Properties of Energy-Price Forecasts for Scheduling

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- 3 Energy-Price Forecasts
- Energy-Aware Scheduling

5 Conclusion



The Rising Cost of Electricity (Source: Eurostat)

Electricity prices for industrial consumers



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Properties of Energy-Price Forecasts for Scheduling

Scheduling with Variable Energy-Price

- Energy-aware scheduling can save money (but need good energy-price forecasts)
- Recent work focuses on schedules that reduce both power-usage and cost
- Missing big picture: analyse real electricity market, design reliable energy-price-forecasts and use them for energy-aware scheduling (this work)

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Case-Study: Irish Electricity Market

- Auction-based, spot prices computed every half-hour by Market Operator (SEMO)
- System Marginal Price (SMP) = last accepted supply bid (Shadow Price) + additional costs (Uplift Price)
- Min 20% renewable energy target by 2020 (mostly wind-generated)



Irish Electricity Market: Price vs Demand



Statistics of the Irish SMP for 2009 to mid-2011

Year	Min	Median	Mean	Stdev	Max
2009	4.12	38.47	43.53	24.48	580.53
2010	-88.12	46.40	53.85	35.49	766.35
2011	0	54.45	63.18	35.79	649.48



Market Operator (SEMO) Price Forecast

- SEMO publishes a 24h-ahead price forecast
- It is not known how this forecast is computed
- Can we do better?

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SEMO Forecast: Price Linked to Load



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SEMO Actual: Surprises Happen





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Data/Features

- From SEMO and Eirgrid: historical/forecasted price, load, wind generation, expected supply (planned outages, generator bids). Other: weather forecasts, calendar data
- Real data is messy: missing data, units and granularity of data from SEMO and Eirgrid different (SEMO data for every 30mins, in MWh; Eirgrid data for every 15 mins, in MW)
- Use year 2010 for training, first half of 2011 for validation and testing

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Day-Ahead Forecasting Models

- FM1 Predict the SMP using historical and forecasted SMP, shadow price, load and supply.
- FM2 Predict the SMP using the local average-SMP and a learned difference-from-average model. Average price in each time period is quite stable, predict difference from average price.
- Learning algorithm: Support Vector Machines with RBF kernel (software: LIBSVM; learning time: 30 mins on PC)

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Day-Ahead Forecasting Models

Actual Price vs Forecasts on Test Data (first day of testset in 2011)



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Evaluation (Errors and paired t-tests)

Model	MAE		MSE			
SEMO	12.64	10	1086.25			
FM1	11.14	8	821.01			
FM2	11.21	7	781.72			
Baseline Price			SEMO		FM1	FM2
Actual		L	761.8		513.5	486.9
		U	1410.7		1128.4	1076.4
SEMO		L	-		172.4	209.7
		U		-	358.0	399.3

- (FM1, FM2) price-forecasts are stat-significantly better than SEMO (24-28% better MSE)
- For many applications this is enough
- Does this mean we produce better schedules?

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Use Case: Feed Mill Scheduling (Simonis 2006)

- Animal feed production in UK
- Day-by-Day schedule (only need prices 24/36h ahead)
- Energy use depends on recipe
- Optimize schedule-energy-cost with forecast, evaluate with actual price

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Evaluation: Schedule-Cost Stats for 880 Runs

Price	Min	Median	Mean	Max
Actual	4,383,718	5,934,654	6,093,365	9,805,821
SEMO	4,507,136	6,054,220	6,272,768	10,218,804
FM1	4,499,811	6,058,093	6,266,800	10,070,541
FM2	4,570,552	6,094,818	6,283,261	10,059,264

The Good News

- We can produce high-quality energy-aware-schedules (5-10% off optimal solution that has perfect knowledge of future price)
- This is lower than the mark-up that suppliers require for fixed/ToU prices (encouraging for using market prices)

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But: t-test Schedule-Cost Comparison between Forecasts

Price		SEMO	FM1	FM2
Actual	L	-200, 564.9	-193,646.7	-211,094.4
	U	-158,241.3	-153, 222.5	-168,697.4
SEMO	L	-	-1,506.1	-17, 262.6
	U	-	13, 443.1	-3 , 722.9

- Statistically significantly better forecast (wrt MSE) does not lead to better schedule-cost
- More important to predict when price peaks/valleys occur, rather than exact price
- We tested this in the paper

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Peak-Price Classifiers for Scheduling

- Set peak-price threshold at € 60 (the 66th price percentile on validation data)
- All price forecasts (SEMO, FM1, FM2) have 78% accuracy for peak-classification (thus similar scheduling-cost)
- Obtain gradually better peak classifiers by correcting error, and check effect on scheduling-cost
- Better peak classification leads to better schedules. Type of error matters: missing price-peaks, more important than missing price-valleys

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- Electricity price is rising. Energy-aware scheduling can save us money, better for environment
- Proposed day-ahead price-forecasts for irish electricity market (24% better MSE than Market Operator)
- Better forecast wrt MSE does not mean better schedule-cost
- Peak-price classification more important

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Thank You/Questions?

Data Online:

4c.ucc.ie/~gifrim/Irish-electricity-market/

