Recent advances in electricity price forecasting: A 2018 perspective

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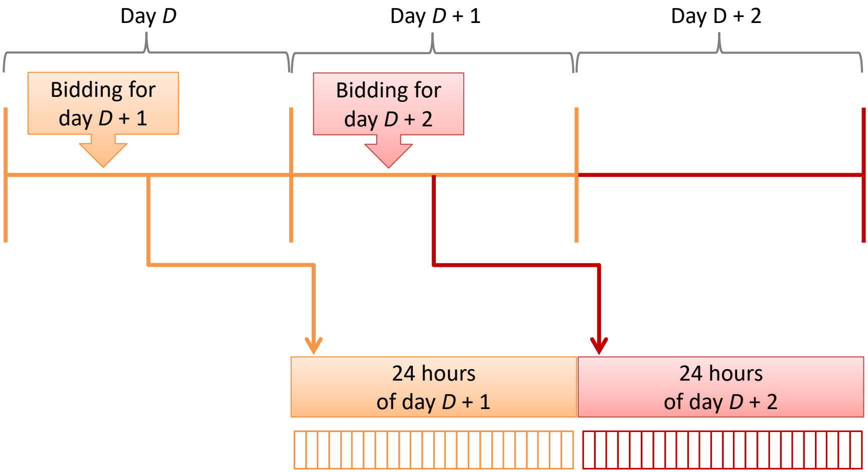
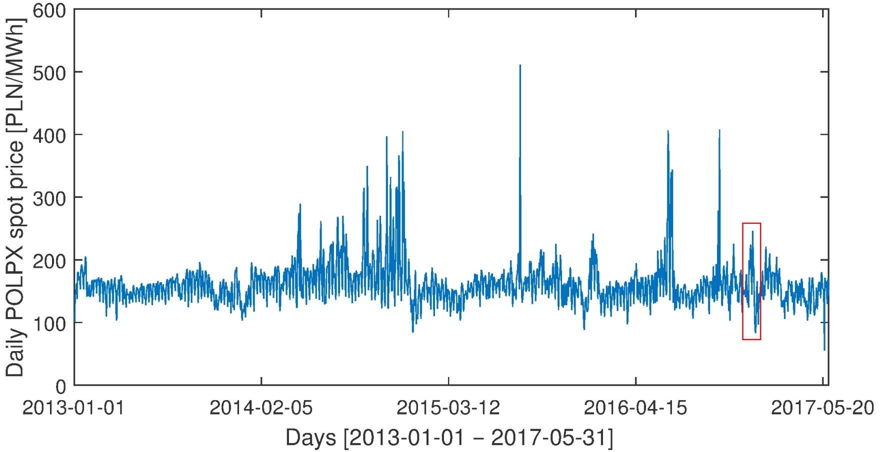
J.Nowotarski (BNY Mellon), F.Ziel (Essen)

The workhorse of European power trading

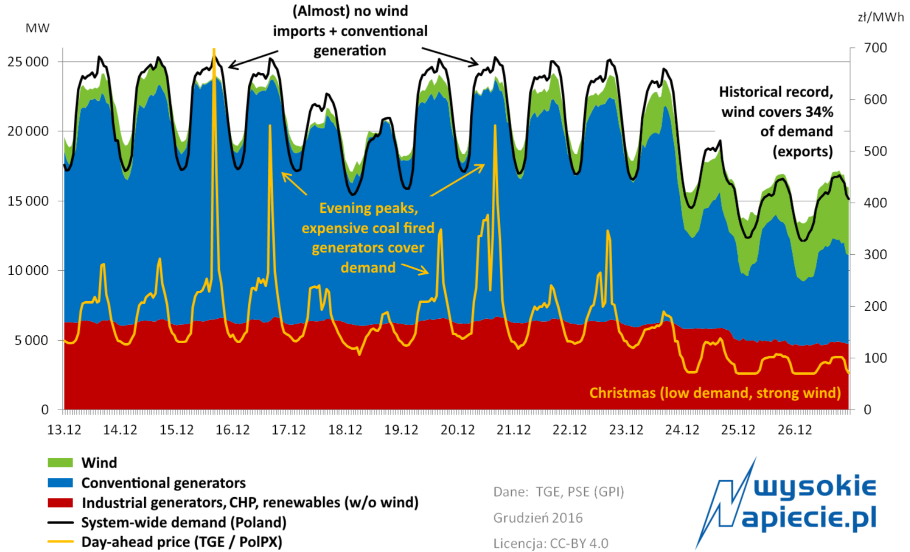
The day-ahead market (ca. 93% of papers)



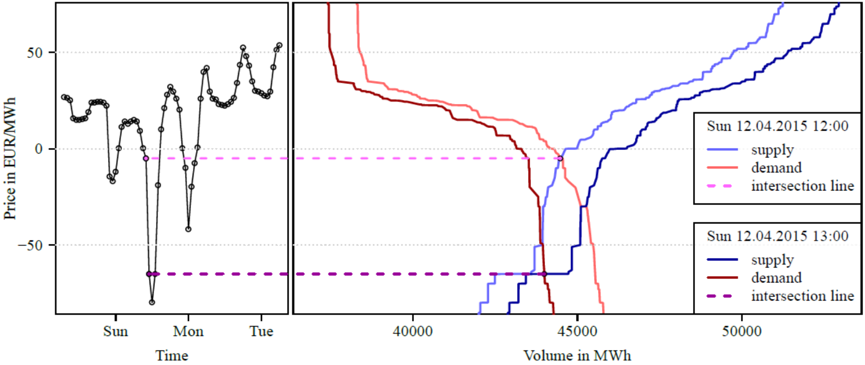
Seasonality, mean-reversion and price spikes



A closeup on two weeks in December 2016

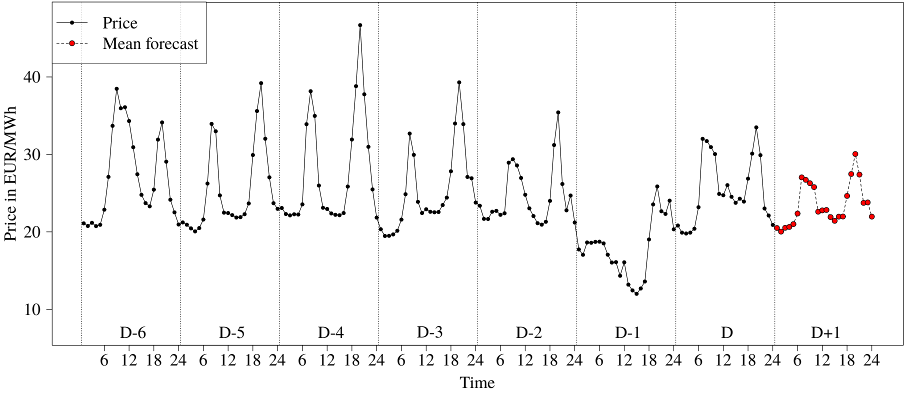


Supply and demand, renewables and negative prices

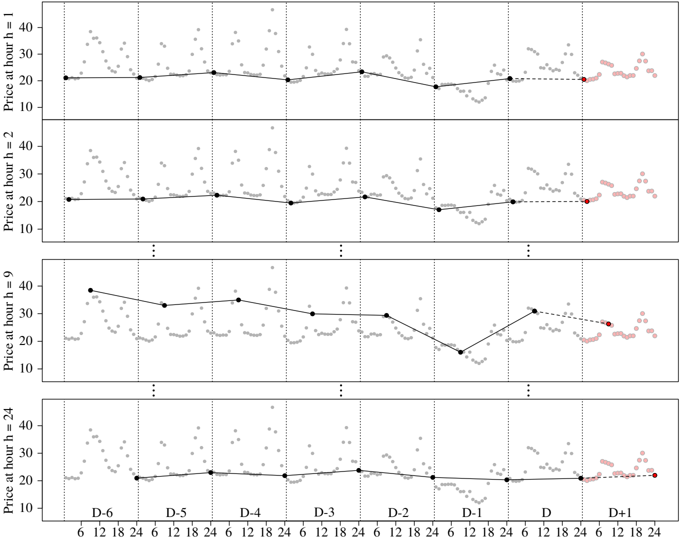


Source: Ziel & Steinert (2016, ENEECO)

Day-ahead point forecasting: Univariate ...



... or multivariate?



Day-ahead point forecasting: Regression ...

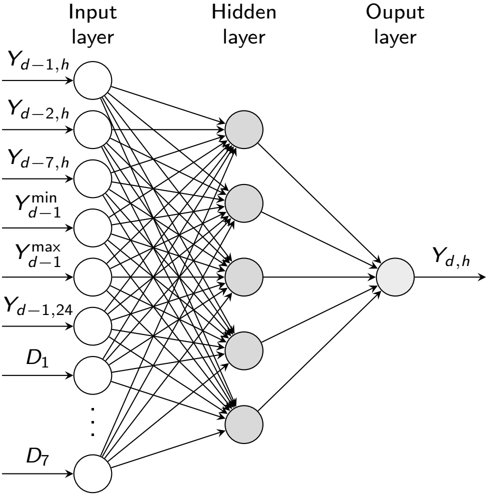
Electricity price for day d and hour h:

$$Y_{d,h} = \underbrace{\beta_{h,1} Y_{d-1,h} + \beta_{h,2} Y_{d-2,h} + \beta_{h,3} Y_{d-7,h}}_{\text{autoregressive terms}}$$

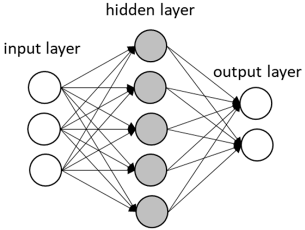
$$+ \underbrace{\beta_{h,4} Y_{d-1}^{\min} + \beta_{h,5} Y_{d-1}^{\max}}_{\text{non-linear effects}} + \underbrace{\beta_{h,6} Y_{d-1,24}}_{\text{end-of-day effect}}$$

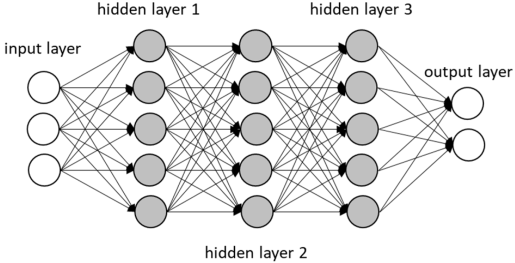
$$+ \underbrace{\sum_{j=1}^{7} \beta_{h,j+6} D_j}_{\text{weekday dummies}} + \varepsilon_{d,h},$$

... neural nets ...


Input
layer
Hidden
layer
Ouput
layer
$Y_{d-1,h}$
$Y_{d-2,h}$
$Y_{d-7,h}$
$Y_{d-1}^{\min}$
$Y_{d-1}^{\max}$
$Y_{d-1,24}$
D_1
D_7
$Y_{d,h}$

... or deep neural nets (DNN)?





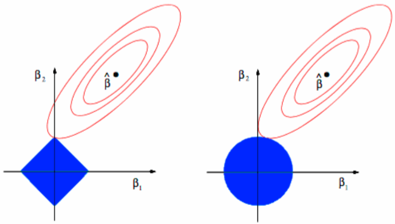
Variable (feature) selection using LASSO

(Uniejewski et al., 2016, Energies; Ziel & Weron, 2018, ENEECO)

Day	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 $(d-1)$	$\phi_{h,1,1,0}$	21.42	10.61	9.04	21.81	21.58	11.41	12.62	13.04	12.07	8.86	8.89	8.62	7.10	8.43	6.13	5.93	3.17	0.92	1.63	3.26	4.87	9.18	13.31	19.85
	$\phi_{h,1,2,0}$	41.75	24.36	11.67	4.86	5.44	11.05	16.98	9.80	7.99	6.77	10.67	7.19	6.35	10.08	11.18	10.70	8.47	4.43	4.91	3.58	6.20	5.52	9.19	27.72
	$\phi_{h,1,3,0}$	31.88	39.68	34.41	16.96	9.72	11.60	7.48	2.46	1.29	1.62	1.82	0.64	1.10	2.06	2.39	2.40	4.34	5.21	9.95	10.41	8.36	10.53	10.91	21.31
	$\phi_{h,1,4,0}$	21.50	29.19	39.28	58.20	40.34	11.96	3.39	3.25	4.58	4.36	3.61	2.66	3.26	0.75	0.67	0.25	0.42	1.02	3.02	3.37	2.65	3.66	1.14	9.88
	$\phi_{h,1,5,0}$	32.53	28.35	35.31	51.97	63.97	45.06	13.95	13.64	16.55	15.18	15.80	10.09	11.89	7.81	5.01	3.56	4.77	1.17	1.04	0.74	5.41	7.99	3.39	6.69
	$\phi_{h,1,6,0}$	39.64	41.88	41.60	44.22	54.20	72.06	42.67	20.43	12.95	12.71	6.73	6.12	7.24	4.20	5.07	3.16	2.35	1.75	2.59	2.39	4.03	4.41	1.55	4.67
	$\phi_{h,1,7,0}$	14.67	17.46	10.22	9.48	12.07	19.85	59.92	24.92	14.61	10.70	3.68	7.14	10.71	11.75	10.44	10.80	7.79	7.74	6.96	5.86	6.98	3.43	0.37	0.27
	$\phi_{h,1,8,0}$	10.51	16.08	15.98	16.44	18.32	17.81	19.94	50.14	43.98	15.24	5.71	5.87	6.80	6.71	6.25	7.10	7.60	2.82	2.14	8.68	10.28	4.71	4.77	1.70
	$\phi_{h,1,9,0}$	4.55	3.23	3.04	3.29	3.26	4.73	3.44	10.45	29.03	16.02	6.90	5.66	13.84	13.96	15.17	13.27	20.25	19.73	12.12	7.87	6.27	3.52	3.95	2.94
	$\phi_{h,1,10,0}$	1.06	0.67	1.70	3.14	2.71	4.41	2.55	0.85	6.53	12.52	10.24	4.29	3.46	7.52	10.73	17.44	28.05	29.79	14.38	10.66	5.65	7.72	4.44	3.46
	$\phi_{h,1,11,0}$	9.82	0.19	4.06	3.58	4.56	4.58	1.80	2.58	11.75	19.77	8.90	2.99	0.31	0.00	0.00	0.17	2.62	4.57	3.84	0.54	0.07	0.12	0.41	0.02
	$\phi_{h,1,12,0}$	3.18	0.54	3.59	5.93	12.65	8.56	6.02	2.27	5.97	27.63	33.81	23.73	7.70	1.39	0.61	2.69	6.35	8.62	8.90	6.10	4.08	2.32	2.24	0.15
	$\phi_{h,1,13,0}$	2.61	2.15	2.05	10.61	10.86	5.85	5.27	3.58	4.75	6.53	13.51	25.40	26.51	10.94	3.80	1.42	0.82	3.80	3.62	1.76	1.72	2.51	3.43	2.72
	$\phi_{h,1,14,0}$	8.11	3.18	5.33	6.03	7.05	5.39	6.29	8.75	6.23	16.75	32.36	48.57	55.45	46.23	27.45	8.23	4.38	1.85	2.65	1.00	0.90	2.04	1.39	1.05
	$\phi_{h,1,15,0}$	5.69	5.40	1.01	1.24	1.20	1.04	0.09	5.44	6.44	22.26	30.49	28.40	36.55	43.33	40.31	21.81	4.59	1.32	0.80	0.74	0.61	2.13	1.68	2.46
	$\phi_{h,1,16,0}$	8.71	9.36	5.90	5.94	4.72	14.99	11.28	17.03	23.49	22.16	25.10	30.27	41.13	37.42	45.01	46.93	19.64	6.17	4.26	6.80	4.30	1.24	0.85	5.83
	$\phi_{h,1,17,0}$	15.47	17.07	7.86	5.12	5.31	10.53	10.93	4.56	7.90	8.56	14.35	28.22	35.94	46.70	61.90	69.02	71.11	21.76	5.54	3.82	1.66	1.06	2.20	2.52
	$\phi_{h,1,18,0}$	45.87	38.17	34.61	36.67	38.24	35.07	30.71	26.87	20.60	27.90	36.43	44.84	53.83	60.77	67.40	76.67	96.86	98.27	46.23	11.23	2.72	5.66	6.31	11.48
	$\phi_{h,1,19,0}$	40.18	54.28	61.40	53.42	46.69	49.64	22.85	43.51	39.30	42.98	46.41	32.88	29.82	32.84	25.37	28.45	27.92	67.46	93.92	28.63	4.60	5.87	8.42	19.06
	$\phi_{h,1,20,0}$	26.83	36.61	33.45	23.02	25.11	49.99	63.97	61.77	42.97	41.38	36.44	27.63	28.21	22.75	19.95	19.69	18.18	10.17	43.88	94.59	46.29	7.63	3.84	9.61
	$\phi_{h,1,21,0}$	35.19	31.57	23.84	23.38	23.04	45.30	77.22	69.11	67.79	67.09	63.11	59.66	43.68	42.45	41.45	38.86	35.14	25.28	26.83	51.94	92.74	48.93	11.74	16.59
	$\phi_{h,1,22,0}$	43.63	38.34	39.88	45.70	47.89	50.66	70.33	61.18	68.10	60.56	63.11	64.87	52.10	48.25	47.32	47.90	42.08	27.31	25.42	28.63	75.75	99.17	60.31	32.36
	$\phi_{h,1,23,0}$	30.38	22.55	18.56	18.73	22.85	17.96	25.37	30.99	41.82	50.92	62.93	70.34	65.37	61.04	57.70	56.01	51.60	46.40	38.14	37.16	32.31	63.60	95.44	68.07
	$\phi_{h,1,24,0}$	100	100	100	100	100	100	99.99	96.41	94.71	93.01	91.30	90.15	92.68	93.25	95.27	95.59	91.48	90.29	87.18	77.23	77.69	81.20	90.89	100
Day $(d-2)$	$\phi_{h,2,1,0}$	15.84	1.79	4.21	5.25	5.34	3.34	3.83	5.68	6.57	8.00	10.54	10.66	8.02	11.72	11.28	11.46	14.86	11.63	9.81	6.47	7.57	17.03	12.15	32.15
	$\phi_{h,2,2,0}$	11.33	11.67	7.23	5.03	4.41	6.66	12.34	6.97	4.28	5.55	4.67	5.33	8.32	8.02	7.12	5.63	4.00	6.00	5.11	3.81	3.23	3.82	2.50	10.75
	$\phi_{h,2,3,0}$	6.16	19.18	16.01	5.20	3.99	12.08	14.63	12.38	13.78	9.46	5.96	5.47	6.82	7.90	7.75	9.05	9.76	8.52	7.94	4.85	5.64	3.63	1.80	5.23
	$\phi_{h,2,4,0}$	7.46	7.07	17.57	28.57	20.01	20.24	15.02	14.12	10.38	4.21	4.35	2.68	2.03	7.60	9.97	8.58	5.64	5.61	5.57	2.74	2.69	2.10	0.26	1.05
	$\phi_{h,2,5,0}$	28.03	22.72	22.68	31.32	44.40	26.97	23.42	20.64	17.51	13.66	7.71	3.55	6.29	5.84	8.70	8.59	6.37	5.43	6.28	1.62	0.25	2.31	4.53	6.02
	$\phi_{h,2,6,0}$	5.56	12.60	6.95	7.92	8.61	17.33	19.61	14.77	8.82	7.02	8.17	8.44	9.15	8.67	5.67	5.31	5.11	4.59	6.25	5.51	6.62	4.47	3.62	2.76
	$\phi_{h,2,7,0}$	7.69	7.04	6.93	9.31	7.69	5.55	13.85	10.65	5.23	1.87	2.63	2.86	6.14	7.68	5.06	3.25	3.08	0.70	0.50	2.54	0.89	0.49	1.06	3.11
	$\phi_{h,2,8,0}$	3.06	4.69	9.56	8.40	10.46	14.53	7.63	6.42	3.82	3.07	3.20	6.65	11.17	10.39	11.62	12.43	12.32	10.38	4.77	4.20	2.95	5.24	3.71	2.50
	$\phi_{h,2,9,0}$	4.38	4.91	6.96	7.16	4.28	6.49	0.88	0.83	2.22	0.50	0.13	0.22	0.25	2.50	5.54	9.77	16.26	18.22	13.66	14.32	6.20	3.02	6.17	8.61
	$\phi_{h,2,10,0}$	0.58	3.38	9.78	12.23	8.61	8.68	2.64	4.91	6.27	8.20	1.41	0.90	0.71	1.51	1.19	3.80	6.17	8.54	5.95	4.83	2.51	1.85	0.35	0.29
	$\phi_{h,2,11,0}$	4.12	5.40	6.54	8.88	5.96	7.08	0.78	2.43	4.39	8.82	7.44	2.22	0.91	0.92	0.83	2.70	4.55	6.91	10.88	9.55	4.27	0.87	1.10	1.12
	$\phi_{h,2,12,0}$	2.87	7.99	10.28	16.54	15.03	8.20	2.49	3.39	2.09	5.72	10.04	4.87	0.77	0.07	0.14	0.03	0.08	1.01	2.95	2.84	4.55	1.37	2.40	2.96
	$\phi_{h,2,13,0}$	1.60	2.15	7.18	9.78	9.10	8.91	9.30	4.47	2.52	3.00	9.57	16.71	20.59	10.52	8.47	5.60	2.31	4.66	10.47	7.13	2.42	0.82	4.37	2.99
	$\phi_{h,2,14,0}$	0.34	3.70	4.58	5.43	7.52	6.51	2.43	2.35	1.31	1.12	2.02	3.82	5.66	5.38	3.44	0.63	0.21	3.03	3.84	5.05	3.62	0.74	0.01	0.40
	$\phi_{h,2,15,0}$	0.53	2.00	7.82	8.78	11.00	8.52	15.17	12.04	5.29	1.82	2.79	8.16	9.21	7.86	5.62	0.28	0.42	6.18	2.34	6.29	1.78	2.78	0.22	2.90
	$\phi_{h,2,16,0}$	2.25	3.88	5.04	6.00	7.62	7.56	1.89	4.49	2.91	2.73	1.85	4.04	4.37	5.83	5.29	8.06	5.37	12.93	12.28	6.63	1.72	3.06	2.85	12.53
	$\phi_{h,2,17,0}$	1.87	2.68	8.77	10.66	15.49	9.29	1.75	4.29	7.67	8.33	1.10	1.99	6.61	8.02	14.35	19.60	22.91	10.93	5.91	1.53	0.50	0.47	0.96	3.47
	$\phi_{h,2,18,0}$	0.45	5.17	7.79	6.99	7.79	6.17	6.30	6.01	1.53	1.50	2.35	4.88	14.11	16.96	23.02	35.14	55.58	71.47	19.41	2.91	0.60	1.75	3.62	6.15
	$\phi_{h,2,19,0}$	1.13	0.78	1.21	0.59	0.90	2.40	0.99	2.20	1.07	0.86	1.85	8.21	9.90	11.38	11.78	15.90	20.69	22.86	65.00	7.55	10.46	2.90	3.92	4.87
	$\phi_{h,2,20,0}$	8.56	3.10	4.47	4.71	6.34	2.30	8.83	8.58	4.52	3.57	3.77	9.78	13.00	14.00	13.53	15.40	13.24	13.86	15.47	78.76	18.60	12.22	15.66	16.72
	$\phi_{h,2,21,0}$	10.20	15.79	20.62	28.96	26.19	13.22	9.92	18.27	3.90	9.20	9.18	7.61	8.50	15.20	15.75	13.42	10.50	9.22	8.66	20.05	70.64	18.09	11.22	8.16
	$\phi_{h,2,22,0}$	17.33	31.56	25.33	22.22	18.10	15.44	7.23	8.50	1.41	0.87	2.39	6.00	2.21	1.54	5.28	6.41	5.99	3.83	1.45	6.88	6.76	57.21	24.05	5.87
	$\phi_{h,2,23,0}$	21.07	25.48	36.76	34.48	41.17	42.37	25.07	18.53	14.87	11.26	14.30	13.81	9.53	9.50	7.35	7.67	12.92	6.47	5.57	6.29	9.65	13.14	49.49	30.34
	$\phi_{h,2,24,0}$	14.67	14.58	24.65	33.56	34.54	25.40	16.97	16.40	12.55	10.68	10.74	11.94	22.76	19.63	15.06	14.10	9.93	2.97	7.17	12.21	14.60	27.42	38.10	54.77
Day $(d-3)$	$\phi_{h,3,1,0}$	6.76	4.68	5.62	8.37	9.62	6.95	12.04	4.02	5.48	5.87	3.20	4.20	4.75	6.05	5.69	7.44	6.69	3.50	5.22	4.71	4.83	6.12	6.56	21.20
	$\phi_{h,3,2,0}$	6.71	6.10	4.81	1.07	0.17	3.75	4.57	9.02	8.90	6.80	8.74	9.71	8.63	12.30	9.25	10.05	11.82	8.93	9.36	2.98	5.10	8.73	10.69	16.67
	$\phi_{h,3,3,0}$	9.07	16.58	10.43	3.99	1.45	2.82	2.76	2.82	2.61	1.22	0.74	2.87	3.20	2.54	2.06	1.33	2.04	0.61	0.79	0.90	1.29	1.12	4.29	1.71
	$\phi_{h,3,4,0}$	11.31	16.38	24.62	25.34	29.17	24.38	9.08	7.18	1.13	3.04	2.11	2.52	4.20	4.14	5.01	2.93	5.00	2.91	2.68	0.34	2.51	0.53	1.22	1.86
	$\phi_{h,3,5,0}$	7.51	5.12	5.18	11.50	13.86	10.25	4.71	4.42	2.25	3.15	3.46	6.39	6.50	2.19	4.91	4.63	6.75	5.63	6.11	3.54	1.71	0.69	0.52	1.79
	$\phi_{h,3,6,0}$	13.44	5.62	5.04	10.06	11.01	24.92	7.88	3.92	5.14	5.53	3.90	5.35	4.41	3.86	3.85	5.16	7.73	10.25	6.99	3.58	3.67	4.78	3.50	2.63
	$\phi_{h,3,7,0}$	14.88	15.06	22.54	21.76	17.35	15.99	24.22	20.67	17.07	14.44	11.17	9.17	3.54	3.58	5.84	4.86	4.48	10.15	9.30	16.67	4.84	2.52	0.84	1.69
	$\phi_{h,3,8,0}$	2.08	5.13	6.03	8.81	3.08	1.13	4.88	9.29	3.95	2.60	1.28	0.58	0.11	0.18	2.14	2.79	3.34	1.53	2.32	2.19	2.29	1.57	3.82	1.81
	$\phi_{h,3,9,0}$	2.95	3.12	1.51	5.82	4.95	2.60	1.45	8.35	11.09	5.59	2.15	1.59	0.71	0.49	1.80	3.25	5.84	8.81	7.98	7.24	6.00	5.61	4.56	4.46
	$\phi_{h,3,10,0}$	4.74	7.72	2.39	2.12	0.76	0.61	0.82	5.03	9.25	8.54	5.29	1.84	0.76	0.38	2.64	3.20	2.93	4.66	3.88	3.67	5.40	3.38	3.78	7.51
	$\phi_{h,3,11,0}$	2.71	0.50	1.67	2.93	3.18	3.77	7.27	12.10	4.69	6.89	6.04	2.51	0.08	2.90	3.18	1.04	0.91	2.49	1.58	1.63	0.49	0.31	0.49	1.09
	$\phi_{h,3,12,0}$	0.95	2.48	2.33	2.80	3.99	7.35	2.23	0.57	1.34	3.40	6.99	12.17	7.93	3.26	2.52	3.32	2.12	1.64	3.67	3.69	1.50	0.61	0.92	3.07
	$\phi_{h,3,13,0}$	1.51	0.77	1.83	3.64	4.05	2.26	2.06	1.21	1.35	5.31	8.46	17.77	25.33	16.77	8.93	6.91	5.25	0.92	0.06	2.53	1.20	0.49	2.56	4.59
	$\phi_{h,3,14,0}$	2.09	1.48	2.70	4.38	6.91	6.25	5.37	3.13	3.46	0.21	0.31	4.82	7.43	6.88	5.60	3.29	2.32	2.27	0.58	1.29	2.96	0.93	2.35	5.52
	$\phi_{h,3,15,0}$	0.18	1.83	1.13	2.36	3.11	3.55	4.05	3.76	5.32	0.71	0.34	0.13	0.29	4.58	9.83	12.53	5.95	6.97	8.04	3.82	2.68	2.76	3.18	6.47
	$\phi_{h,3,16,0}$	3.33	3.45	5.66	7.45	12.35	5.57	2.80	2.70	3.26	1.92	0.62	0.55	0.44	1.27	2.96	7.10	0.25	0.57	4.34	5.17	2.96	5.56	4.21	2.19
	$\phi_{h,3,17,0}$	0.55	0.65	6.17	8.98	11.99	12.71	15.72	12.11	15.58	15.59	7.68	4.72	5.74	9.33	9.37	7.54	18.29	7.02	6.31	7.39	3.89	2.39	2.46	0.59
	$\phi_{h,3,18,0}$	4.20	1.31	3.42	3.02	3.20	1.92	0.53	1.33	0.87	2.22	8.35	4.44	9.65	9.77	13.13	16.15	26.09	43.75	11.98	0.84	1.38	4.57	3.18	1.88
	$\phi_{h,3,19,0}$	3.68	3.48	4.53	3.18	3.07	4.96	4.24	0.47	0.07	2.25	5.67	5.29	5.11	2.04	1.43	1.25	3.92	11.59	46.20	7.92	1.84	4.00	3.25	3.54
	$\phi_{h,3,20,0}$	3.02	1.09	0.79	2.69	2.05	3.38	7.04	2.56	1.78	2.44	1.25	0.61	2.79	0.74	1.12	1.42	2.56	1.33	1.87	46.83	11.70	0.65	0.82	1.66
	$\phi_{h,3,21,0}$	5.73	3.04	4.21	7.49	7.74	2.76	18.60	11.10	6.76	2.87	1.35	2.77	3.19	1.88	4.40	2.58	5.53	3.78	2.71	8.09	34.61	6.37	2.49	1.03
	$\phi_{h,3,22,0}$	3.90	8.02	5.68	7.28	9.30	1.82	2.31	4.21	5.82	3.29	0.87	2.37	2.75	3.94	7.44	5.71	8.61	12.19	14.01	2.47	4.59	21.98	3.95	3.08
	$\phi_{h,3,23,0}$	5.57	14.75	16.49	16.00	12.54	8.54	4.50	2.11	3.83	4.15	7.82	4.86	4.80	3.53	3.24	5.44	4.35	4.63	7.63	8.56	4.66	11.53	29.60	12.28
	$\phi_{h,3,24,0}$	2.56	4.32	10.43	13.79	11.89	7.55	4.66	9.26	3.64	3.13	6.52	11.26	11.33	8.73	7.67	6.34	8.65	5.25	3.51	2.12	4.19	9.10	17.41	41.48

Minimize the residual sum of squares (RSS) + a penalty:

$$\hat{\beta} = \underset{\beta_j}{\operatorname{argmin}} \left\{ RSS + \lambda \sum_{j=1}^{n} |\beta_j|^q \right\}$$



Blue areas – constraint regions, e.g., $|\beta_1| + |\beta_2| \leqslant t$

Red ellipses – contours of the LS error function

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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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:
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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,
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

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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.

Energy Economics 57 (2016) 228–235

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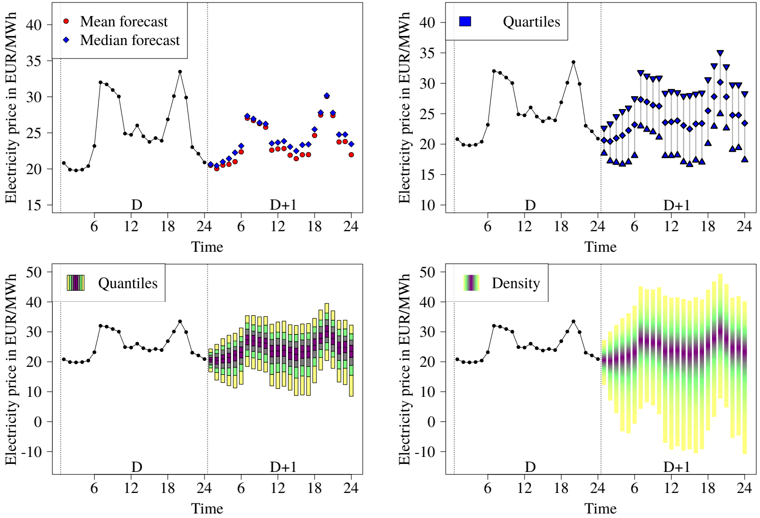
A new hype: Point → probabilistic forecasting
(ca. 7% of EPF papers)



(Very) recent reviews of probabilistic EPF

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Probabilistic mid- and long-term electricity price forecasting

Florian Ziel[a,*], Rick Steinert[b]

[a] *Universität Duisburg-Essen, Berliner Platz 6-8, 45127 Essen, Germany*
[b] *Europa-Universität Viadrina, Große Scharrnstraße 59, 15230 Frankfurt, Oder, Germany*

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Electricity prices

ABSTRACT

The liberalization of electricity markets and the development of renewable energy sources has led to new challenges for decision makers. These challenges are accompanied by an increasing uncertainty about future

Global Energy Forecasting Competition 2014

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

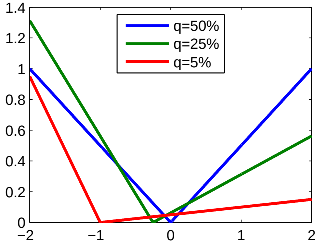
GEFCOM 2014 Load Forecasting | GEFCOM 2014 Price Forecasting | GEFCOM 2014 Wind Forecasting | GEFCOM 2014 Solar Forecasting | IEEE PES Power & Energy Society®

- Incremental data sets released on weekly basis
- Price Track:
  - 287 contestants
  - Submit 99 quantiles (=percentiles) for 24h of the next day
- Evaluation based on the Pinball Score ('discrete' CRPS)

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
- For an aggregate score average:
  - across all hours in the test period
  - across different 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)

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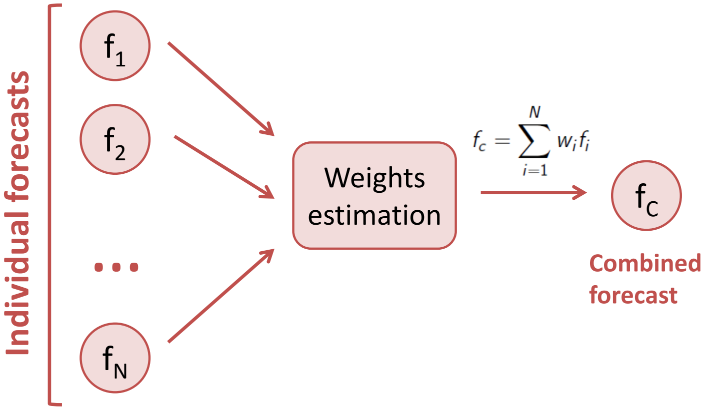
Point forecast averaging: The idea



- 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 !

Quantile Regression Averaging (QRA)

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

CrossMark

ORIGINAL PAPER

OPEN ACCESS

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
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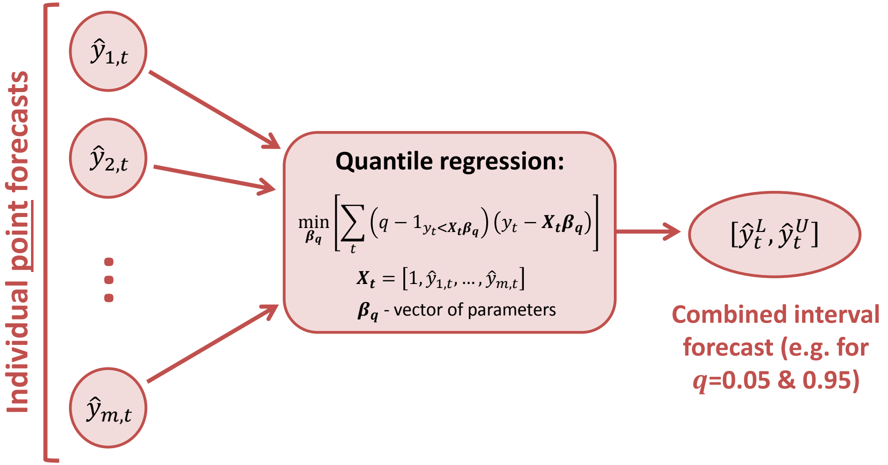
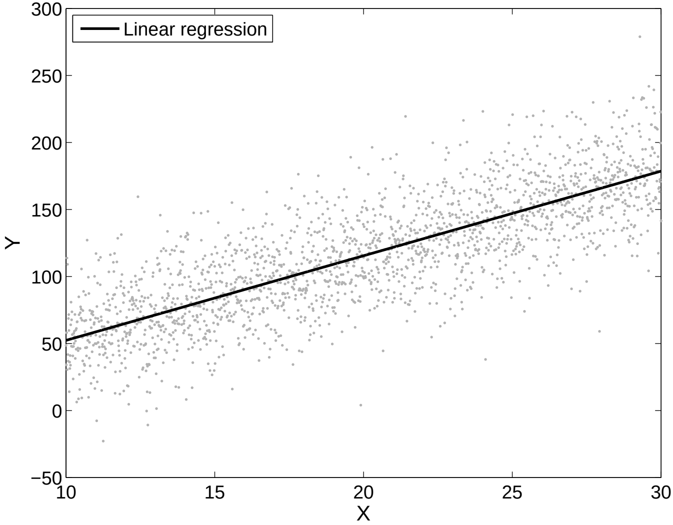
Abstract We examine possible accuracy gains from forecast averaging in the context of interval forecasts of electricity spot prices. First, we test whether constructing empirical prediction intervals (PI) from combined electricity spot price forecasts leads to better forecasts than those obtained from 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

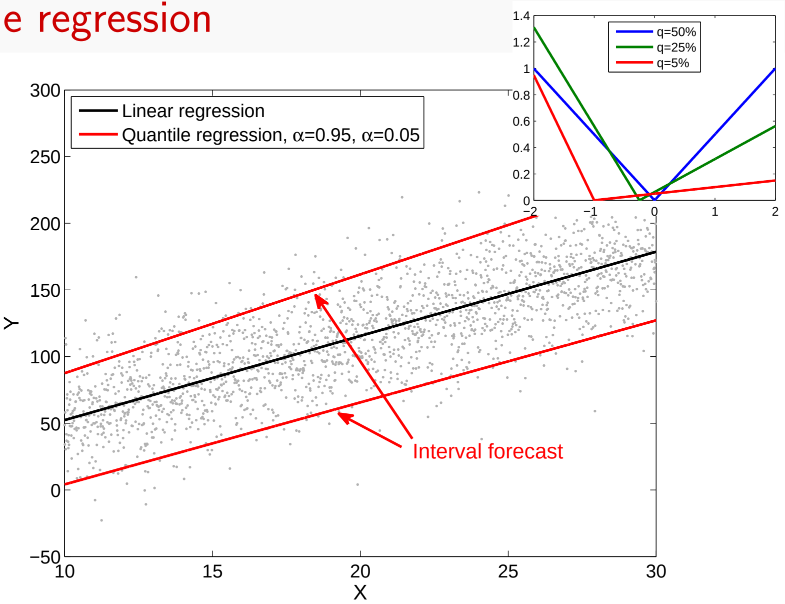
Quantile Regression Averaging: The idea



Quantile regression

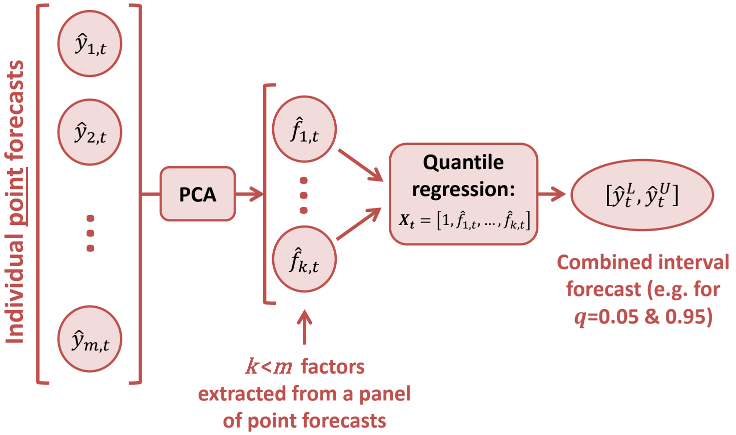


Quantile regression



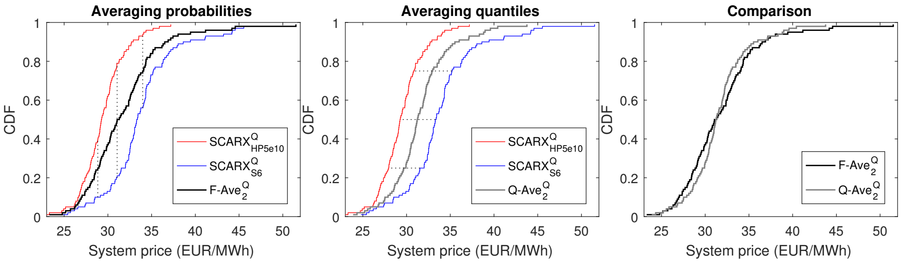
FQRA: When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



Combining probabilistic forecasts is more tricky

- 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 (always 'sharper' = 'more concentrated')



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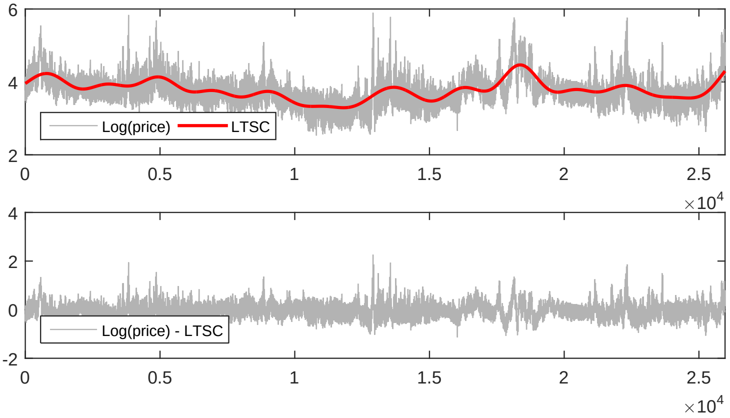
LTSC and short-term price forecasting

- 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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A B S T R A C T

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.

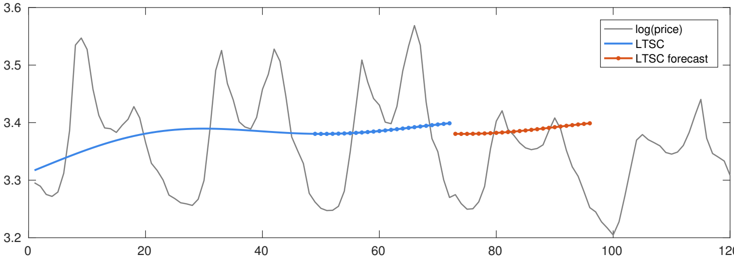
The SCAR modeling framework

(Nowotarski & Weron, 2016, ENEECO; Uniejewski et al., 2018, ENEECO)

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)

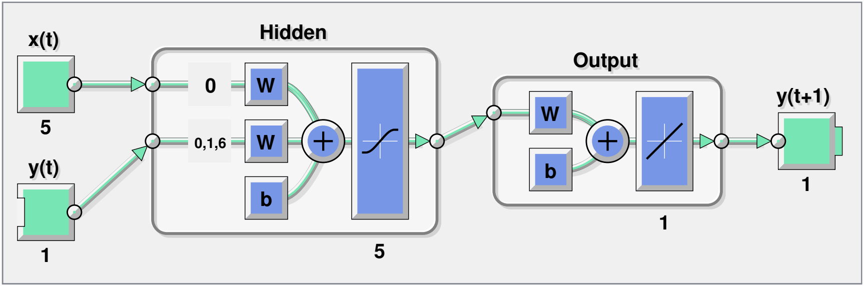
The SCAR modeling framework cont.



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., $\hat{P}_{d+1,h} = \exp\left(\hat{p}_{d+1,h}\right)$

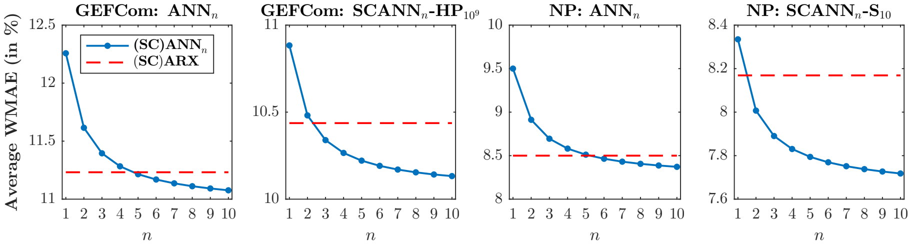
The SCANN modeling framework

(Marcjasz, Uniejewski & Weron, 2018, IJF)



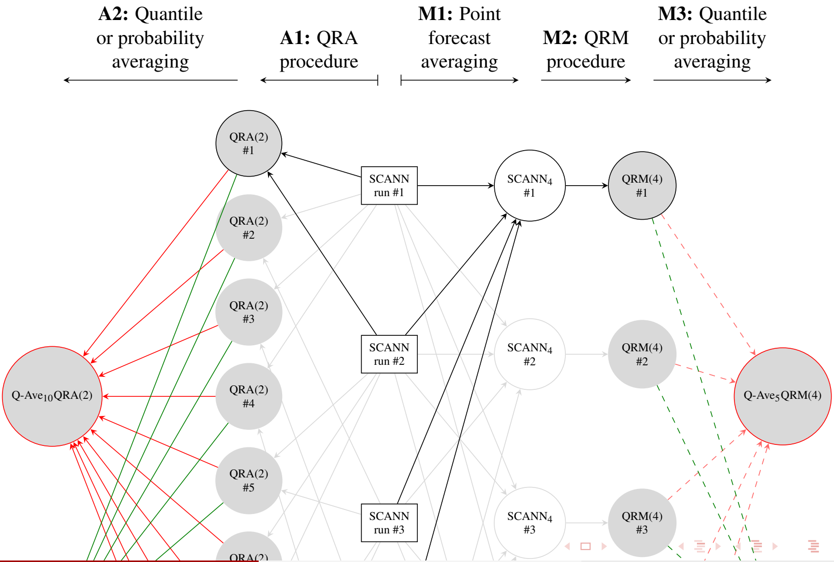
- One hidden layer with 5 neurons and sigmoid activation functions
- NARX inputs identical as in the **ARX** model
- Trained using Matlab's `trainlm` function, utilizing the Levenberg-Marquardt algorithm for supervised learning

Sample gains from using committee machines



- Forecast errors roughly scale as a power-law function of the number of networks in a committee machine
- We should use as large committee machines as we can ...
- ... or use a more efficient training algorithm → FANN library, see Marcjasz, Uniejewski & Weron (2018, WP)

Combining point or probabilistic forecasts?



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

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ARTICLE INFO

Keywords:
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Reliability
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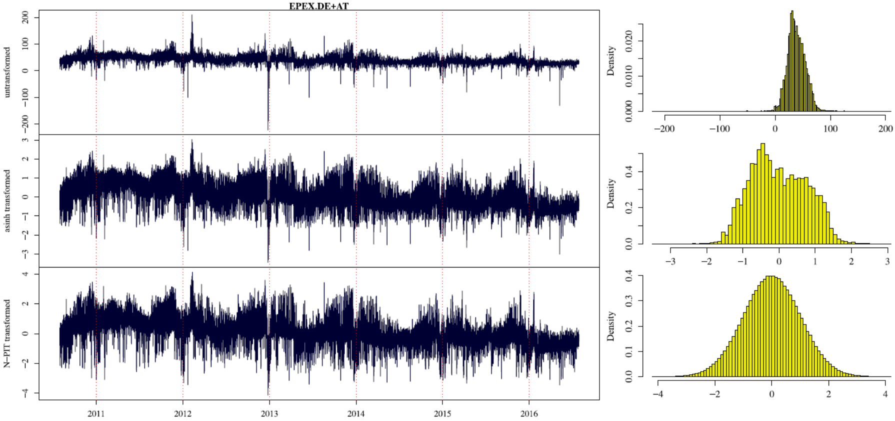
Day-ahead market
Autoregression
Neural network

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.

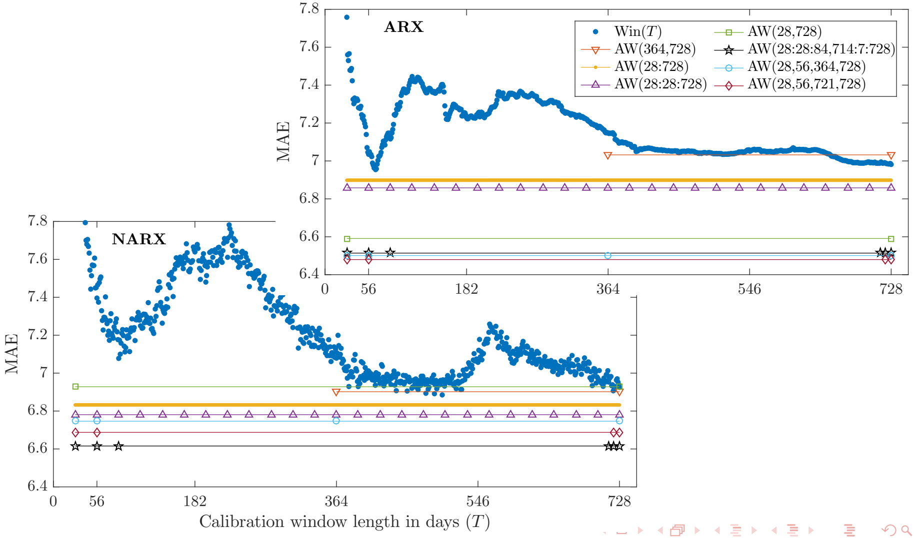
Variance stabilizing transformations (VSTs)

(Uniejewski, Weron & Ziel, 2018, IEEE-TPWRS)



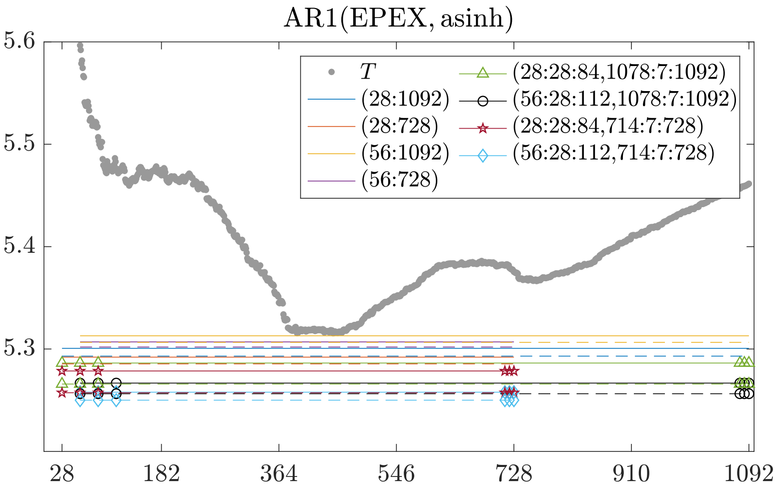
Averaging across calibration windows

(Hubicka, Marcjasz & Weron, 2018, IEEE-TSE)

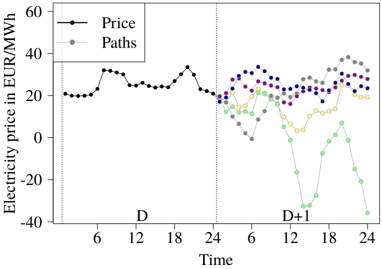


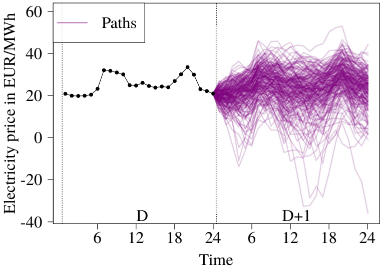
Past performance-weighted averaging

(Marcjasz, Serafin & Weron, 2018, Energies) '—' AW, '- -' WAW



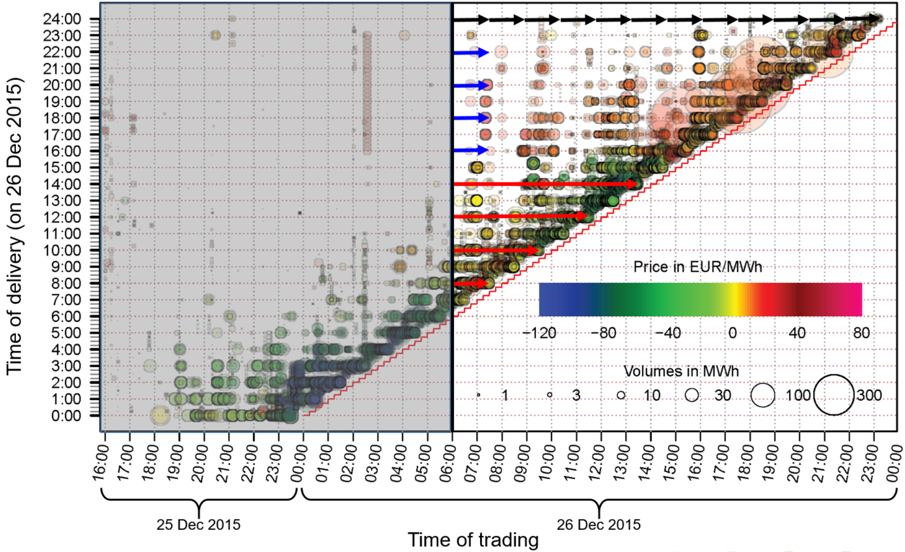
Not yet a hype: Probabilistic → path forecasting





- 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

INREC 2018 hype: Intraday forecasting



Forecast evaluation

- Point forecasts: MAE, RMSE, MAPE $\rightarrow$ Mean Absolute Scaled Error (MASE; Hyndman & Koehler, 2006, IJF)
- Prediction intervals:

Interval forecasts **Statistics**	**Tests**
Reliability/calibration/unbiasedness	
Unconditional coverage [46,77]	Kupiec [77]
Conditional coverage [46] (CC = UC + Independence)	Christoffersen [46] (*Lagged* [81]) *Ljung-Box Christoffersen* [82] *Duration-based tests* [83,84] *Dynamic Quantile (DQ)* [85] *VQR* [86]
Sharpness (and reliability)	
Pinball loss [87,88] Winkler (interval) score [89]	Diebold-Mariano [90,91] *Model confidence set* [92] *Forecast encompassing* [93]

Forecast evaluation cont.

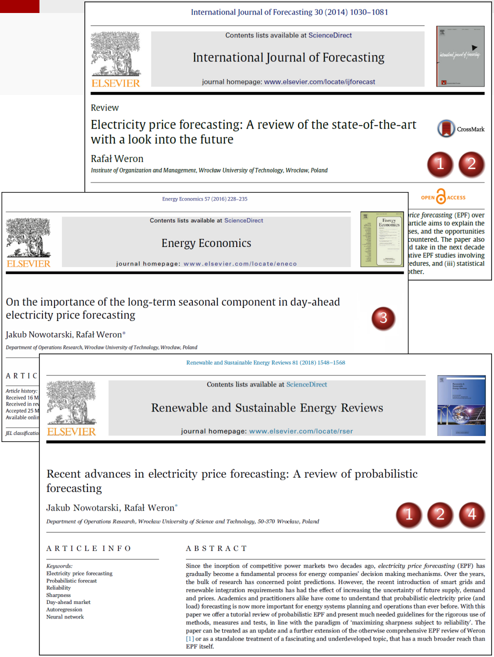
- Distributional forecasts:

Density forecasts Statistics	Tests
Probability Integral Transform (PIT) [15,78] Berkowitz CC statistic [48]	Visual 'tests' [15,17] *Tests for uniformity* [79,80] Berkowitz [48]
Continuous Ranked Probability Score (CRPS) [16,94] *Logarithmic score* [95]	Diebold-Mariano [90,91] *Model confidence set* [92] *Forecast encompassing* [93]

- Path (multivariate) forecasts: Energy score (Gneiting & Raftery, 2007), variogram-based scores (Scheuerer & Hamill, 2015)
- Predictive ability: unconditional (Diebold & Mariano, 1995), conditional (Giacomini & White, 2006)

Agenda

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


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

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Energy Economics 57 (2016) 228–235

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Energy Economics

journal homepage: www.elsevier.com/locate/eneco

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

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3

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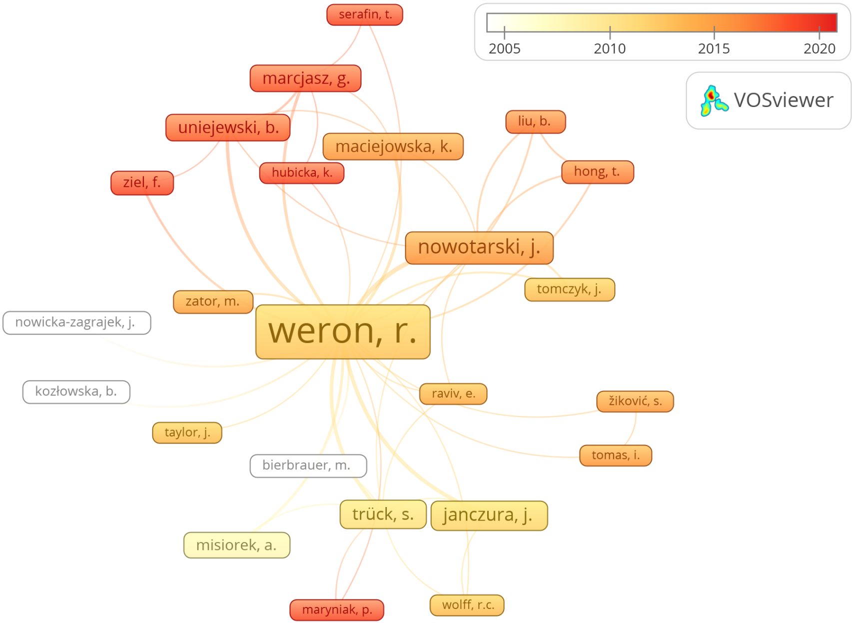
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VOSviewer
serafin, t.
marcjasz, g.
uniejewski, b.
maciejowska, k.
liu, b.
hong, t.
hubicka, k.
ziel, f.
nowotarski, j.
tomczyk, j.
zator, m.
nowicka-zagrajek, j.
weron, r.
kozłowska, b.
raviv, e.
žiković, s.
taylor, j.
tomas, i.
bierbrauer, m.
trück, s.
janczura, j.
misiorek, a.
maryniak, p.
wolff, r.c.