers power supplies with different costs
- Setting c closed to -1, proposed model can produce solutions with low cost
- Sampling M points for solution selection, and rejecting scenarios with low feasibility scores.

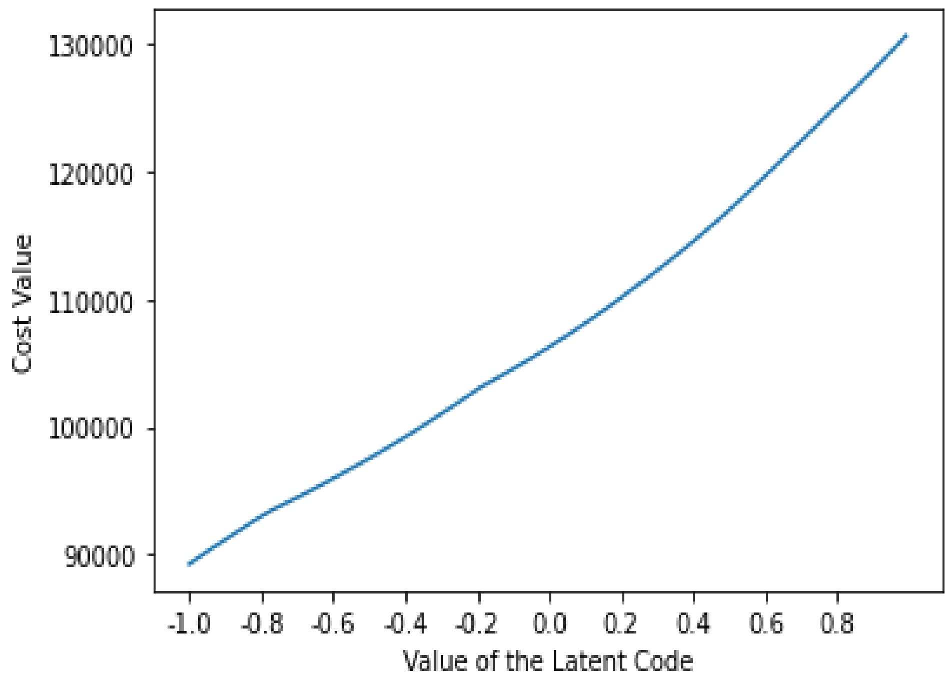

Figure 3. The Relationship between the Latent Code and Cost

Experiment

- Resulting 3% optimality gap to traditional solvers with much shorter time
- Feasibility is guaranteed by points selection based on the feasibility score

Table 1: Comparison with traditional solvers for IEEE 118-bus system.

M	Gap to SDP(%)	Gap to IPM(%)	Time(s)	Feasibility
50	3.97±0.49	3.79±0.47	0.12	✓
100	3.87±0.48	3.27±0.39	0.21	✓
200	3.63±0.45	3.44±0.42	0.27	✓
500	3.52±0.44	2.97±0.38	0.29	✓
1000	3.18±0.38	3.00±0.37	0.34	✓
3000	2.90±0.35	2.70±0.33	0.56	✓
5000	2.92±0.35	2.71±0.35	0.65	✓

- Dataset: http://www.cse.yorku.ca/~psrikan/pf_dataset.html

Reference

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Thank you
谢谢
Terima kasih
Gracias
धन्यवाद
Obrigado
Danke
Merci
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Grazie
謝謝
شكرا
Спасибо
شكرا
धन्यवाद
ありがとう
ధన్యవాదాలు
நன்றி
ขอบคุณ
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