



The effect of market integration when forecasting day-ahead electricity prices

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- 1 PhD Outline
- 2 Day-ahead price forecasting
- 3 Market Integration
- 4 Future Work

- 1 PhD Outline
 - ▶ Energy Markets and RES
 - ▶ PhD Aim
- 2 Day-ahead price forecasting
- 3 Market Integration
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Primary Problems

1. Bad predictability.
2. Intermittent generation.
3. Low inertia.

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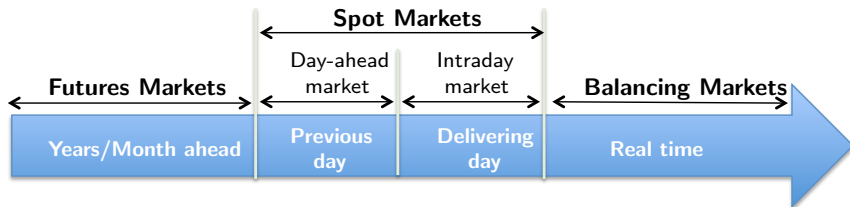
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Result

How much *renewable energy sources (RES)* can be put into the electrical grid without compromising the operational safety?

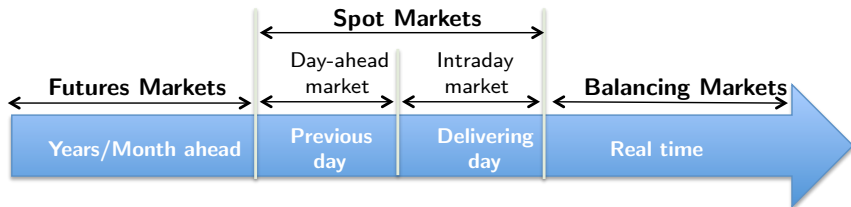
Markets for renewable energy sources

- ▶ Energy price is settled in a continuous supply/demand trading.



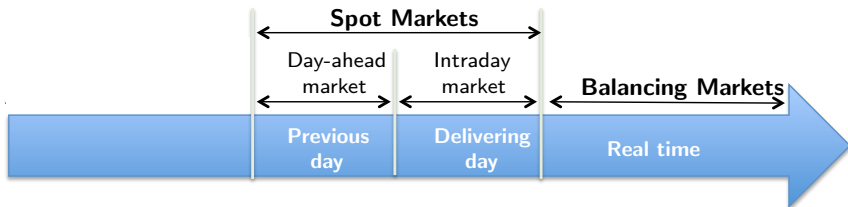
Markets for renewable energy sources

- ▶ Energy price is settled in a continuous supply/demand trading.
- ▶ Production of renewable energy depends on weather conditions
⇒ Energy production from RES is uncertain.



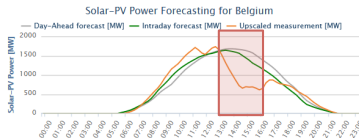
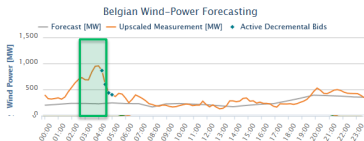
Markets for renewable energy sources

- ▶ Energy price is settled in a continuous supply/demand trading.
- ▶ Production of renewable energy depends on weather conditions
⇒ Energy production from RES is uncertain.
- ▶ Most of the produced renewable energy can only be traded on the spot and real time markets.



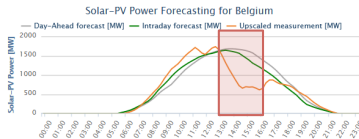
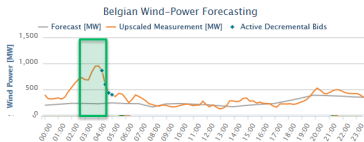
Issues of RES in Energy Markets

1. Due to weather conditions, energy production from RES is uncertain.
2. Production uncertainty leads to volatile markets and imbalanced grids.
3. Volatility and imbalances make RES less attractive and profitable.
4. Market share of RES is limited.



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Support and stabilize the energy market to:

1. Allow more integration of RES.
2. Mitigate some of the negative effects of RES.

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Facts

1. Low prices occur when generation is larger than consumption and high prices appear in the opposite situation.
2. Some of the problems of RES are related to these mismatches between generation and consumption.
3. Market agents have economic incentives to buy when prices are low, i.e. increasing the consumption, and reduce the consumption when prices are high.

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Methodology

Development of control algorithms that can influence and stabilize the price of the energy market.

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Second step: Multi-market Controller

Model a multi-market controller that takes into account prices and uncertainty in all markets and selects economically optimal actions for various energy systems.

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Available Forecasters

- ▶ Forecasting day-ahead electricity prices is an old research topic dating to the end of the 90's.
- ▶ Vast collection of methods has been proposed.

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State of the art models

- ▶ Discrepancy in the community regarding which are the best models.
- ▶ Performance depends on period and market under study.

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Research on three different areas.

1. Reach consensus on the accuracy of forecasters by building a complete and large benchmark.
2. Develop a modeling framework based on deep learning. The framework obtains state-of-the-art results.
3. Investigate the effect of market integration in forecasting accuracy.

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 - ▶ Definition
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Facts

1. In the last decade, The EU has passed laws to pursue a single and integrated electricity market [MB08, JP05].
2. Evidence suggests that, in recent years, the level of integration across markets has been increasing [BG10].

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Scientific Gaps

1. Nonexistent analysis to study the influence of market integration in the accuracy of predicting prices.
2. Nonexistent general models to use market integration information to improve predictive accuracy.

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Develop a feature selection algorithm based on Bayesian Optimization [BBBK11] and functional ANOVA [HHLB14] that:

1. Selects the optimal features as the x_i, z_i with relevant contributions.

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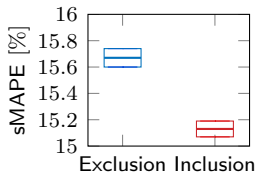
1. Selects the optimal features as the x_i, z_i with relevant contributions.
2. Analyzes the contribution of each x_i, z_i to the accuracy of $F(\mathbf{x}, \mathbf{z})$.

Description

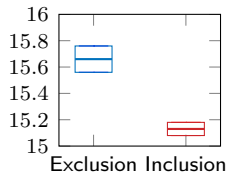
- ▶ Influence of features in the French market when forecasting day-ahead prices in the Belgian market.
- ▶ Input features:
 1. Past prices in Belgium and France.
 2. Day-ahead forecast of grid load in Belgium and France.
 3. Day-ahead forecast of available generation in Belgium and France.
 4. Holiday calendar in both countries.
- ▶ Four years of data (2010-2014) for estimating the model F .
- ▶ An extra year (2015) as validation set to perform the feature selection.

Table: Importance of input features

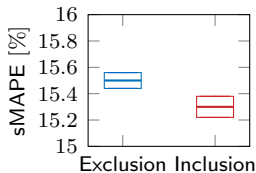
	Contribution to \mathbb{V}_a
Load France	28.4%
Prices France	25.7%
Generation France	4.78%
Load Belgium	1.0%



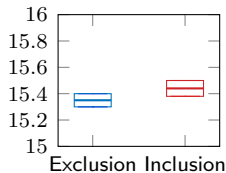
(a) French load.



(b) French prices.



(c) French generation.



(d) Belgian load.

Figure: Accuracy of F when including/excluding features

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Questions to be answered

1. The previous analysis considered a forecaster F . What F is exactly?
2. The analysis provided a qualitative assessment. How large is really the improvement? Is there statistical evidence to claim that market integration improves the predictive accuracy?
3. So far, market integration modeled with input features. Can the accuracy be improved by modeling other market integration effects?

Based on the results from the research in deep learning and benchmarking, the best model is a standard neural network with two hidden layers.

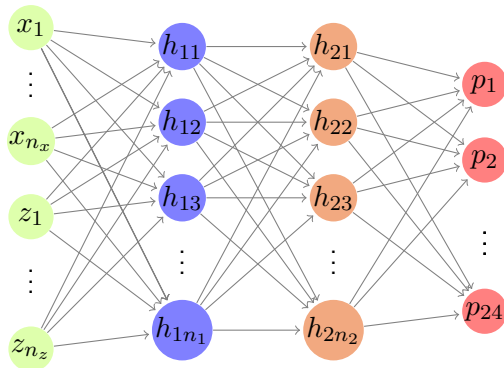


Figure: Deep neural network to forecast day-ahead prices.

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Problem definition

Given:

- ▶ A time series vector $\mathbf{Y} = [y_1, \dots, y_N]^\top$ to be forecasted.
- ▶ Two prediction models M_1 and M_2 .
- ▶ Forecasting errors $\boldsymbol{\varepsilon}^{M_1} = [\varepsilon_1^{M_1}, \dots, \varepsilon_N^{M_1}]^\top$, $\boldsymbol{\varepsilon}^{M_2} = [\varepsilon_1^{M_2}, \dots, \varepsilon_N^{M_2}]^\top$.

Is the accuracy of M_1 statistically significant better than the one of M_2 ?

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Diebold-Mariano (DM) Test for Hypothesis Testing [DM95]

1. Null hypothesis H_0 : the accuracy of M_1 is equal or worse than the accuracy of M_2 .
2. Alternative hypothesis H_1 : the accuracy of M_1 is better:

Description

- ▶ Deep neural network as the forecaster F .
- ▶ Five years of data (2010-2015) for training F .
- ▶ An extra year (2016) as test set to perform the statistical testing.
- ▶ DM test performed for every predictive horizon, i.e. hour of the day, at 5% significance level, i.e. with a p-value of 0.05.

Description

DM test to compare accuracy between:

- ▶ Forecaster F_{MI} with market integration.
- ▶ Model F_{no} without market integration.

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Table: sMAPE Comparison

	sMAPE
F_{no}	15.7%
F_{MI}	13.2%

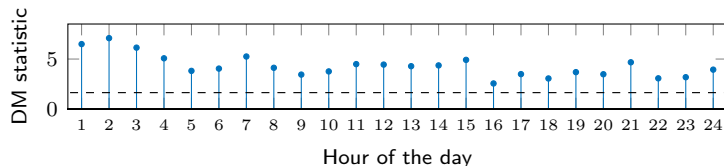


Figure: DM test comparing F_{MI} and F_{no} . Values above dashed line reject H_0 at a 5% significance level and are cases where the accuracy of F_{MI} is statistically significantly better.

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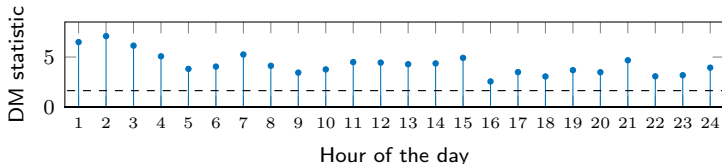


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Predictive accuracy of a forecaster with market integration is statistically significantly better than the accuracy of a forecaster without it.

Questions to be answered

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Definition

- ▶ Forecaster that predicts prices in two connected markets instead of a single one.

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- ▶ Prices in both markets are interrelated and have similar dynamics.
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Foundations

- ▶ Deep Neural Networks, which learn multiple similar tasks, can learn relations that can, to some extent, generalize across tasks [YCBL14].
- ▶ By forcing DNNs to learn auxiliary related tasks, the performance and learning speed can be improved [JMC⁺16, NH16, LZW⁺16].

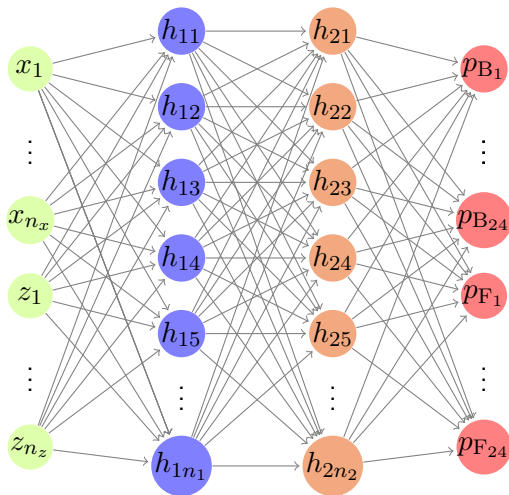


Figure: Deep Neural Network to simultaneously forecast day-ahead prices in the Belgian and French markets.

Forecaster Evaluation

Comparison between predictive accuracy of:

- ▶ Single-market forecaster F_{Single} .
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F_{Dual}	12.5%

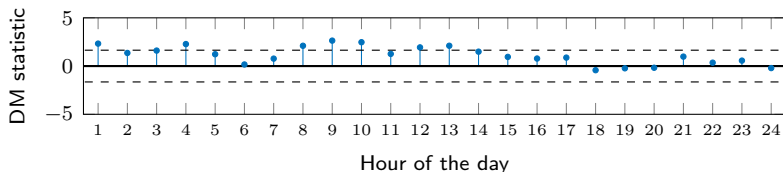


Figure: DM test results when comparing F_{Single} and F_{Dual} . Values above the top dashed line represent cases where, with a 95 % confidence level, F_{Dual} is significantly better. Values below the lower dashed line accept at a 95 % confidence level that F_{Dual} is significantly worse.

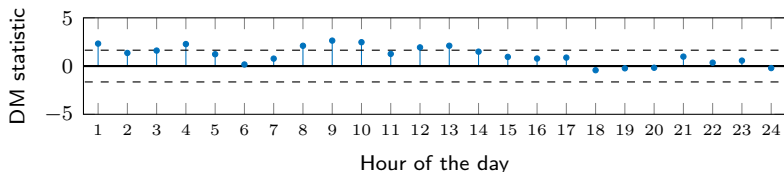


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Observations

1. The H_0 in the regular test is rejected 8 of 24 times.
 $\implies F_{\text{Dual}}$ statistically significantly better in 1/3 of the hours.
2. The \hat{H}_0 of the complementary test is never rejected. $\implies F_{\text{Dual}}$ is never statistically significantly worse.

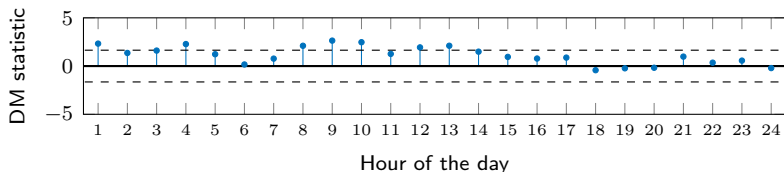


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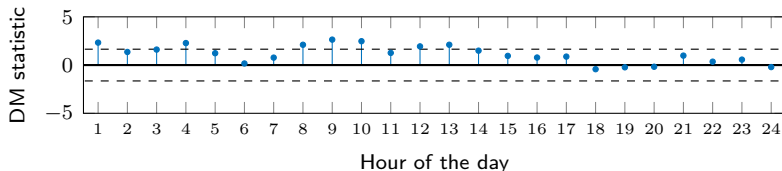


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Result

Predictive accuracy of the dual market forecaster is statistically significantly better than the accuracy of a single-market forecaster.

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1. Implement forecaster for obtaining relations between day-ahead and real time market.
2. Develop a multi-market controller for the Ecovat system, a large water storage system.
3. Extend the forecasting to other markets.
4. Generalize the multi-market controller to more systems.

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Thank you. Any Questions?






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-  James Bergstra, Rémi Bardenet, Yoshua Bengio, and Balázs Kégl, *Algorithms for hyper-parameter optimization*, Advances in Neural Information Processing Systems, 2011, <http://papers.nips.cc/paper/4443-algorithms-for-hyper-parameter-optimization>, pp. 2546–2554.
-  Derek W. Bunn and Angelica Gianfreda, *Integration and shock transmissions across European electricity forward markets*, Energy Economics **32** (2010), no. 2, 278–291.
-  Francis X. Diebold and Roberto S. Mariano, *Comparing predictive accuracy*, Journal of Business & Economic Statistics **13** (1995), no. 3, 253–263.

-  Frank Hutter, Holger Hoos, and Kevin Leyton-Brown, *An efficient approach for assessing hyperparameter importance*, Proceedings of the 31st International Conference on International Conference on Machine Learning, ICML'14, vol. 32, 2014, <http://proceedings.mlr.press/v32/hutter14.pdf>, pp. 754–762.
-  Max Jaderberg, Volodymyr Mnih, Wojciech Marian Czarnecki, Tom Schaul, Joel Z. Leibo, David Silver, and Koray Kavukcuoglu, *Reinforcement learning with unsupervised auxiliary tasks*, arXiv eprint, 2016.
-  Tooraj Jamasb and Michael Pollitt, *Electricity market reform in the European union: review of progress toward liberalization & integration*, The Energy Journal **26** (2005), no. Special Issue, 11–41.

-  Xi Li, Liming Zhao, Lina Wei, Ming-Hsuan Yang, Fei Wu, Yueting Zhuang, Haibin Ling, and Jingdong Wang, *DeepSaliency: Multi-Task Deep Neural Network model for salient object detection*, IEEE Transactions on Image Processing **25** (2016), no. 8, 3919–3930.
-  Leonardo Meeus and Ronnie Belmans, *Electricity market integration in Europe*, Proceedings of the 16th Power Systems Computation Conference, 2008.
-  H. Nam and B. Han, *Learning multi-domain convolutional neural networks for visual tracking*, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 4293–4302.



Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson, *How transferable are features in deep neural networks?*, Advances in Neural Information Processing Systems 27 (Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, eds.), Curran Associates, Inc., 2014, <https://papers.nips.cc/paper/5347-how-transferable-are-features-in-deep-neural-networks>, pp. 3320–3328.