Price-Aware Deep Learning for Electricity Markets

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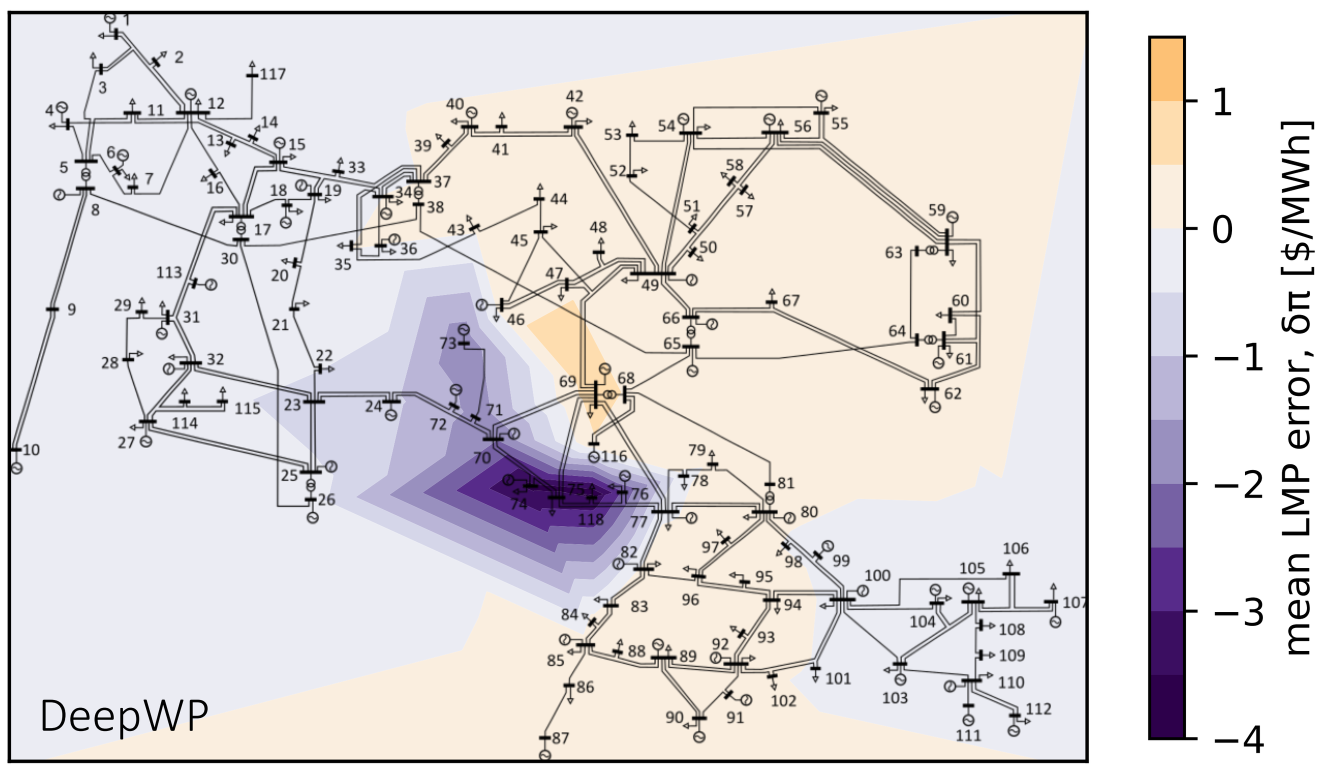
Motivation

- As of 2022, the share of electricity generation from wind energy sources worldwide constitutes 7.3%.
- Most of electricity in power grid is priced and traded using a *forecast* of variable and uncertain wind power generation, i.e., before the actual realization of power generation is known.
- As a result, forecast errors translate into locational marginal price (LMP) errors.
- Our preliminary study revealed significant LMP errors and spatial disparities across power networks.



The figure demonstrates how wind power forecast errors from a single wind power plant at bus 37 translate into LMP errors across the IEEE 118-Bus reliability test system. Majority of the buses demonstrate near zero errors, but electricity at certain buses is systematically over- or under-priced due to network congestion.

- In this work, we analyze the propagation of forecast errors into electricity LMP errors and develop a new deep learning architecture for wind power forecast which balances power forecast and LMP errors.

From power forecast to LMP errors

Given a wind power forecast $\widehat{w}$, electricity is priced using the dual solution to the DC Optimal Power Flow (OPF) optimization problem:

$$\min_{\underline{p}\leqslant p\leqslant\overline{p}} \quad p^\top C p + c^\top p \qquad \textit{conventional generator dispatch cost} \qquad (1a)$$

$$\text{s.t.} \quad \mathbb{1}^\top(p+\widehat{w}-d)=0 : \widehat{\lambda}_b, \qquad \textit{power balance condition} \qquad (1b)$$

$$|F(p+\widehat{w}-d)| \leqslant \overline{f} : \widehat{\lambda}_{\overline{f}}, \widehat{\lambda}_{\underline{f}}, \qquad \textit{power flow limits} \qquad (1c)$$

and the LMPs are computed using matrix F of power transfer distribution factor as:

$$\pi(\widehat{w}) = \underbrace{\widehat{\lambda}_b\cdot\mathbb{1}}_{\text{uniform price}} - \underbrace{F^\top(\widehat{\lambda}_{\overline{f}}-\widehat{\lambda}_{\underline{f}})}_{\text{adjustment due to congestion}} \qquad (2)$$

which is unique with respect to forecast $\widehat{w}$!

The price error is then defined as:

$$\delta\pi = \pi(\widehat{w}) - \pi(w) \qquad (3)$$

i.e., the distance between LMPs induced on the forecast ($\widehat{w}$) and actual realization (w) of wind power.

Property 1 (spatial disparity): In congested networks, for which $\mathbb{1}^\top(\widehat{\lambda}_{\overline{f}}+\widehat{\lambda}_{\underline{f}})>0$, the price error at bus i is proportional to the i^{th} column of matrix F of power transfer distribution factors.

Property 2 (reference bus r): Since the r^{th} column of F is all zeros, the price error at the reference bus only includes the error of the system-wide term in (2).

Measuring spatial disparity of LMP errors

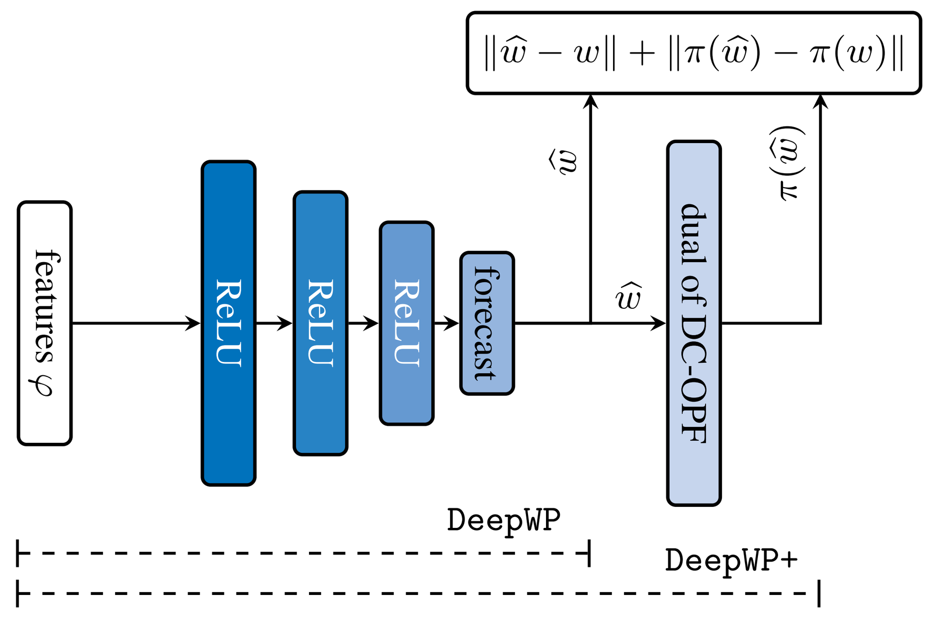
- The spatial disparities is measured using the notion of $\alpha-$fairness:

$$\alpha = \max_{i\in 1,\dots,n} \|\mathbb{E}[\|\delta\pi_i\|] - \mathbb{E}[\|\delta\pi_r\|]\|. \qquad (4)$$

  where the expectation is with respect to the dataset distribution.
- Parameter α is called the fairness bound, with smaller values denoting stronger fairness.

Price-awareness for deep learning

- Dataset $\{(\varphi_1, w_1),\dots,(\varphi_m, w_m)\}$ of m wind power records, with features φ and measurements w.
- Two deep learning architectures DeepWP and DeepWP+ to map features into wind power:



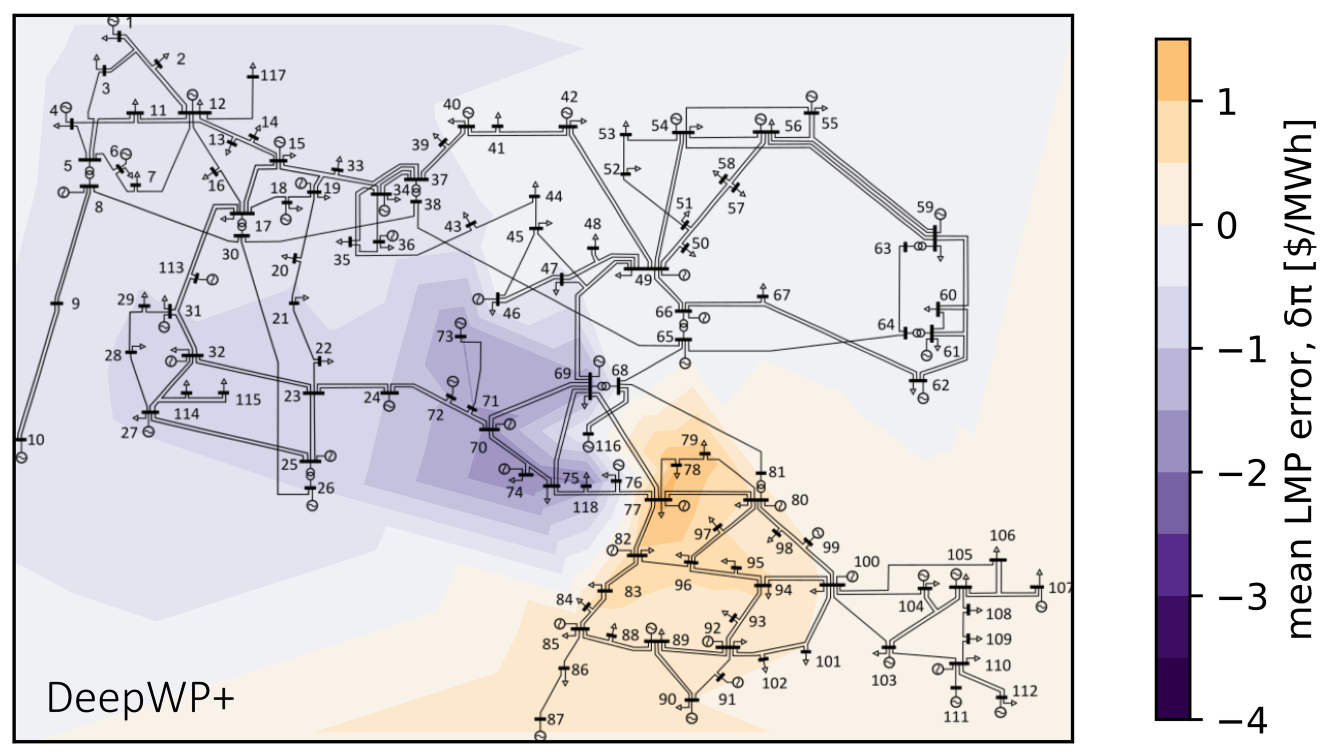
- DeepWP – fully connected feedforward architecture, trained to minimize the forecast error $\|w-\widehat{w}\|$
- DeepWP+ – enhanced architecture which incorporates the electricity market-clearing optimization problem as a deep learning layer. The layer evaluates electricity LMPs induced on a particular forecast while the loss function penalizing the deviation of predicted prices from the ground truth.
- We use the dual of the DC-OPF problem as it is less constrained and easier to differentiate through.

Experiment settings

- Standard power system test cases from `PowerModels.jl` and 1,000 wind power records.
- DeepWP has 4 hidden layers with 30 neurons each. DeepWP+ additionally includes an opt. layer.
- ADAM optimizer with varying learning rate (see all settings by scanning the QR code in the header).

Experiment results and key findings

- The statistical summary of forecast and price errors is provided in the bottom table
- DeepWP: LMP errors vary between 0.62 and 11.15 $/MWh
- DeepWP+: LMP errors reduced by 0.6 to 24.7% relative to the DeepWP
- Larger LMP error reductions are observed across 10% of the worst-case outcomes
- LMP error reduction, however, comes at the expense of increasing power forecast errors
- None of the price-aware predictions resulted in infeasible OPF solutions
- In congested systems, $\alpha-$fairness improvement varies between 3.8% to 27.2%.
- Relative to DeepWP, the DeepWP+ architecture significantly reduces the spatial disparity:



- LMP error minimization implicitly reduces the spatial disparities
- Overall, embedding market clearing as a deep learning layer informs predictions on market outcomes and improves algorithmic fairness in electricity markets

Wind power prediction and LMP errors under conventional (DeepWP) and price-aware (DeepWP+) deep learning architectures

case	wind power data			DeepWP				DeepWP+							
	bus	capacity	$\overline{f}$-scale	RMSE($\widehat{w}$)	RMSE($\widehat{\pi}$)	CVaR($\widehat{\pi}$)	$\alpha-$value	RMSE($\widehat{w}$)		RMSE($\widehat{\pi}$)		CVaR($\widehat{\pi}$)		$\alpha-$value	
		MW	[p.u.]	MWh	$/MWh	$/MWh	$/MWh	MWh	gain	$/MWh	gain	$/MWh	gain	$/MWh	gain
14_ieee	14	100	1.00	0.35	0.62	1.52	0	0.35	+0.6%	0.61	**−0.6%**	1.50	−0.8%	0	—
57_ieee	38	600	0.60	2.31	11.03	34.64	32.08	2.60	+11.2%	10.72	**−2.9%**	33.59	−3.1%	30.92	−3.8%
24_ieee	15	1,000	0.75	4.08	8.62	37.70	27.48	4.51	+9.6%	8.33	**−3.5%**	36.35	−3.7%	26.26	−4.6%
39_epri	6	1,500	0.70	5.94	11.15	31.21	17.53	6.43	+7.6%	10.19	**−9.4%**	28.02	−11.4%	15.84	−10.7%
73_ieee	41	1,000	0.80	4.02	5.12	16.21	32.83	5.51	+26.9%	4.24	**−20.8%**	13.41	−20.9%	26.63	−23.3%
118_ieee	37	500	0.75	2.29	3.59	11.32	17.91	2.60	+12.1%	2.88	**−24.7%**	9.06	−25.0%	14.09	−27.2%

The table displays forecast and price errors across the range of the standard power grid test cases. All cases host a single wind farm with identical power records in p.u. RMSE - root mean square error, CVaR - conditional value-at-risk (here, across 10% of the worst-case scenarios).