Probabilistic electricity price forecasting (EPF) ... and related topics

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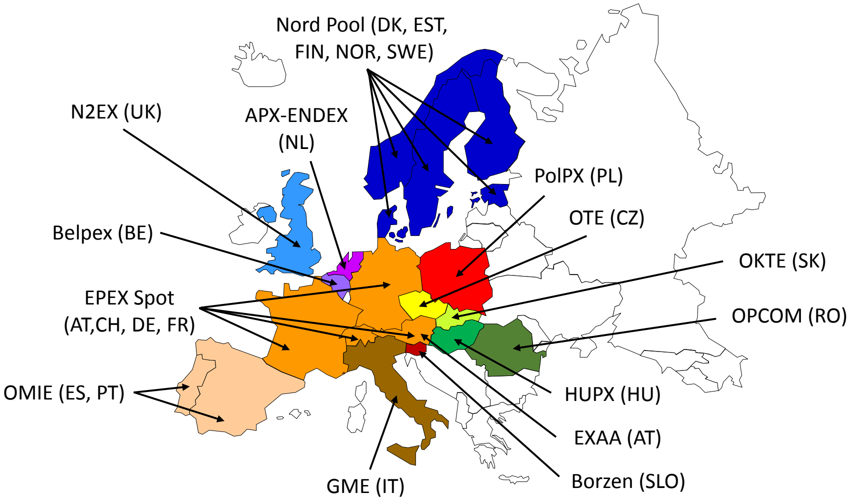
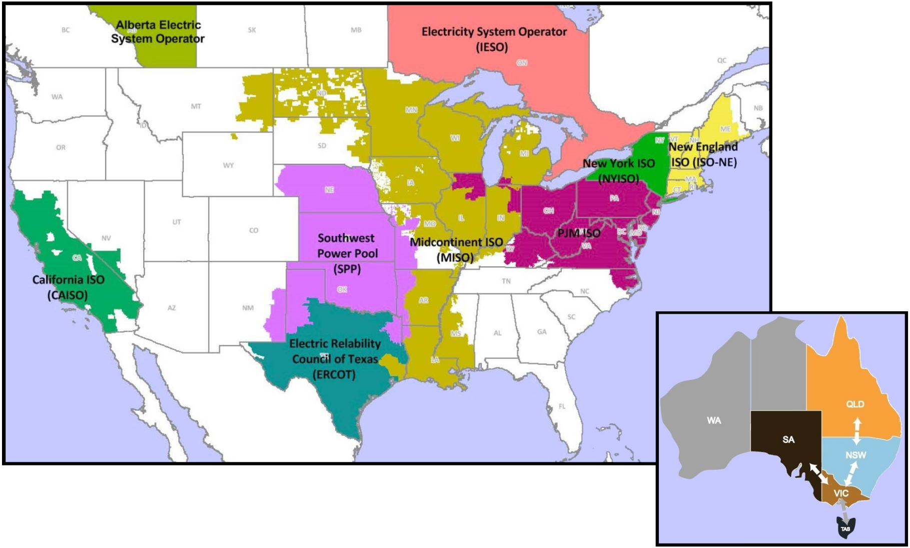
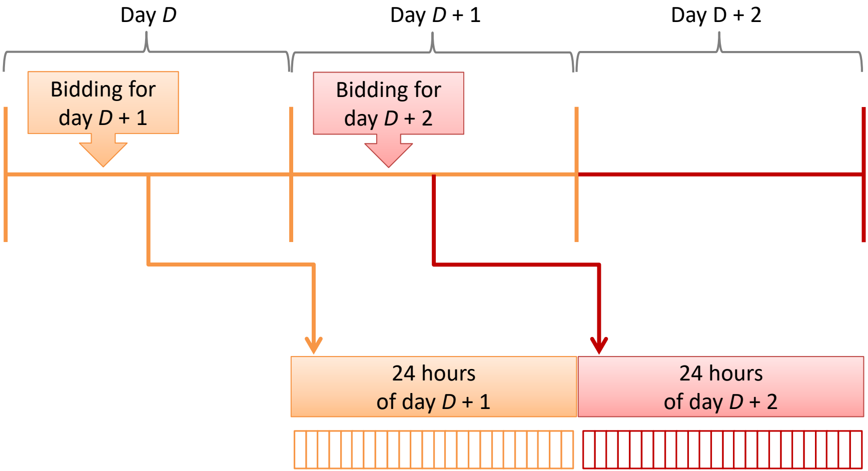
Markets for electricity in Europe



... in North America and Australia

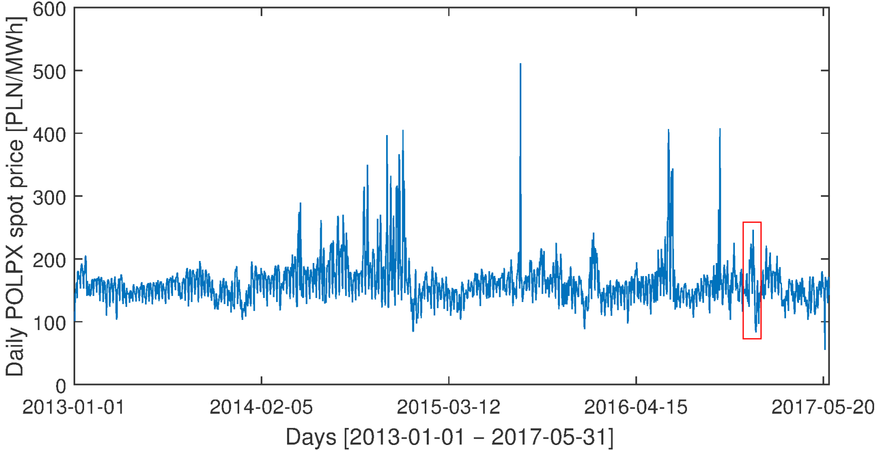


The day-ahead market

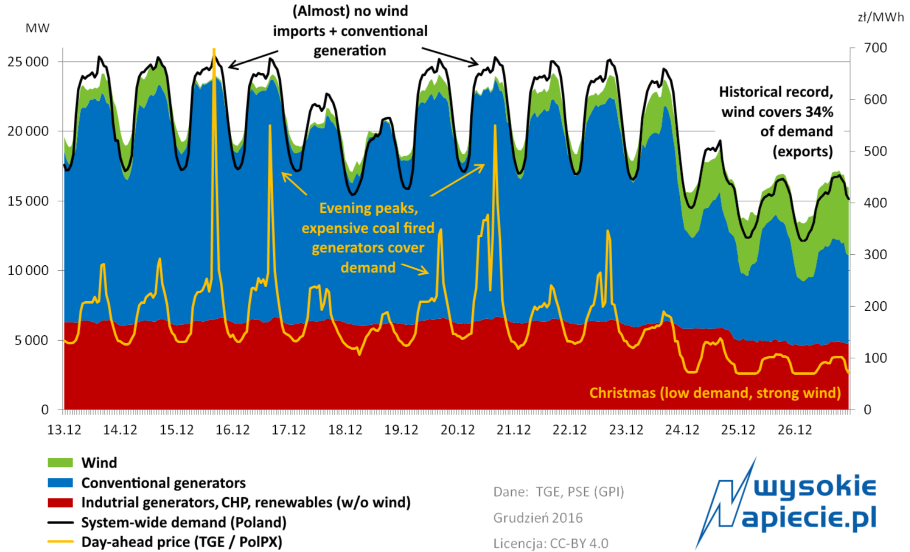


Electricity price time series

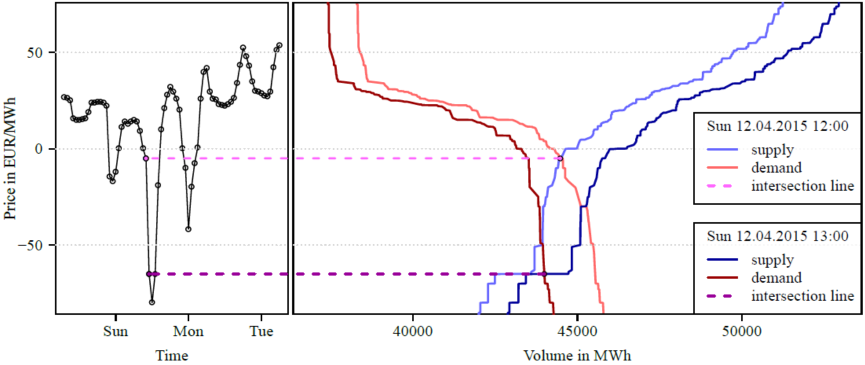
Seasonality, mean-reversion and price spikes



A closeup on two weeks in December 2016

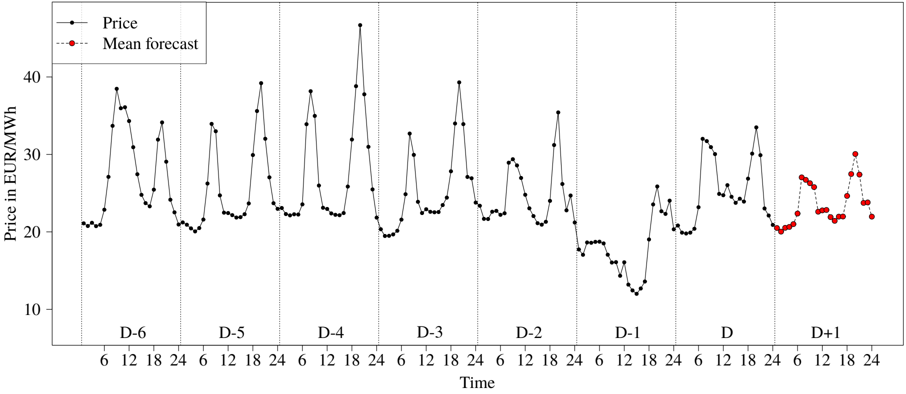


Supply and demand, renewables and negative prices

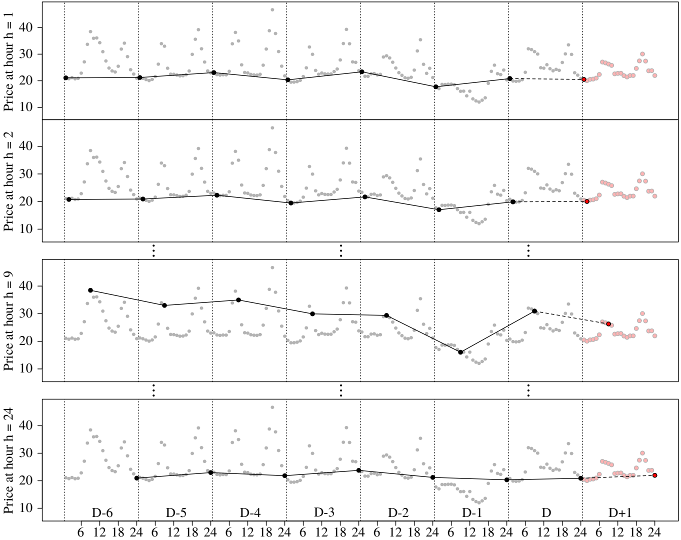


Source: Ziel & Steinert (2016)

Day-ahead point forecasting: Univariate ...



... or multivariate?

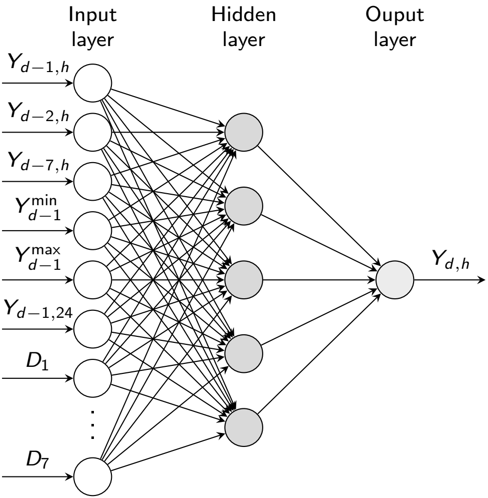


Day-ahead point forecasting: Regression ...

Electricity price for day d and hour h:

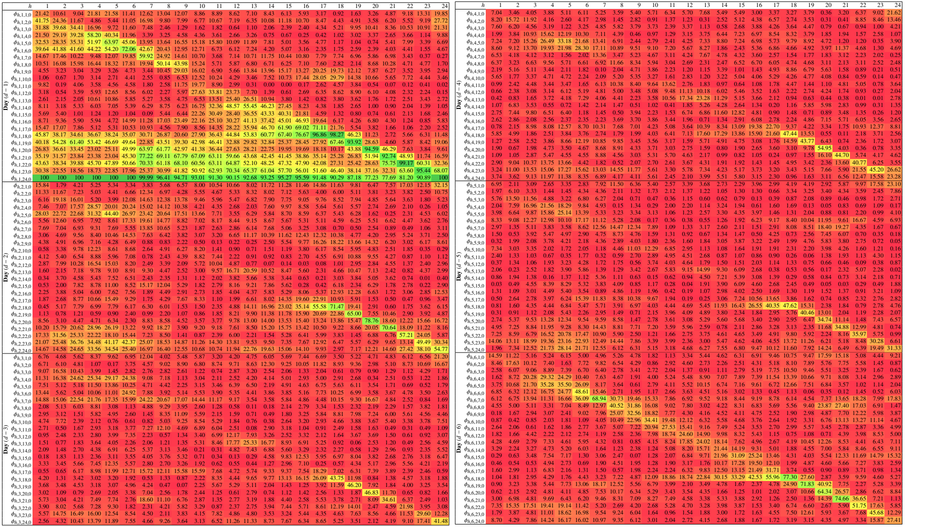
$$
\begin{aligned}
Y_{d,h} = \beta_{h,1} &+ \underbrace{\beta_{h,2} Y_{d-1,h} + \beta_{h,3} Y_{d-2,h} + \beta_{h,4} Y_{d-7,h}}_{\text{autoregressive terms}} \\
&+ \underbrace{\beta_{h,5} Y_{d-1}^{\min} + \beta_{h,6} Y_{d-1}^{\max}}_{\text{non-linear effects}} + \underbrace{\beta_{h,7} Y_{d-1,24}}_{\text{end-of-day effect}} \\
&+ \underbrace{\sum\nolimits_{j=1}^{7} \beta_{h,j+7} D_j}_{\text{weekday dummies}} + \varepsilon_{d,h},
\end{aligned}
$$

... or neural nets?



Variable (feature) selection using LASSO

(Ziel & Weron, 2016, RePEc)



Variable (feature) selection using LASSO cont.

(Ziel & Weron, 2016, RePEc)

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Day $(d-7)$	$\phi_{h,7,1,0}$	7.63	5.08	3.28	11.69	8.09	8.32	18.94	20.24	12.53	6.10	5.94	8.06	6.96	7.17	12.78	10.98	11.13	7.86	5.03	11.65	13.40	6.63	10.35	10.54
	$\phi_{h,7,2,0}$	16.14	11.99	4.62	3.70	2.92	3.55	5.05	4.44	11.14	7.41	6.32	5.74	3.29	2.73	3.46	2.97	4.23	2.38	1.77	2.54	1.32	1.49	4.26	2.13
	$\phi_{h,7,3,0}$	1.65	10.53	14.62	6.82	4.46	3.43	4.02	1.83	2.20	3.16	0.97	0.41	0.17	1.26	1.88	3.93	3.42	6.11	6.35	2.36	1.01	0.73	5.93	7.78
	$\phi_{h,7,4,0}$	7.89	14.45	28.85	32.46	18.52	4.86	10.64	5.65	6.67	6.48	7.67	9.94	17.36	13.55	16.59	12.07	11.26	11.73	12.06	8.80	6.65	2.24	0.98	1.79
	$\phi_{h,7,5,0}$	5.21	5.88	11.13	17.71	28.45	9.01	6.09	1.43	1.56	4.23	8.84	11.41	11.21	12.19	10.50	7.18	5.89	6.53	5.90	2.28	6.20	3.85	1.63	0.83
	$\phi_{h,7,6,0}$	5.00	2.84	7.63	6.19	15.50	43.53	12.10	4.73	11.38	10.83	7.28	6.44	5.37	4.96	2.35	3.12	2.86	2.23	4.12	6.06	5.88	2.55	1.37	8.15
	$\phi_{h,7,7,0}$	5.99	4.39	2.83	4.79	9.45	37.85	74.12	34.04	18.63	11.32	5.94	5.88	8.05	7.11	8.02	7.40	7.43	10.37	16.85	21.78	28.56	32.35	12.63	21.31
	$\phi_{h,7,8,0}$	3.20	5.40	6.25	6.09	9.49	16.02	41.35	63.65	47.78	27.13	14.78	8.92	5.73	7.79	7.44	7.63	8.76	6.76	17.32	17.44	20.32	17.89	11.19	16.41
	$\phi_{h,7,9,0}$	6.76	7.22	9.06	7.16	7.29	5.64	6.15	18.23	48.89	45.78	23.62	16.16	9.05	6.86	5.43	4.41	5.85	3.72	11.26	5.79	4.48	6.48	12.23	10.53
	$\phi_{h,7,10,0}$	8.02	7.89	8.82	10.34	7.53	4.73	2.92	8.38	19.97	40.90	26.43	16.12	13.11	8.84	3.83	3.81	3.67	2.81	2.40	6.92	7.19	5.73	3.92	3.51
	$\phi_{h,7,11,0}$	3.70	5.69	4.66	2.22	2.50	3.87	0.26	0.22	3.90	11.45	23.37	14.97	5.28	4.83	2.64	1.93	0.30	0.92	3.55	4.95	6.20	5.69	2.54	4.18
	$\phi_{h,7,12,0}$	0.35	1.04	2.75	4.93	6.16	3.89	0.33	0.80	4.52	11.54	23.58	25.99	14.21	10.18	7.84	4.39	4.77	3.79	5.97	8.33	9.88	10.76	9.23	5.54
	$\phi_{h,7,13,0}$	8.67	14.66	10.44	6.65	1.95	4.12	2.00	1.31	1.45	3.44	13.25	20.35	23.09	17.65	9.94	3.94	4.42	10.78	14.03	14.69	18.83	13.79	16.34	7.68
	$\phi_{h,7,14,0}$	0.98	3.28	4.48	3.80	4.68	3.14	0.46	3.28	5.48	16.18	24.23	31.74	40.15	39.80	33.42	25.45	11.10	10.58	11.57	11.17	9.28	9.85	10.78	11.24
	$\phi_{h,7,15,0}$	2.51	2.48	1.88	3.55	4.23	3.67	2.36	5.51	5.07	8.20	8.46	19.33	29.07	33.27	31.92	20.39	11.72	11.09	2.91	2.50	1.75	4.80	10.69	9.05
	$\phi_{h,7,16,0}$	1.71	1.37	2.61	1.23	1.56	1.18	2.96	8.90	6.31	7.56	7.45	9.05	18.90	30.08	40.75	43.55	26.06	13.35	15.82	11.09	7.72	8.80	12.07	9.67
	$\phi_{h,7,17,0}$	1.15	0.10	1.22	3.24	0.78	1.68	1.66	5.41	3.00	11.73	19.36	23.54	23.14	32.93	43.37	50.99	74.85	44.31	14.12	8.74	5.34	7.43	8.15	12.32
	$\phi_{h,7,18,0}$	5.17	4.04	3.54	3.47	5.08	5.51	1.80	5.13	5.29	9.02	14.89	16.87	31.49	36.37	31.46	25.29	33.01	64.05	38.59	4.06	3.80	1.07	3.03	3.31
	$\phi_{h,7,19,0}$	2.28	8.38	7.88	8.89	11.79	11.65	13.45	19.51	14.12	10.86	14.54	12.97	9.90	13.94	8.90	14.39	13.80	31.28	64.06	39.26	8.67	8.23	8.92	10.24
	$\phi_{h,7,20,0}$	6.90	3.15	8.81	13.58	17.73	17.47	14.03	4.51	6.36	7.14	4.36	4.77	5.70	5.99	4.44	5.98	6.36	1.02	4.20	64.78	35.84	13.33	7.72	0.41
	$\phi_{h,7,21,0}$	1.94	5.95	11.41	15.17	15.01	19.16	16.86	9.81	9.61	4.19	1.90	3.44	3.92	5.08	6.38	6.69	12.72	6.25	1.92	2.44	21.43	10.86	4.80	4.89
	$\phi_{h,7,22,0}$	1.92	9.97	12.42	13.71	9.17	10.11	8.71	4.24	6.52	5.05	3.55	0.83	1.59	3.79	9.39	8.51	9.19	14.18	15.43	4.14	0.58	20.74	9.44	2.53
	$\phi_{h,7,23,0}$	3.06	14.16	25.30	28.82	30.17	36.45	28.01	20.00	10.29	10.65	5.89	2.38	3.73	8.66	17.44	22.40	27.80	38.14	33.85	23.71	10.64	2.35	11.74	5.47
	$\phi_{h,7,24,0}$	1.48	4.50	4.36	10.01	13.63	18.41	17.36	15.93	12.52	8.19	6.52	7.43	10.97	12.09	18.52	18.73	22.12	22.65	23.41	22.86	10.06	2.78	3.32	14.86
Day $(d-8)$	$\phi_{h,8,1,0}$	5.88	6.91	15.66	20.37	22.41	20.24	17.72	18.14	15.94	11.14	4.26	5.04	5.84	7.88	7.94	10.02	11.18	10.41	14.16	12.92	10.13	7.03	4.33	3.76
	$\phi_{h,8,2,0}$	17.69	3.78	5.43	2.55	2.91	4.06	5.59	4.12	4.61	1.64	3.43	5.17	3.76	3.67	4.53	3.10	6.29	3.89	2.39	2.70	8.73	6.11	5.93	4.30
	$\phi_{h,8,3,0}$	4.15	4.83	6.61	6.46	6.49	6.69	4.27	5.57	3.95	1.49	3.93	3.87	3.02	5.50	4.56	6.86	5.40	4.91	5.71	4.19	4.89	7.03	5.49	4.02
	$\phi_{h,8,4,0}$	11.20	8.46	7.18	11.54	15.78	17.29	6.24	4.83	8.18	3.87	5.82	2.19	4.28	5.65	7.90	11.29	15.53	14.31	12.58	16.80	14.51	10.53	2.80	10.74
	$\phi_{h,8,5,0}$	0.27	2.15	4.47	9.21	9.26	5.91	5.03	7.37	6.97	5.64	5.57	8.18	11.15	9.40	7.90	6.55	8.36	4.05	2.59	3.64	2.17	0.45	1.25	1.94
	$\phi_{h,8,6,0}$	10.72	7.53	8.52	12.95	12.53	17.23	5.86	1.19	2.07	0.63	2.47	4.03	3.34	4.59	2.97	2.88	2.73	3.43	4.77	4.01	1.97	0.54	0.39	1.05
	$\phi_{h,8,7,0}$	8.81	7.72	10.22	9.29	6.51	5.46	9.04	2.10	2.04	3.52	5.26	5.87	13.78	17.31	16.14	13.55	11.60	7.62	5.67	7.67	5.84	3.44	3.21	0.65
	$\phi_{h,8,8,0}$	4.66	3.17	4.08	6.15	6.49	3.50	2.51	4.39	2.98	1.84	1.42	2.29	2.39	1.83	2.56	3.74	4.18	3.26	4.79	5.99	7.79	5.16	2.82	2.47
	$\phi_{h,8,9,0}$	3.13	1.67	3.79	3.18	3.40	4.29	4.10	0.76	0.43	0.81	0.59	0.43	0.55	0.87	2.50	2.12	13.36	7.87	6.47	3.09	4.44	4.18	3.86	0.62
	$\phi_{h,8,10,0}$	5.83	2.25	0.88	1.13	2.08	6.66	6.47	1.08	0.29	1.60	2.49	4.73	5.84	7.38	6.11	6.97	10.43	12.64	11.80	9.22	4.73	1.13	1.56	2.26
	$\phi_{h,8,11,0}$	8.79	3.54	5.52	1.91	6.17	3.53	6.37	3.69	2.83	1.62	1.41	0.46	0.09	0.09	0.43	1.43	1.11	1.84	3.16	2.85	1.77	0.93	3.06	0.35
	$\phi_{h,8,12,0}$	3.27	3.30	5.23	4.42	5.16	8.83	4.32	2.98	1.76	2.16	1.53	1.83	0.54	0.09	0.29	0.46	0.63	2.31	4.66	1.62	1.34	0.46	0.15	1.10
	$\phi_{h,8,13,0}$	0.36	0.19	1.05	1.50	2.84	3.01	6.30	2.61	2.82	1.32	3.46	4.78	2.72	1.62	2.72	2.98	2.98	2.29	0.66	0.07	0.39	0.16	0.00	1.77
	$\phi_{h,8,14,0}$	0.46	3.25	4.82	5.10	4.88	8.39	3.63	4.69	3.54	1.21	1.37	2.59	5.73	3.88	2.55	1.60	0.50	1.63	0.54	0.51	2.19	1.20	1.58	1.50
	$\phi_{h,8,15,0}$	2.19	0.73	0.43	3.11	6.34	0.54	3.39	5.84	6.03	1.99	0.66	1.17	1.79	2.17	2.68	2.88	5.60	5.23	1.91	0.15	0.21	0.18	0.82	1.15
	$\phi_{h,8,16,0}$	1.44	0.17	0.51	0.39	1.39	0.99	0.47	0.81	1.09	1.86	2.07	6.94	9.02	8.58	8.83	9.69	2.49	0.68	0.53	0.35	0.22	0.81	2.34	2.54
	$\phi_{h,8,17,0}$	2.40	0.85	0.89	2.46	5.15	6.12	6.21	1.46	3.99	1.03	0.12	3.53	2.27	5.12	3.19	8.51	17.71	12.80	4.82	6.57	6.28	9.64	8.58	8.68
	$\phi_{h,8,18,0}$	2.52	1.07	0.80	0.94	4.46	3.60	6.07	2.51	6.72	4.24	3.01	1.92	3.06	4.27	4.58	6.70	12.62	33.95	14.70	1.75	1.91	9.46	6.98	2.66
	$\phi_{h,8,19,0}$	7.50	3.67	3.57	7.86	9.93	6.87	2.20	6.61	12.92	7.01	2.59	3.42	3.50	5.13	5.20	2.38	0.79	3.05	23.49	11.22	0.78	7.32	5.08	1.11
	$\phi_{h,8,20,0}$	4.16	2.46	8.50	11.45	13.97	12.30	9.71	15.00	6.37	5.97	6.68	5.25	5.85	4.23	4.84	5.81	4.88	3.70	3.47	20.80	7.43	2.55	5.23	1.74
	$\phi_{h,8,21,0}$	7.25	12.75	16.64	17.77	16.35	7.40	3.42	15.39	7.08	8.85	6.45	9.65	6.87	5.48	12.20	9.48	10.70	9.66	6.38	5.55	14.34	1.82	4.11	5.72
	$\phi_{h,8,22,0}$	4.33	8.93	10.04	16.30	12.54	7.28	4.64	4.91	3.29	0.34	1.96	1.72	1.56	1.07	2.47	1.92	3.46	6.31	6.93	1.18	8.10	26.47	8.96	4.88
	$\phi_{h,8,23,0}$	4.56	15.33	26.87	30.59	31.56	20.93	21.06	9.42	6.06	3.55	2.21	3.01	5.48	5.35	5.33	5.20	7.48	11.30	12.26	9.60	3.58	5.07	23.33	7.84
	$\phi_{h,8,24,0}$	7.34	7.58	11.25	12.36	13.77	17.66	13.78	13.75	11.42	10.62	10.16	6.56	7.43	8.48	10.14	10.85	8.36	9.18	5.80	4.67	3.00	3.83	9.83	11.31

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Daily minimums	$\phi_{h,1,min,0}$	57.99	66.16	80.84	87.56	81.33	54.23	26.01	25.68	20.48	12.72	6.94	5.83	5.42	4.45	7.03	5.54	7.51	5.76	3.28	1.68	5.52	2.91	3.02	7.03
	$\phi_{h,2,min,0}$	1.01	8.69	13.20	16.20	14.91	12.35	7.52	5.59	3.04	0.15	0.80	1.04	0.95	2.96	3.39	2.68	2.46	1.30	3.75	2.50	1.61	2.15	1.31	3.23
	$\phi_{h,3,min,0}$	14.29	22.78	22.77	27.55	24.29	18.38	7.56	4.16	4.36	1.51	1.15	1.67	2.45	1.71	1.26	0.97	2.66	1.23	1.70	2.63	5.09	4.54	2.83	3.50
	$\phi_{h,4,min,0}$	7.84	8.01	11.65	18.02	16.59	12.95	10.40	6.07	1.03	1.34	1.55	2.70	4.06	3.14	5.44	4.67	9.50	15.95	13.49	7.01	6.25	2.85	2.45	3.22
	$\phi_{h,5,min,0}$	11.53	11.88	21.48	24.25	24.12	13.21	4.08	3.53	0.79	1.89	3.01	4.72	5.50	4.94	4.06	6.11	7.26	3.43	4.33	1.60	2.67	3.86	2.25	1.44
	$\phi_{h,6,min,0}$	5.37	13.53	23.47	21.92	27.64	25.79	5.19	1.04	3.11	2.32	1.92	2.08	4.27	2.84	2.87	6.69	5.96	3.65	1.56	1.22	1.75	0.50	1.60	2.70
	$\phi_{h,7,min,0}$	6.48	8.76	13.14	13.48	13.01	5.66	1.90	2.00	0.86	0.26	0.60	1.44	3.69	1.77	1.67	3.56	3.01	3.91	4.35	5.00	5.07	4.00	3.01	1.14
	$\phi_{h,8,min,0}$	2.46	2.39	6.19	8.26	13.44	7.23	6.97	8.70	6.67	8.64	9.21	10.91	13.49	14.41	13.37	13.08	8.00	7.85	5.49	4.43	3.72	3.80	5.30	6.04
Daily maximums	$\phi_{h,1,max,0}$	24.53	13.83	21.30	26.21	27.31	21.85	21.41	55.76	62.53	47.56	31.51	25.43	14.92	9.67	6.72	4.31	7.13	7.79	10.33	15.28	7.53	4.03	3.48	3.90
	$\phi_{h,2,max,0}$	18.14	22.28	25.77	22.57	24.48	16.80	29.67	28.34	24.89	19.93	17.27	14.70	13.86	12.42	6.20	5.94	7.78	2.30	2.96	5.66	8.43	12.15	10.50	7.15
	$\phi_{h,3,max,0}$	4.96	2.13	7.05	6.47	9.85	10.09	17.09	17.45	15.70	18.45	12.69	8.36	5.49	4.18	0.85	2.04	1.72	0.57	3.99	8.18	15.13	5.33	6.29	4.23
	$\phi_{h,4,max,0}$	8.31	6.60	5.04	6.54	9.67	6.31	11.52	12.08	10.09	7.87	12.16	8.80	5.78	4.59	4.28	1.30	1.23	1.66	1.87	1.64	3.80	3.60	5.17	11.70
	$\phi_{h,5,max,0}$	4.73	0.99	4.84	6.88	6.73	3.34	12.91	12.73	11.82	10.93	15.06	15.22	13.08	12.24	11.68	11.31	7.51	8.38	9.51	9.74	4.63	1.08	0.49	0.87
	$\phi_{h,6,max,0}$	4.04	4.79	4.34	2.91	1.65	1.12	9.46	30.53	30.04	22.47	6.36	2.66	2.35	4.07	4.14	4.70	5.36	6.53	7.78	11.33	9.90	5.09	5.95	2.27
	$\phi_{h,7,max,0}$	5.20	6.41	13.87	12.78	7.82	14.09	11.58	12.96	15.77	9.49	8.63	8.26	7.30	8.10	7.71	8.68	3.50	3.59	2.66	1.86	2.93	0.89	1.13	3.55
	$\phi_{h,8,max,0}$	3.87	3.78	2.41	2.89	4.93	5.86	4.38	2.19	2.95	4.50	2.98	2.97	2.02	1.81	2.10	2.56	2.91	2.43	6.39	7.43	6.87	7.05	9.85	9.80
DoW dummies	$\phi_{h,0,0,1}$	22.61	22.29	27.32	25.24	22.66	60.04	88.09	85.89	93.59	97.73	95.53	94.01	95.86	97.22	99.46	99.71	99.94	99.97	99.73	96.70	93.83	87.32	73.40	53.01
	$\phi_{h,0,0,2}$	27.80	46.46	42.87	42.67	45.42	40.12	36.81	43.44	37.81	34.31	30.82	38.15	31.30	37.60	46.98	51.57	52.96	53.39	40.40	28.78	32.96	40.62	33.46	24.70
	$\phi_{h,0,0,3}$	20.98	13.92	15.17	16.09	8.92	14.69	14.61	14.43	14.14	16.02	13.59	15.13	9.03	15.42	19.23	16.85	13.52	17.48	18.64	17.04	19.64	14.92	7.36	3.24
	$\phi_{h,0,0,4}$	23.87	14.91	21.66	21.47	18.69	18.97	20.21	19.36	13.52	14.35	10.08	10.34	14.68	12.45	12.84	14.37	16.01	15.17	23.05	17.48	12.33	7.32	13.14	7.89
	$\phi_{h,0,0,5}$	9.69	12.23	10.71	9.38	10.49	6.86	7.96	5.14	9.29	6.80	7.45	6.65	5.25	6.49	21.41	35.71	26.50	13.57	24.00	38.13	32.87	45.01	29.89	7.29
	$\phi_{h,0,0,6}$	74.08	60.13	55.84	50.60	30.44	92.69	93.32	97.92	99.54	98.71	98.26	93.64	95.58	99.32	99.88	99.84	99.45	97.65	95.34	94.63	97.24	90.99	74.01	64.73
	$\phi_{h,0,0,7}$	52.63	76.93	78.50	78.29	87.97	90.70	89.07	100	100	100	100	100	100	100	100	100	100	98.57	90.35	82.90	73.49	66.47	34.57	50.06
Periodic on $Y_{*,h}$	$\phi_{h,1,h,1}$	18.71	12.25	13.46	14.93	20.98	19.94	20.08	26.92	16.09	22.81	25.79	24.16	22.43	22.62	21.48	23.51	34.66	33.15	34.28	41.74	43.25	34.87	20.82	17.60
	$\phi_{h,1,h,2}$	21.02	16.13	20.15	15.90	13.89	15.38	32.89	33.32	31.00	27.40	31.94	25.89	19.21	24.91	33.36	37.56	44.95	43.46	39.35	32.49	33.03	27.80	30.85	9.19
	$\phi_{h,1,h,3}$	13.65	15.59	26.42	25.76	27.98	31.84	68.69	70.35	72.61	51.85	45.71	48.85	51.43	60.35	67.56	72.94	65.23	58.87	55.16	48.27	33.88	31.34	25.93	15.86
	$\phi_{h,1,h,4}$	35.22	29.29	28.70	35.39	32.62	34.95	63.99	58.20	40.96	31.24	30.25	36.67	42.75	50.46	64.26	66.44	56.31	42.92	38.92	45.47	50.13	49.53	32.71	27.66
	$\phi_{h,1,h,5}$	14.19	28.57	37.94	46.53	36.81	33.22	69.44	76.08	58.60	50.74	47.77	33.40	29.93	19.74	12.16	18.72	26.38	21.65	49.85	32.55	29.84	22.96	15.27	15.82
	$\phi_{h,1,h,6}$	14.39	20.29	19.67	21.81	24.78	44.99	33.90	59.18	48.95	41.35	33.06	33.66	34.78	33.12	31.68	27.99	28.23	13.78	16.30	31.64	19.69	18.37	7.03	27.03
	$\phi_{h,1,h,7}$	29.57	28.45	26.33	28.86	34.16	40.50	24.74	14.12	17.23	13.60	19.40	39.36	41.85	51.45	55.81	54.55	47.65	45.33	36.21	22.29	32.53	33.50	20.88	45.95
Periodic on $Y_{*,24}$	$\phi_{h,1,24,1}$	26.28	24.95	33.33	45.40	41.39	40.10	35.49	25.15	35.69	28.84	26.79	24.19	23.58	14.07	13.97	16.84	18.89	24.81	28.17	26.45	20.64	17.31	14.14	
	$\phi_{h,1,24,2}$	19.80	32.47	45.61	46.47	53.83	57.98	44.03	41.65	33.04	30.98	28.06	27.04	29.38	28.67	30.53	30.74	31.22	32.76	28.73	27.22	19.48	18.88	5.30	
	$\phi_{h,1,24,3}$	18.96	32.24	34.27	42.07	36.84	40.72	31.93	45.29	34.20	29.24	23.01	23.69	22.46	17.62	16.92	15.80	19.28	22.54	18.85	13.86	19.55	11.35	15.59	
	$\phi_{h,1,24,4}$	12.84	27.89	35.46	31.46	40.28	46.01	41.86	44.74	49.17	36.89	27.92	25.85	24.19	18.63	21.74	25.02	30.40	31.96	33.81	27.32	16.69	11.51	12.94	
	$\phi_{h,1,24,5}$	9.65	13.64	19.73	29.84	30.10	23.46	27.57	27.44	30.70	23.16	16.36	16.51	15.68	21.26	29.18	27.49	25.98	25.70	18.82	18.04	23.68	20.49	19.56	
	$\phi_{h,1,24,6}$	35.57	37.69	52.08	52.65	37.73	31.88	41.40	51.12	55.28	49.51	49.57	51.32	51.22	43.32	39.75	32.02	33.27	41.09	40.48	42.39	44.14	35.53	30.17	
	$\phi_{h,1,24,7}$	45.76	40.57	40.44	41.43	35.29	25.55	30.70	35.73	42.99	44.31	43.30	43.39	43.64	24.10	20.25	21.58	28.77	39.88	41.91	46.51	38.83	30.33	33.96	

First read on electricity price forecasting (EPF)

R.Hyndman: "this paper alone is responsible for 0.7 of the current $\mathrm{IF}_{2Y}=2.642$" ;-)

International Journal of Forecasting 30 (2014) 1030–1081

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Review

Electricity price forecasting: A review of the state-of-the-art with a look into the future

CrossMark

Rafał Weron

Institute of Organization and Management, Wrocław University of Technology, Wrocław, Poland

ARTICLE INFO

Keywords:
Electricity price forecasting
Day-ahead market
Seasonality
Autoregression
Neural network
Factor model
Forecast combination
Probabilistic forecast

ABSTRACT

A variety of methods and ideas have been tried for *electricity price*
the last 15 years, with varying degrees of success. This review artic
complexity of available solutions, their strengths and weaknesses, a
and threats that the forecasting tools offer or that may be encoun
looks ahead and speculates on the directions EPF will or should ta
or so. In particular, it postulates the need for objective comparative
(i) the same datasets, (ii) the same robust error evaluation procedu
testing of the significance of one model's outperformance of another

Agenda

1. Beyond point forecasts
   $\Rightarrow$ probabilistic forecasts
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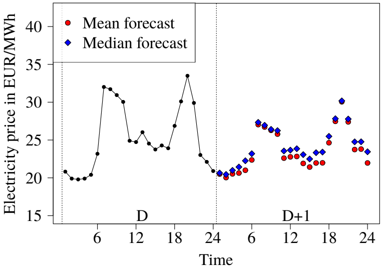
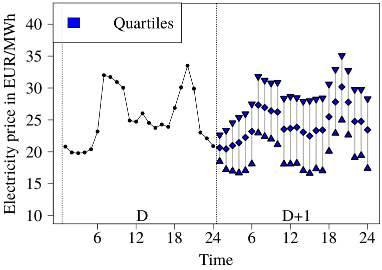
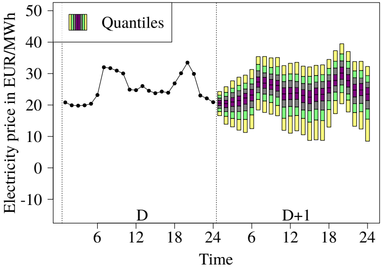
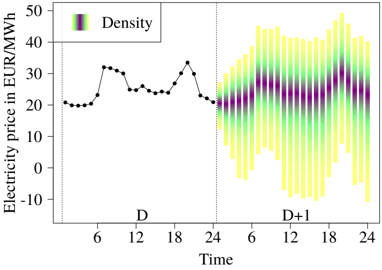
A new hype: Point → probabilistic forecasting









A (very) recent review of probabilistic forecasting

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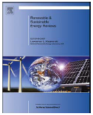

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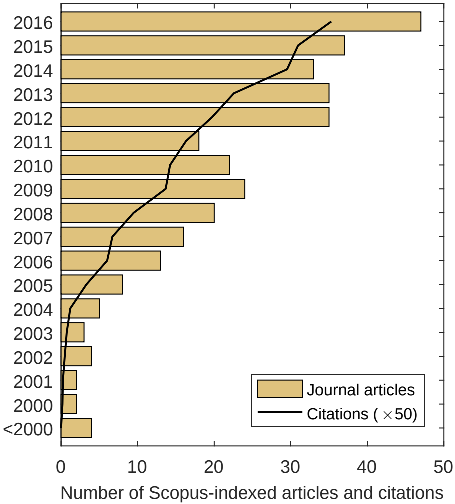
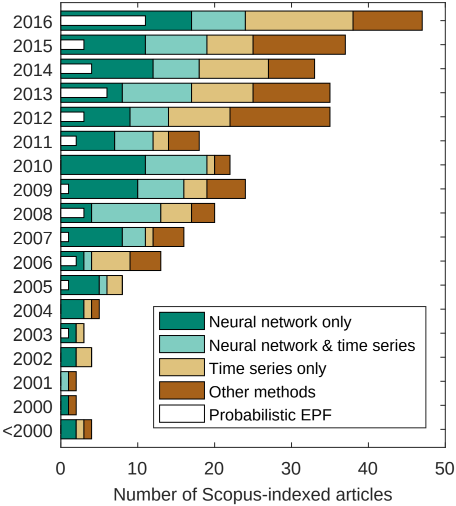
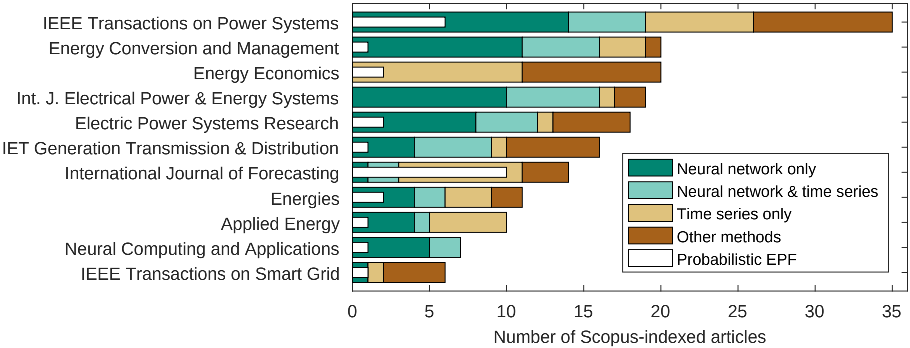
How popular is probabilistic EPF: Papers, cites





How popular is probabilistic EPF: Journals



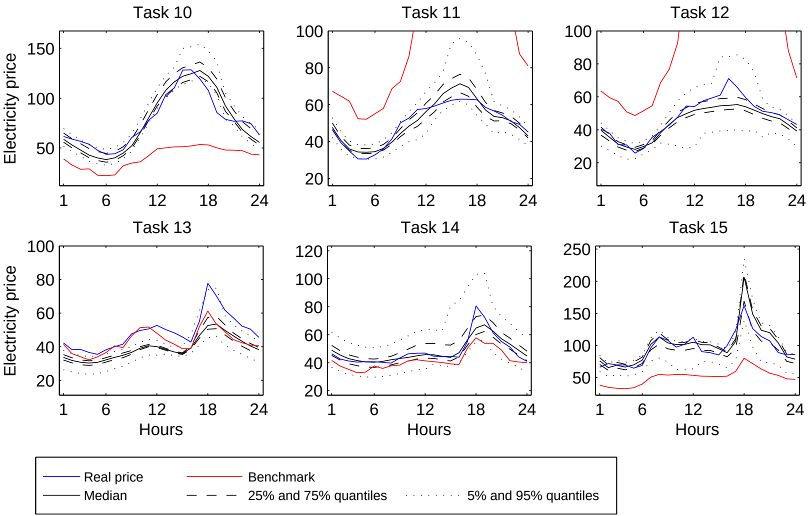
GEFCom2014

(Hong, Pinson, Fan et al., 2016, IJF)

GEFCOM 2014 Load Forecasting | GEFCOM 2014 Price Forecasting | GEFCOM 2014 Wind Forecasting | GEFCOM 2014 Solar Forecasting | IEEE PES Power & Energy Society®

- Incremental data sets released on weekly basis
- Price Track:
  - 287 contestants
  - Submit 99 quantiles (=percentiles) for 24h of the next day

Price Track


Task 10
Task 11
Task 12
Task 13
Task 14
Task 15
Electricity price
Hours
1 6 12 18 24
Real price
Benchmark
Median
25% and 75% quantiles
5% and 95% quantiles

Price Track: Top winning teams

(1st and) 2nd place for QRA!

1. Pierre Gaillard, Yannig Goude, Raphaël Nedellec (EDF R&D, F)
2. Katarzyna Maciejowska, Jakub Nowotarski (Wrocław UT, PL)
3. Grzegorz Dudek (Częstochowa UT, PL)
4. Zico Kolter, Romain Juban, Henrik Ohlsson, Mehdi Maasoumy (C3 Energy, USA)
5. Frank Lemke (KnowledgeMiner Software, D)

Agenda

1. Beyond point forecasts ⇒ probabilistic forecasts
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   - Point forecasts
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ABSTRACT

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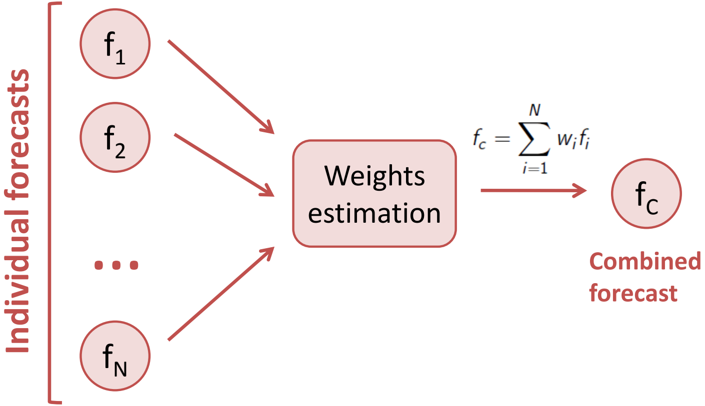
Point forecast averaging: The idea



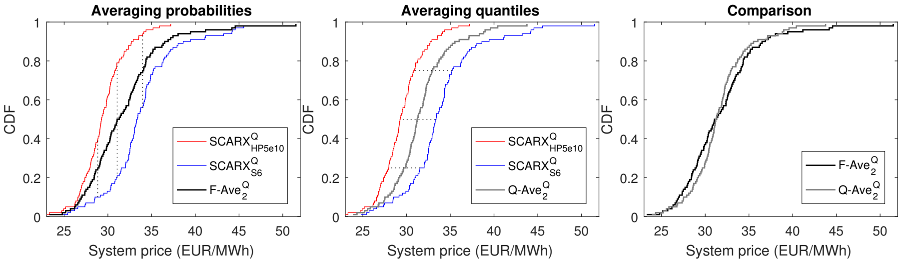
- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger

In the 'AI world' ...

- *Committee machines, ensemble averaging, expert aggregation*
- Weron (2014): Forecast combinations and committee machines seem to *evolve independently*, with researchers from both groups not being aware of the parallel developments !

Combining probabilistic forecasts is more tricky

- Gneiting & Ranjan (2013): a linearly combined probabilistic forecast is more dispersed than the least dispersed of the component distributions
  - Helps if the component distributions tend to be underdispersed
- Lichtendahl et al. (2013): averaging quantiles is better (sharper)



Alternative: Quantile Regression Averaging (QRA)

(Submitted on 31.12.2013, 21:26 ;-)

Comput Stat (2015) 30:791–803
DOI 10.1007/s00180-014-0523-0

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ORIGINAL PAPER

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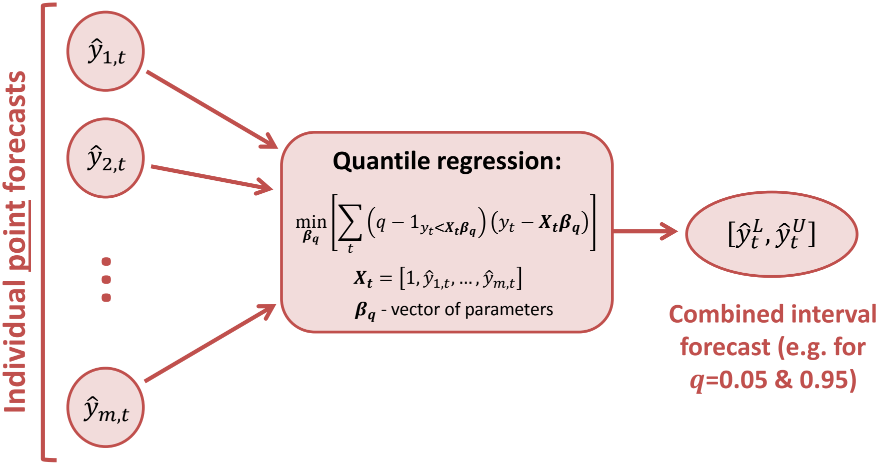
Computing electricity spot price prediction intervals using quantile regression and forecast averaging

Jakub Nowotarski · Rafał Weron

Received: 31 December 2013 / Accepted: 6 August 2014 / Published online: 19 August 2014

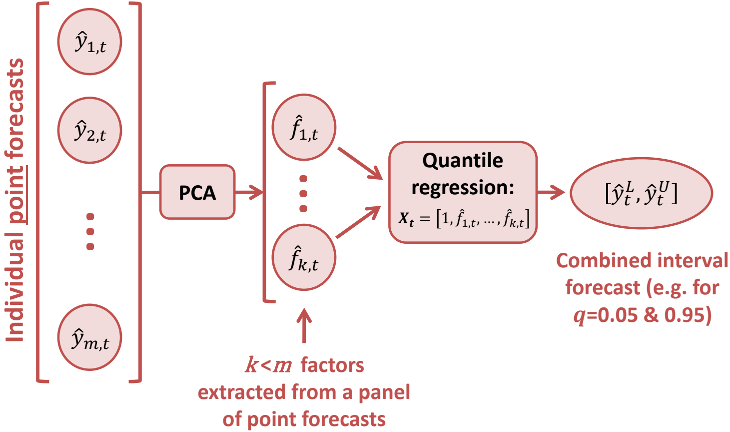
Abstract We examine possible accuracy gains from forecast averaging in the context of interval forecasts of electricity spot prices. First, we test whether constructing empirical prediction intervals (PI) from combined electricity spot price forecasts leads to better forecasts than those obtained from individual methods. Next, we propose a new method for constructing PI—Quantile Regression Averaging (QRA)—which utilizes the concept of quantile regression and a pool of point forecasts of individual

Quantile Regression Averaging: The idea



FQRA: When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



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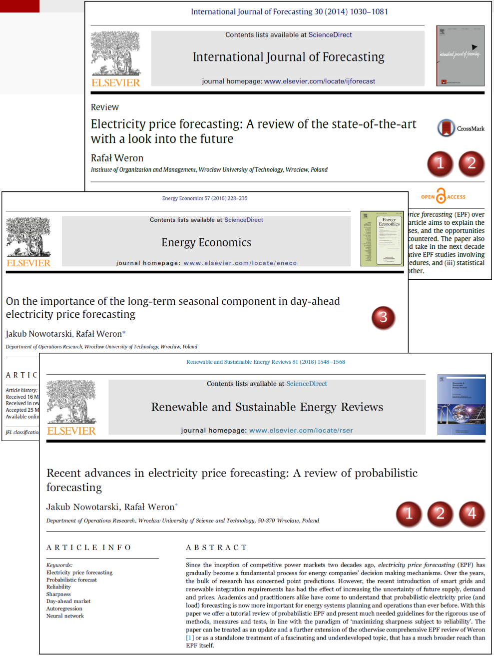

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rice forecasting (EPF) over
article aims to explain the
ses, and the opportunities
ountered. The paper also
d take in the next decade
tive EPF studies involving
edures, and (iii) statistical
other.

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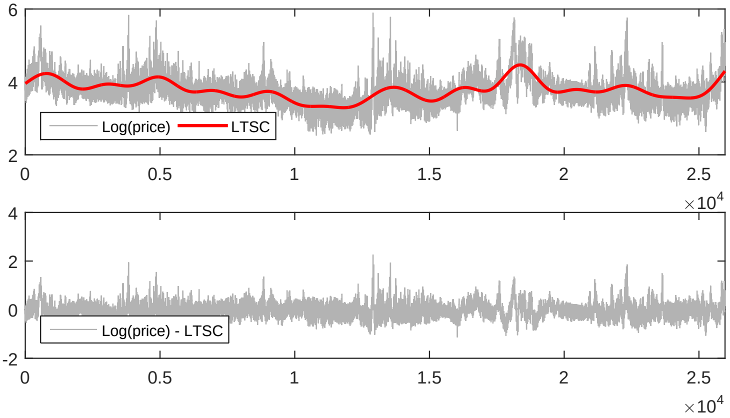
LTSC and short-term price forecasting

- Can the long-term trend-seasonal component (LTSC) impact short-term (day-ahead) electricity price forecasts?



LTSC and short-term price forecasting cont.

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On the importance of the long-term seasonal component in day-ahead electricity price forecasting

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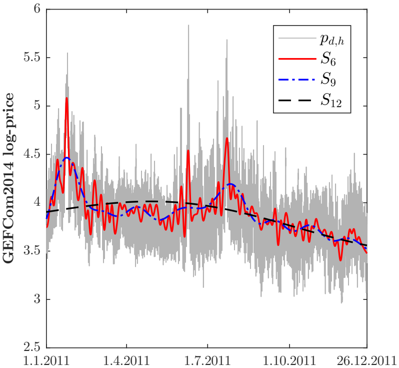
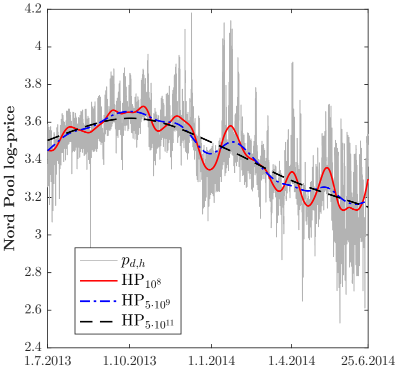
ABSTRACT

In day-ahead *electricity price forecasting* (EPF) the daily and weekly seasonalities are always taken into account, but the long-term seasonal component (LTSC) is believed to add unnecessary complexity to the already parameter-rich models and is generally ignored. Conducting an extensive empirical study involving state-of-the-art time series models we show that (i) decomposing a series of electricity prices into a LTSC and a stochastic component, (ii) modeling them independently and (iii) combining their forecasts can bring – contrary to a common belief – an accuracy gain compared to an approach in which a given time series model is calibrated to the prices themselves.

Wavelet and HP-filter based LTSCs





- **Wavelet filters (-S$_J$)**: $S_5, S_6, \ldots, S_{14}$, ranging from 'daily' smoothing ($S_5 \rightarrow 2^5$ hours) up to 'biannual' ($S_{14} \rightarrow 2^{14}$ hours)
- **HP-filters (-HP$_\lambda$)**: with $\lambda = 10^8, 5 \cdot 10^8, 10^9, \ldots, 5 \cdot 10^{11}$

The **ARX** model

For the log-price, i.e., $p_{d,h} = log(P_{d,h})$, the model is given by:

$$p_{d,h} = \underbrace{\beta_{h,1} p_{d-1,h} + \beta_{h,2} p_{d-2,h} + \beta_{h,3} p_{d-7,h}}_{\text{autoregressive effects}} + \underbrace{\beta_{h,4} p_{d-1,\min}}_{\text{non-linear effect}}$$
$$+ \underbrace{\beta_{h,5} z_t}_{\text{load forecast}} + \underbrace{\sum_{i=1}^{3} \beta_{h,i+5} D_i}_{\text{Mon, Sat, Sun dummies}} + \varepsilon_{d,h} \quad (1)$$

- $p_{d-1,min}$ is yesterday's minimum hourly price
- z_t is the logarithm of system load/consumption
- Dummy variables D_1, D_2 and D_3 refer to Monday, Saturday and Sunday, respectively

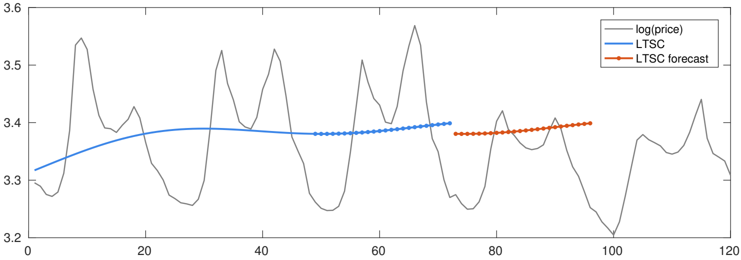
The SCAR modeling framework

(Nowotarski & Weron, 2016, ENEECO; Uniejewski, Marcjasz & Weron, 2017, WP)

The *Seasonal Component AutoRegressive* (SCAR) modeling framework consists of the following steps:

1. (a) Decompose the log-price in the calibration window into the LTSC $T_{d,h}$ and the stochastic component $q_{d,h}$
   (b) Decompose the exogenous series in the calibration window using the same type of LTSC as for prices
2. Calibrate the **ARX** model to q_t and compute forecasts for the 24 hours of the next day (24 separate series)

The SCAR modeling framework cont.



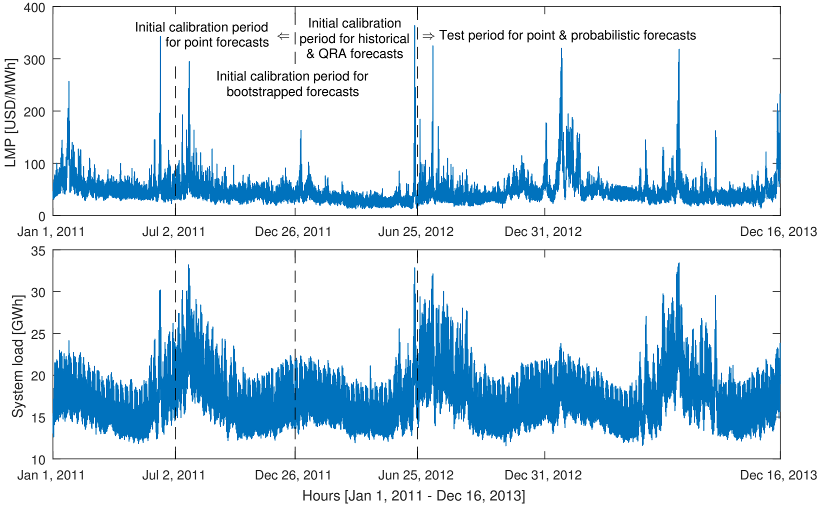
3. Add stochastic component forecasts $\hat{q}_{d+1,h}$ to persistent forecasts $\hat{T}_{d+1,h}$ of the LTSC to yield log-price forecasts $\hat{p}_{d+1,h}$
4. Convert them into price forecasts of the **SCARX** model, i.e., $\hat{P}_{d+1,h} = \exp\left(\hat{p}_{d+1,h}\right)$

Three methods of constructing PIs

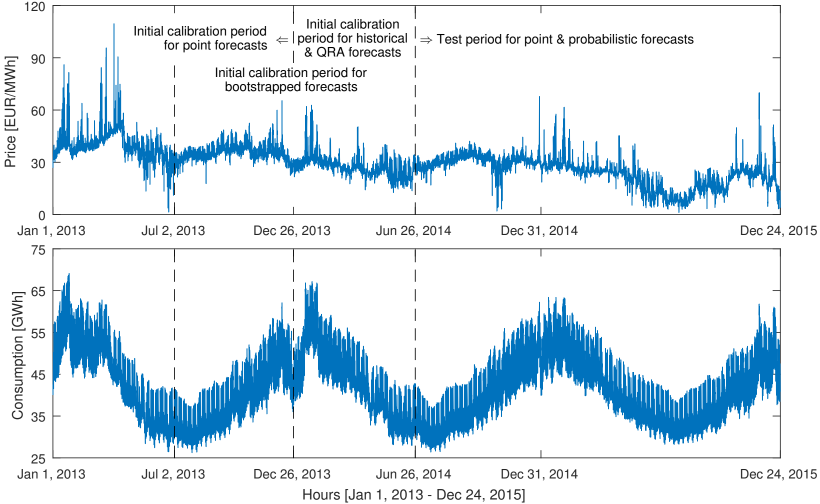
1. Historical simulation (**H**), which consists of computing sample quantiles of the empirical distribution of $\varepsilon_{d,h}$'s
2. Bootstrapping (**B**), which first generates pseudo-prices recursively using sampled normalized residuals, then computes desired quantiles of the bootstrapped prices
   - Takes into account not only historical forecast errors but also parameter uncertainty
3. Quantile Regression Averaging (**Q**)

Note: All require that one-day ahead point prediction errors are available in the calibration window for probabilistic forecasts

Datasets: GEFCom 2014

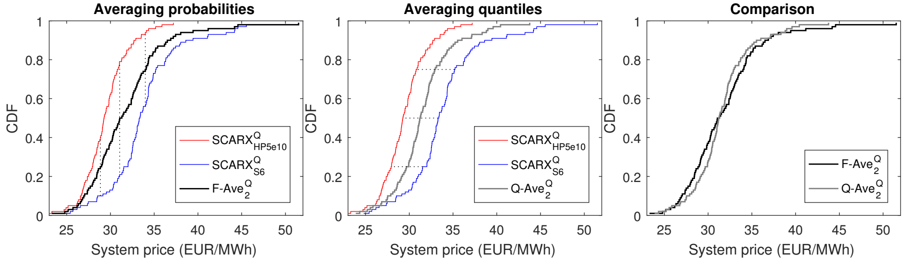


Datasets: Nord Pool



Combining probabilistic forecasts

- Average probability forecast: $\textbf{F-Ave}_n^* \equiv \frac{1}{n}\sum_{i=1}^n \hat{F}_i(x)$
  $\Rightarrow$ a vertical average of predictive distributions
- Average quantile forecast: $\textbf{Q-Ave}_n^* \equiv \hat{Q}^{-1}(x)$
  with $\hat{Q}(x) = \frac{1}{n}\sum_{i=1}^n \hat{Q}_i(x)$ and quantile forecast $\hat{Q}_i(x) = \hat{F}_i^{-1}(x)$
  $\Rightarrow$ a horizontal average
- $* =$ **H**, **B** or **Q** denotes the method of constructing PIs



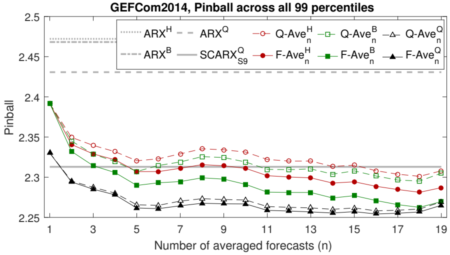
Sharpness and the pinball loss

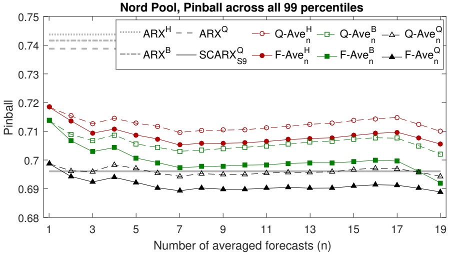
$$\textbf{Pinball}\left(\hat{Q}_{P_t}(q), P_t, q\right) = \begin{cases} (1-q)\left(\hat{Q}_{P_t}(q) - P_t\right), & \text{for } P_t < \hat{Q}_{P_t}(q), \\ q\left(P_t - \hat{Q}_{P_t}(q)\right), & \text{for } P_t \geqslant \hat{Q}_{P_t}(q), \end{cases}$$

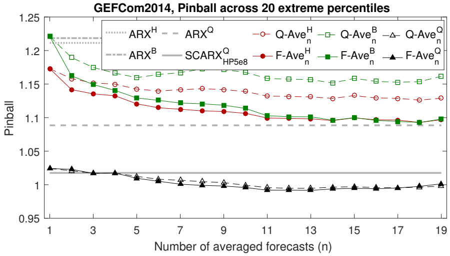
- $\hat{Q}_{P_t}(q)$ is the price forecast at the q-th quantile
- P_t is the actually observed price

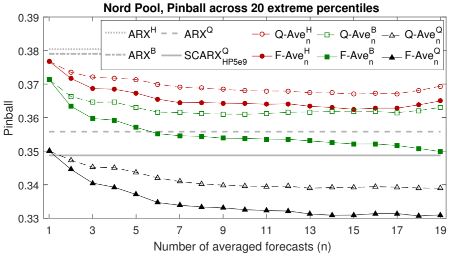
- To provide an aggregate score we average:
    - across all hours in the test period
    - across different quantiles (all 99 or extreme 20 percentiles)

How many models should we average?









Diebold-Mariano (DM) tests

Define the 'multivariate' loss differential series in the $\| \cdot \|_1$-norm as:

$$\Delta_{X,Y,d} = \|\pi_{X,d}\|_1 - \|\pi_{Y,d}\|_1$$

where

- $\pi_{X,d} = (\pi_{X,d,1}, \ldots, \pi_{X,d,24})'$ is the vector of pinball scores for model X and day d
- $\|\pi_{X,d}\|_1 = \sum_{h=1}^{24} |\pi_{X,d,h}|$ is the average across the 24 hours

As in the standard DM test, we assume that the loss differential series is covariance stationary

Diebold-Mariano (DM) tests cont.

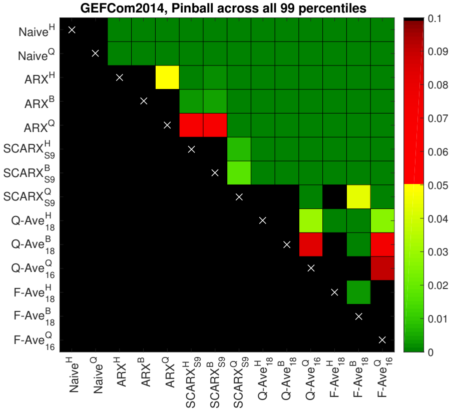
For each model pair we compute two one-sided DM tests:

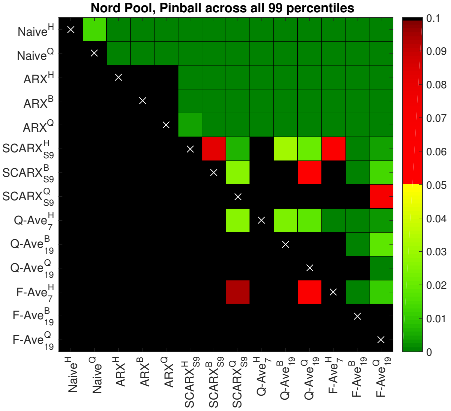
1. $H_0 : E(\Delta_{X,Y,d}) \leqslant 0 \Rightarrow$ X yields better forecasts
2. $H_0^R : E(\Delta_{X,Y,d}) \geqslant 0 \Rightarrow$ Y yields better forecasts

We present results for 14 selected models:

- Both naive benchmarks – $\mathbf{Naive^H}$, $\mathbf{Naive^Q}$
- All three ARX benchmarks – $\mathbf{ARX^H}$, $\mathbf{ARX^B}$, $\mathbf{ARX^Q}$
- The best *ex-post*
    - $\mathbf{SCARX_*^H}$, $\mathbf{SCARX_*^B}$ and $\mathbf{SCARX_*^Q}$ models
    - $\mathbf{Q\text{-}Ave_n^H}$, $\mathbf{Q\text{-}Ave_n^B}$ and $\mathbf{Q\text{-}Ave_n^Q}$ average quantile forecasts
    - $\mathbf{F\text{-}Ave_n^H}$, $\mathbf{F\text{-}Ave_n^B}$ and $\mathbf{F\text{-}Ave_n^Q}$ average probability forecasts

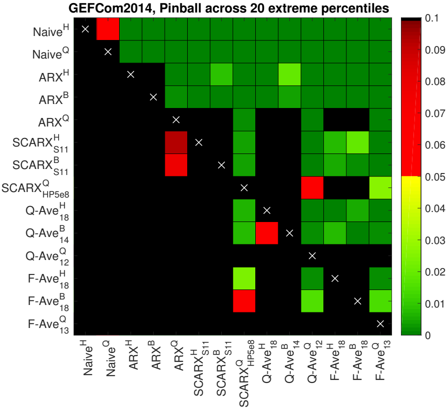
p-values of the DM test across 99 percentiles

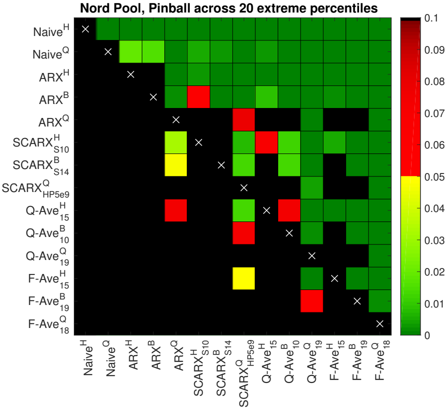




We use a heat map to indicate the range of the p-values – the closer they are to zero ($\rightarrow$ **dark green**) the more significant is the difference between the forecasts of a model on the X-axis (better) and the forecasts of a model on the Y-axis (worse)

p-values of the DM test across 20 percentiles





We use a heat map to indicate the range of the *p*-values – the closer they are to zero (→ **dark green**) the more significant is the difference between the forecasts of a model on the X-axis (better) and the forecasts of a model on the Y-axis (worse)

Main findings

- 'Probabilistic' **SCARX** models (nearly always) significantly outperform the **Naive** and **ARX** benchmarks
  - $\mathbf{SCARX^Q}$ models (nearly always) significantly outperform $\mathbf{SCARX^H}$ and $\mathbf{SCARX^B}$
- Both averaging schemes generally significantly outperform the benchmarks and the non-combined **SCARX** models
- Averaging over probabilities ($\textbf{F-Ave}_n^*$) generally yields better probabilistic EPFs than averaging over quantiles ($\textbf{Q-Ave}_n^*$)
  - In contrast to typically encountered economic forecasting problems (Lichtendahl et al., 2013)

Agenda

1. Beyond point forecasts
   ⇒ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Seasonal components
   & short-term forecasting
   - SCAR framework
   - Case study
4. **New trends in energy forecasting**

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Review

Electricity price forecasting: A review of the state-of-the-art with a look into the future

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1 2

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...rice forecasting (EPF) over ... article aims to explain the ...ses, and the opportunities ...countered. The paper also ...d take in the next decade ...tive EPF studies involving ...edures, and (iii) statistical ...other.

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ELSEVIER

Recent advances in electricity price forecasting: A review of probabilistic forecasting

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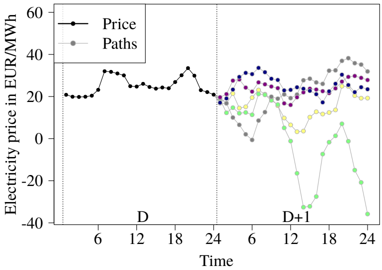
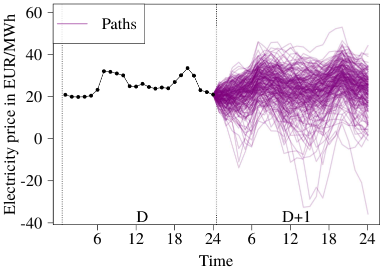
ABSTRACT

Since the inception of competitive power markets two decades ago, *electricity price forecasting* (EPF) has gradually become a fundamental process for energy companies' decision making mechanisms. Over the years, the bulk of research has concerned point predictions. However, the recent introduction of smart grids and renewable integration requirements has had the effect of increasing the uncertainty of future supply, demand and prices. Academics and practitioners alike have come to understand that probabilistic electricity price (and load) forecasting is now more important for energy systems planning and operations than ever before. With this paper we offer a tutorial review of probabilistic EPF and present much needed guidelines for the rigorous use of methods, measures and tests, in line with the paradigm of 'maximizing sharpness subject to reliability'. The paper can be treated as an update and a further extension of the otherwise comprehensive EPF review of Weron [1] or as a standalone treatment of a fascinating and underdeveloped topic, that has a much broader reach than EPF itself.

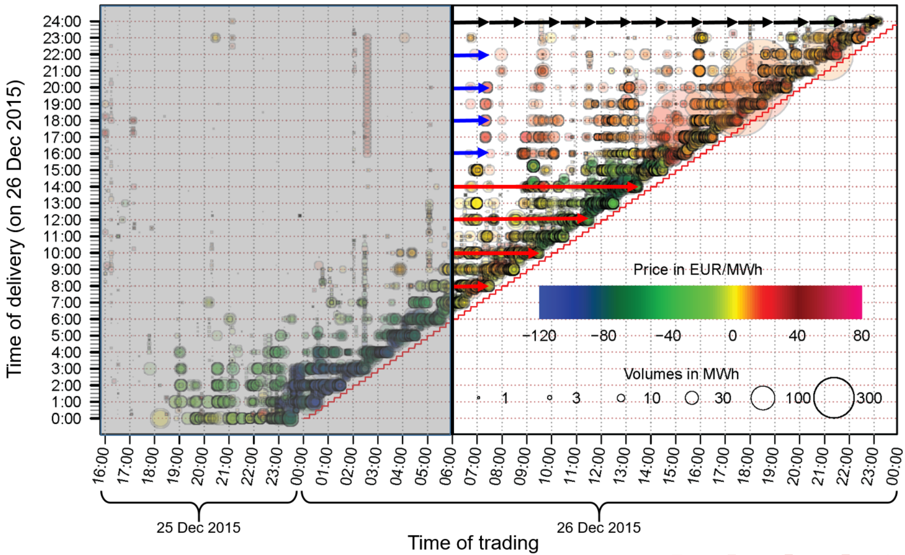
Point → probabilistic → path forecasting





- Relatively novel in EPF (but not in weather forecasting)
- Operational decisions often depend on prices for multiple hours in a row (e.g., ramping costs of power plants)
- Regulatory incentives: in Germany a wind park can receive less subsidies if the electricity price is negative for 6 hours in a row

Intraday forecasting



A new book on EPF ... forthcoming in 2018

Rafał Weron, Florian Ziel

CRC Press
Taylor & Francis Group

Forecasting Electricity Prices: A Guide to Robust Modeling