End-to-end electricity system forecasting via approximate message passing

Anthony Degleris, Akshay Sreekumar, Kamran Tehranchi, Ram Rajagopal

1 Electricity System Forecasting

Goal - Given grid topology, load forecasts, renewable forecasts, etc. predict power flows and nodal prices

Other approaches…

- *In forecasting*—Existing ML methods don't account for underlying physical structure
- *In completion-correction layers*—Such layers typically require fully observed inputs

Our Work

- Combine ML with approximate unrolled optimization steps to encode physical structure and utilize only partially observed problem data

2 DC-OPF

- **DC Optimal Power Flow** determines the optimal power (price) schedule subject to grid constraints

$$\begin{array}{ll} \text{minimize} & c_z(p,v) \\ \text{subject to} & Ap = 0, \quad A^T v = u \end{array} \qquad (\lambda, \omega)$$

Device Costs

Power balance constraints

Phase Consistency Constraints

Dual Variables

- Power network of ***N*** nodes connected to devices via ***T*** terminals; incidence matrix ***A*** , problem data ***z***
- **Solution map**: $y_z^* = (p_z^*, v_z^*, \lambda_z^*, \omega_z^*)$

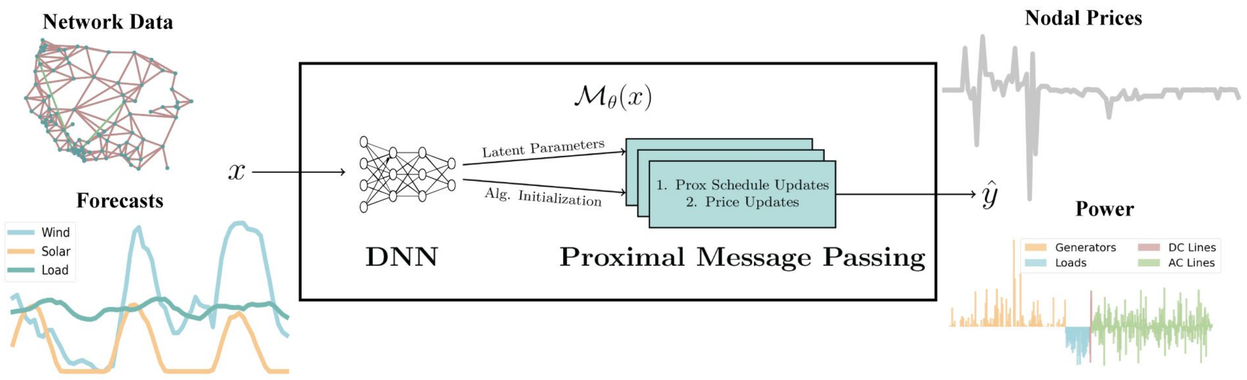
3 Problem Setting

Learn a model $\hat{y}_\theta = \mathcal{M}_\theta(x)$ (parameterized by θ) that predicts the solution map from the observation ***x***

$$\mathcal{M}_\theta(x) \approx y_z^* \quad \text{for all} \quad z, x \sim p(z)p(x|z).$$

- Assume ***z*** is drawn from some unknown random distribution with density *p(z)*
- The forecaster does not observe ***z***, only ***x***
- ***x*** could be a masked, reduced, or noisy version of ***z*** (i.e. we have load forecasts not the actual load)

4 Model Architecture



- Deep neural network (DNN) backbone predicts (i) proximal message passing algorithm initialization and (ii) possibly latent parameters
- Proximal message passing layers are unrolled iterations of a GPU accelerated optimization solver specifically designed for DC-OPF
  - These layers help to encourage physically feasible forecasts

5 Proximal Message Passing

1. Prox Schedule Updates

$$(p^{(i+1)}, v^{(i+1)}) = \mathbf{prox}_{c_z,\rho}\left(\mathbf{resid}(p^{(i)}) - \lambda^{(i)}, \mathbf{avg}(v^{(i)}) - \omega^{(i)}\right),$$

2. Price Updates

$$\lambda^{(i+1)} = \lambda^{(i)} + \mathbf{avg}(p^{(i+1)})$$

$$\omega_n^{(i+1)} = \omega^{(i)} + \mathbf{resid}(v^{(i+1)})$$

6 Experiments + Results

- Joint power and price prediction task on synthetic 100-node Western U.S. grid from PyPSA-USA; 5 years hourly data (2019–2023)
- Three versions of this data:
  - ***Perfect***—Full, perfect information of all inputs
  - ***Outage***—AC transmission lines are dynamically de-rated
  - ***Noisy***—Gaussian noise injected into generation and load forecasts

Metric	Perfect			Noisy			Outage		
	Dense	State	Proxy	Dense	State	Proxy	Dense	State	Proxy
Loss	0.132	**0.122**	0.132	**0.124**	0.130	0.141	0.142	**0.126**	0.141
Price MSE	0.137	0.092	**0.076**	**0.081**	0.141	0.083	0.141	0.113	**0.079**
Power MSE	0.121	**0.042**	0.100	0.125	**0.089**	0.117	0.140	**0.045**	0.106
Power Imbal.	**0.009**	0.039	0.017	**0.007**	0.022	0.018	**0.009**	0.041	0.024
DCPF Infeas.	40.0	**15.1**	23.4	45.9	**26.8**	27.5	42.8	**17.3**	25.7
Gen. Viol.	0.026	**0.00**	0.161	**0.030**	0.354	0.193	0.024	**0.00**	0.293
Line Viol.	0.004	**0.00**	**0.00**	0.006	**0.00**	**0.00**	0.030	**0.00**	**0.00**

7 Conclusion

- We introduce a framework for combining an approximate constrained optimization solver within a neural network

References

1. 2024. Degleris, Rajagopal, and El Gamal. GPU accelerated security constrained optimal power flow
2. 2016. Frank and Rebennack An introduction to optimal power flow: Theory, formulation, and examples
3. 2024. Tehranchi, Barnes, Frysztacki, and Azevedo. Pypsa-usa: A flexible open-source energy system model and optimization tool for the united states.

Anthony Degleris recognizes support by the DOE Computational Science Graduate Fellowship.

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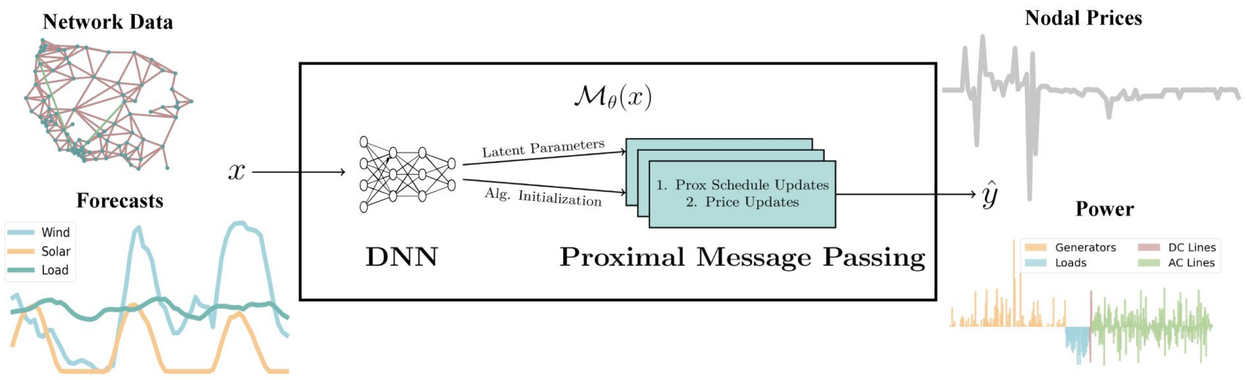

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Price MSE	0.133	**0.076**	0.082	0.085	**0.078**	0.082	0.095	0.117	**0.077**
Power MSE	0.125	0.753	**0.101**	0.119	0.781	**0.106**	0.136	0.740	**0.106**
Power Imbal.	**0.001**	0.043	0.013	0.006	0.033	0.009	**0.007**	0.058	0.016
DCPF Infeas.	40.2	65.5	**24.9**	44.8	65.6	**26.2**	41.9	62.6	**24.0**
Gen. Viol.	0.004	**0.000**	0.159	0.024	**0.00**	0.244	0.017	**0.00**	0.154
Line Viol.	0.014	**0.000**	**0.000**	0.003	**0.00**	**0.00**	0.039	**0.00**	**0.00**

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