Analysis of a structural model for day-ahead electricity price forecasting

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Abstract

This paper aims at analysing an electricity price forecasting model in order to give more insights into structural model for long-term prospective analyses. More precisely, day-ahead markets are concerned and French electricity market is used for application. Local and timescales decomposition models are introduced in the structural model under study. Further analyses of robustness are also conducted.

Keywords — Electricity price forecasting, Day-ahead markets, Structural model, Timescale decomposition

1 Introduction

1.1 Context

With the liberalisation of electricity markets, forecasting electricity prices has become a major concern for energy companies in their decision-making [1]. Portfolio managers have a precise look at daily and yearly markets to optimize their bidding strategies and maximize their profit. However, electricity markets have their own particularities and predicting them a complex task. The two main constraints of electricity markets, namely the fact that stocking electricity is not economically feasible and that production must meet consumption at any time [2], lead to a highly volatile price.

On the other hand, electricity energy mixes, very correlated with electricity prices, are changing quickly over the last decade. Countries are introducing more renewable means of production in their energy mix in order to fight against climate change [3]. Considering its direct impact on electricity price, some models have tried to integrate energy mix, but more for the purpose of global foresight rather than precise forecasting.

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1.2 Related work

In his complete paper [4], Weron details the different methods used in electricity forecasting. To date, the best results in terms of precision of forecasts are obtained by purely statistical models using machine learning [5]. They do not include energy mix changes though and cannot be used for prospective analyses. Structural (also called fundamental [4]) models try to fill this gap by imitating market structure. The development of such models has been fostered by newly available power system data such as ENSTO-E [6].

Working on day-ahead markets, a few structural models focus on forecasting demand and consumption to obtain a market clearing price [7]. Among those is a model developed by Mahler and Al. [8] which gathers producers of a same mean of production altogether (nuclear, oil, gas, coal, hydraulic, curtailment) to reproduce market structure. This strong hypothesis needs to be evaluated in order to validate such an approximation, as it goes counterpart to highly precise optimization of energy companies. Moreover, the model works at a unique timescale, making it difficult to understand if it can well forecast global trends and be used for prospective studies.

1.3 Contribution

Even if our study starts from an already designed model [8], this paper is written to be read on its own (basics of the starting model are explained). It introduces time dependencies to analyse performance and limits of the model. Firstly, a modification is proposed based on time dependent regression parameters. Secondly, an analysis of the model performance at different timescales is achieved using detrending (method to decompose timescale). Lastly, a robustness analysis of producers capacities and of consumption is conducted.

2 Method

2.1 Structural model

This part details the starting model used to predict electricity prices which is a simplified version of the one developed by Valentin Mahler and Al [8]. This simplified model does not consider the specific features of hydraulic production (production at highest price), meteorological aspects and simulated training data with supply and demand curves (see [8] for more details). The main difficulty of a structural approach is that an observed price at a fixed time only gives us information about the sell price of one producer (the price is fixed for all producers at the sell price of the last producer called). However, to effectively forecast electricity prices, prices of all producers need to be predicted. An underlying assumption of such a model is that the energy mix is representative enough to learn from associated observed prices.

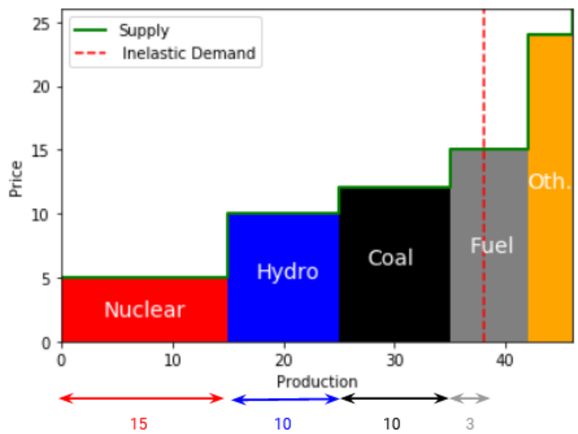


Figure 1: Supposed structure of the market. Producers are gathered by kind of production (nuclear, hydraulic reservoir, coal, fuel, gas, curtailment) and sorted in price ascending order. Each producer length corresponds to its production capacity and width to its production price. Dashed red line: inelastic consumption. Green line: supply (price as a function of production). Colored arrows : production of each producer associated with known consumption

2.1.1 Determination of marginal producers

In day-ahead markets, prices are determined by maximizing social welfare at a given time through supply and demand curve. On a given day each producer makes a bid, composed of an amount of production and a sell price. Once consumption is known (the day after bidding), each producer is attributed a production according to the following rule. Producers with lowest costs are called until the aggregated amount of production balances consumption. The last producer to be called (with the highest price) is said to be *marginal*. The electricity price is the same for all producers and is fixed at the marginal producer sell price. Actually, as no detailed demand curves are accessible, demand is assumed to be inelastic and equals to residual consumption (consumption minus wind and solar power). This structure is represented in figure 1.

Solving a production problem such as explained comes to solving an optimization problem described as follows, with timestamps T and producers M[1]:

$$
\begin{array}{llcll}
\min\limits_{E} & \sum\limits_{t\in T}\sum\limits_{m\in M} \hat{\pi}_{t,m} E_{t,m} & & & \\
\text{s.t.} & E & \leq & \mathbf{P} & \\
 & \sum\limits_{m\in M} E_{t,m} & = & C_t & \forall t \in T \\
 & |E_{t+1,m} - E_{t,m}| & \leq & R_m & \forall t \in T,\ \forall m \in M
\end{array}
\tag{1}
$$

[1]the same notations T and M are used to denote a set and its size

where $E \in \mathbb{R}^{T\times M}$ denotes the production for each timestamp of each producer, $\mathbf{P} \in \mathbb{R}^{T\times M}$ the maximum production capacity for each timestamp of each producer, $C \in \mathbb{R}^{T}$ the consumption for each timestamp and $R \in \mathbb{R}^{M}$ the ramp constraint for each producer. $\hat{\pi}_{t,m}$ denotes the simulated prices at timestamp t for each producer m and its associated matrix is written $\hat{\pi} \in \mathbb{R}^{T\times M}$.

In short, producers parameters (capacity and ramp constraint), consumption and simulated prices are known before solving the optimization problem.

Having determined the production of all producers at each timestamp, a marginal producer for each timestamp can be deduced. Each observed price can then be linked to its marginal producer. All timestamps in which a producer is marginal correspond to the timestamps in which observed prices are the producer sell prices. For each producer, only the timestamps in which it is marginal are kept for calibrating. Timestamps in which a producer m is marginal will be denoted as T_m (T represents all timestamps).

2.1.2 Linear regression

In order to grasp first order variations of prices, observed prices are supposed to linearly depend on drivers. Chosen drivers will be detailed in next section. Regression parameters are calibrated for each producer m using values of drivers and observed prices at timestamps in which m is marginal as described in the following equation.

$$\forall m \in M, \forall t \in T_m, \pi_t^{obs} = \alpha_m^T P_t \tag{2}$$

where $\pi^{obs} \in \mathbb{R}^T$ corresponds to observed prices, $\alpha_m^T \in \mathbb{R}^d$ denotes regression parameters to be calibrated for each producer with d the number of drivers. $P \in \mathbb{R}^{d\times T}$ represents values of drivers at each timestamp and $P_t \in \mathbb{R}^d$ are values of drivers at timestamp t.

Regression parameters are calibrated with a mean square error loss function.

Given regression parameters, prices are simulated for all producers for all timestamps (and not only for timestamps in which a producer is marginal).

$$\forall m \in M, \forall t \in T, \hat{\pi}_{t,m} = \alpha_m^T P_t \tag{3}$$

Having calculated new simulated prices, an optimization problem such as (1) can be solved to get another energy mix, calibrated parameters and simulated prices.

Regression parameters are then trained until a stable RMSE (root mean square error, see later) is obtained. Once regression parameters are satisfying enough, they can be applied to testing data and forecast (or explain) electricity prices.

This model of simulating prices will be called *linear*.

2.1.3 Initialization

Simulated prices are initialized with averaged prices for each producer. Initialization is to be considered carefully since it may impact results a lot, but is not

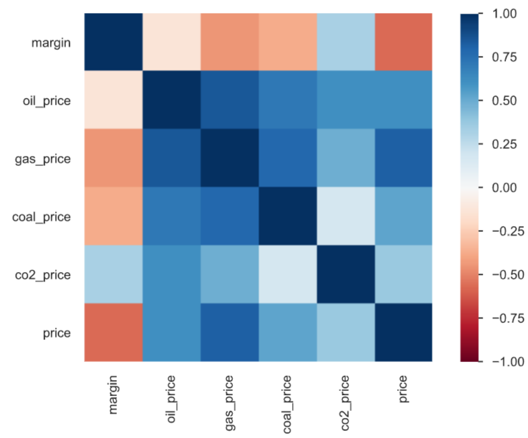


Figure 2: Correlation matrix of selected features

discussed in this paper.

2.2 Selected features

In electricity market, electricity price may be influenced be many drivers. We have chosen to stick to first orders factors which come up through gathering producers of same energy (nuclear, oil, gas, coal, hydropower, curtailment). Among those features are oil price, coal price, gas price and CO_2 price. Another important feature, highly correlated with electricity price, is the production margin, difference of aggregated capacities and consumption (in other words how much can still be produced). Other features concerning unplanned interruptions such as total unplanned unavailable power and unplanned unavailable power per producer have not been taken on for their weak correlations with prices. The final selected features are the following : margin, oil price, coal price, gas price and CO_2 price. The obtained correlation matrix is shown in figure 2.

2.3 Local linear model

Instead of considering all timestamps where a producer is marginal, linear calibration may be improved with fewer but "better" selected timestamps (always marginal for a producer). Regression parameters then depend on time, but are not completely independent *a priori*.

2.3.1 Spatial local model

The first local model relies on two assumptions : there exists within a producer similar cases (features with similar values) ; and similar cases imply similar prices. The latter comes to assume price is continuous of features, a reasonable but debatable assumption (because of possible jumps of price due to market structure). The former is more ambiguous. Even if electricity price is highly volatile, similar situations are prone to occurring thanks to price periodicity. However, because energy mix is not fixed and calibration data vary at each step for each producer, there is no guarantee.

For each timestamp, only k-nearest neighbors (in terms of features) are chosen for calibration.

$$\forall m \in M, \forall t \in T, \forall p \in T_m^k, \pi_p^{obs} = \alpha_m^T(t) P_p \tag{4}$$

where $\alpha_m^T(t) \in \mathbb{R}^{d \times T}$ now depends on time and T_m^k denotes the k-nearest neighbors timestamps of producer m.

Once regression parameters are fixed, simulated prices are deduced from selected features.

$$\forall m \in M, \forall t \in T, \hat{\pi}_{t,m} = \alpha_m^T(t) P_t \tag{5}$$

Choosing k is an important balance : too few neighbors may lead to over-fitting and too many bring back to the first linear model. Moreover, features on which to search for neighbors is another key parameter of the model. Impacts of these two degrees of freedom will be discussed later in this paper.

2.3.2 Time local model

The spatial model supposes similar cases represent a same event and hence too far cases (in terms of features and which may be close temporally) can be overlooked. Yet, electricity price is temporally correlated and two far cases may not have much in common without considering a batch of timestamps of a same context. This second local model proposes to calibrate the model with a sliding window w (among marginal timestamps for a producer).

$$\forall m \in M, \forall t \in T, \forall p \in [t-w, t+w] \cap T_m, \pi_p^{obs} = \alpha_m^T(t) P_p \tag{6}$$

where w is window size and T_m are timestamps at which producer m is marginal.

The key parameter is w and its selection needs to favour sparsity without over-fitting.

2.4 Decomposing timescales

Structural models are mostly used for prospective studies and should therefore be able to grasp global electricity trend. As electricity price is highly periodic, global trend and seasonal variations need to be separated. Three important timescales are brought out : yearly, weekly and daily (see figures 3, 4, 5).

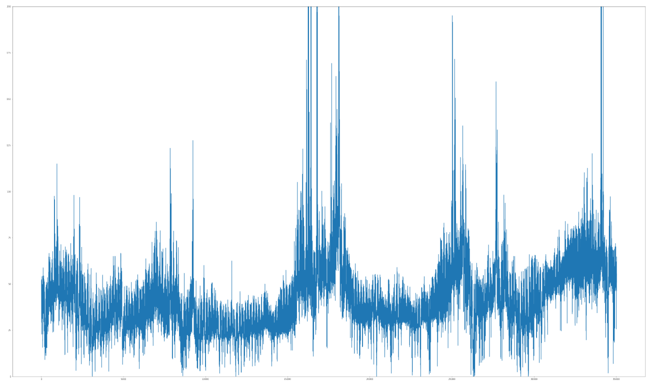


Figure 3: Price as a function of time, 4 years scale

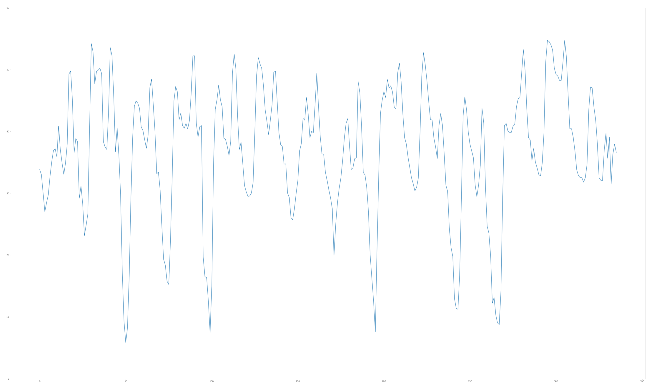


Figure 4: Price as a function of time, 2 weeks scale

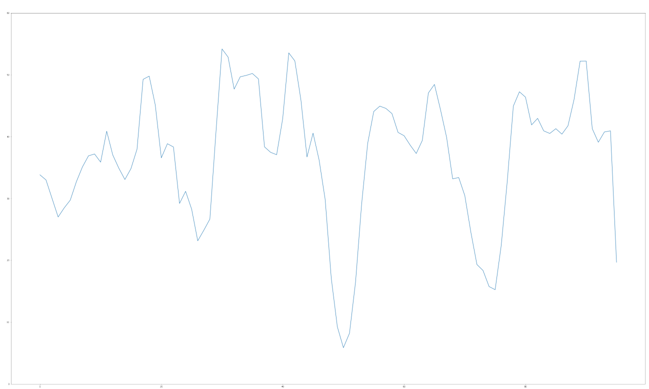
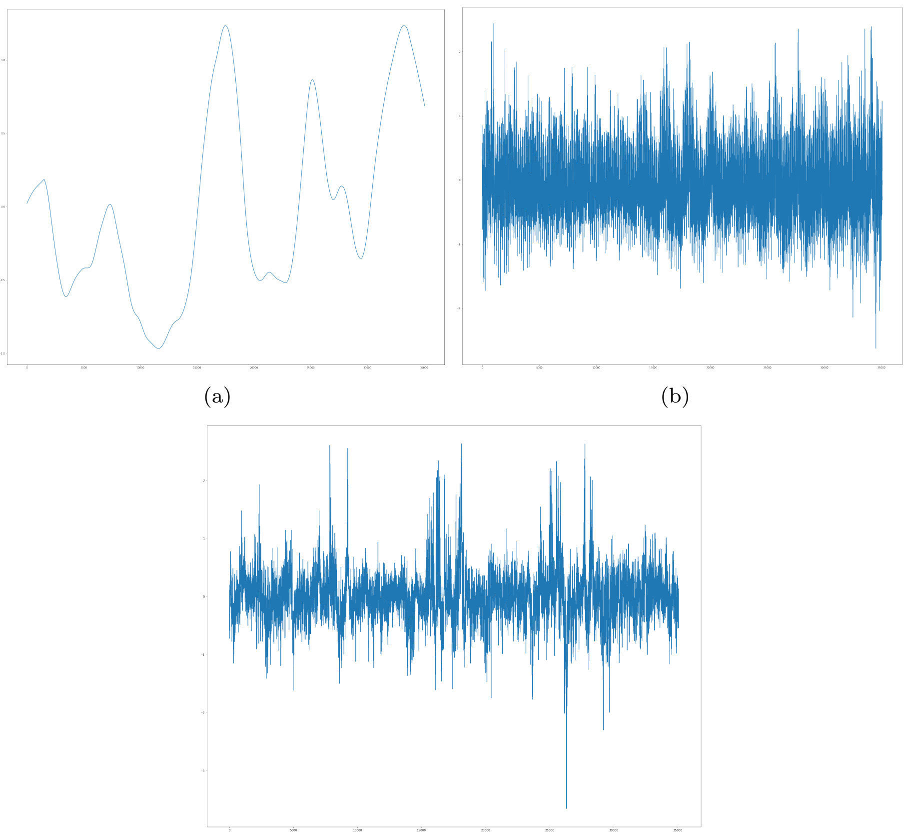


Figure 5: Price as a function of time, 4 days scale

Analysing the linear (and structural) model throughout these three timescales should highlight its performance to forecast global trend. In other words, electricity price is first decomposed in complementary timescales and the linear model is applied to each timescale separately. Simulated prices are obtained by summing results from each model applied to a particular timescale.

2.4.1 Detrending

Detrending is a method used to extract trend and seasonality of a signal. Detrending applied to electricity price gives the following result using python function tsa.seasonal.STL from statsmodels library (see 6) (with input parameters period = 3 months and seasonal = 1 week).



(a) (b) (c)

Figure 6: Price as a function of time (4 years data) (a) Trend (b) Seasonality (c) Residue

In some cases, it may be interesting to keep only residual (input signal differentiated from its trend and seasonality), but in our case trend, seasonality and residual are kept for forecasting. More precisely, the linear model will be applied to both trend and residual, and seasonality will be considered unchanged between train and test.

2.4.2 Extreme values

Electricity price has a high volatility and unexpected spikes can occur. Though those events contain much information, they hugely impact linear regressions with a quadratic cost function and need to be removed. Prices globally follow a Gaussian's distribution (see 7) and prices lower than $m - 3\sigma$ and upper than $m + 3\sigma$ are removed, which approximately represents 300 prices. Appearing gaps are filled with forward fill re-sample.

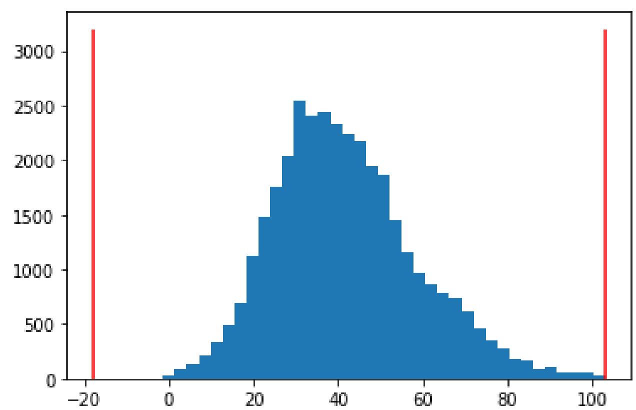


Figure 7: Histogram of prices (extreme values not represented) ; Red vertical lines correspond to $m - 3\sigma$ and $m + 3\sigma$:

2.4.3 Standardisation

Observed prices and features are standardised to be at same scale. This step was not done in the linear and local linear models.

2.5 Robustness

One last point worthy to dwell on is the model sensibility to its presumed input parameters. The model supposes known producers capacities and consumption. Whereas the latter is easily accessible and quite realistic, the former may be more difficult to get precisely. Doing such a robustness test helps to determine how precise those parameters need to be. Starting from the linear model, uncertainties are applied on producers capacities and on consumption. More precisely a uniform distribution between -2% and 2% is applied.

$$\begin{aligned} \mathbf{P}^{disturb} &= \mathbf{P} \times (1 + X_P) \\ C^{disturb} &= C \times (1 + X_C) \end{aligned} \tag{7}$$

where $X_P \in \mathbb{R}^{m \times T}$ and $X_C \in \mathbb{R}^T$ follow a uniform distribution respectively between $[-2\%, 2\%]^{m \times T}$ and $[-2\%, 2\%]^T$ (see figure 8).

Replacing $\mathbf{P}$ and C respectively by $\mathbf{P}^{disturb}$ and $C^{disturb}$, the same optimization as (1) is solved (a few times in training and one in testing). This method is applied N times, each time including another computation of $\mathbf{P}^{disturb}$ and $C^{disturb}$. The mean and standard deviation of the resulting RMSEs are used to evaluate robustness.

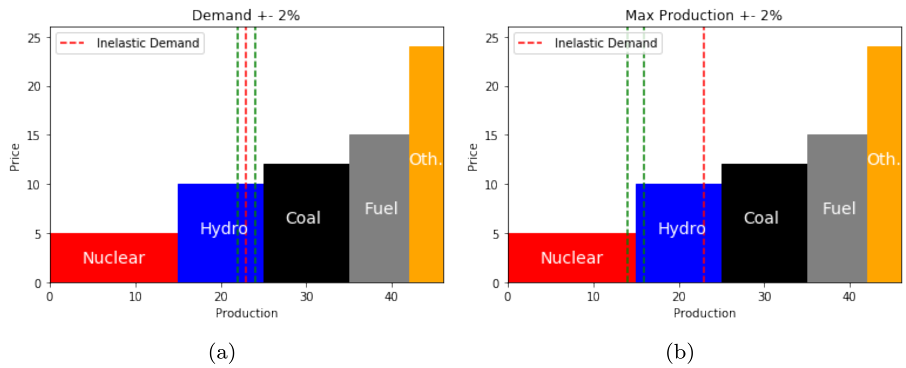


Figure 8: (a) Uncertainty on consumption (b) Uncertainty on producer capacity (only applied to nuclear here)

3 Results

3.1 RMSE and standard deviation difference

To evaluate simulations, root mean square error (RMSE) will be used. Standard deviation difference will also be specified to bring in more information. More precisely, RMSE and standard deviation difference ($\Delta(\sigma)$) are defined as follows, where $\hat{\pi}$ corresponds to simulated prices and π^{obs} to observed prices:

$$RMSE = \sqrt{\frac{1}{|T|}\sum_{t \in T}(\pi^{obs} - \hat{\pi})^2} \tag{8}$$

$$\Delta(\sigma) = \sigma^{obs} - \hat{\sigma} \tag{9}$$

where $|T|$ denotes the number of timestamps, σ^{obs} and $\hat{\sigma}$ respectively correspond to observed prices standard deviation and simulated prices standard deviation.

3.2 Data used

Four years hourly data have been used to get the following results. Data used and their sources are referenced in table 1.

Data	Source
Installed capacity by production class Installed capacity by production units ($P_{nom} > 100MW$) Unavailability by production units ($P_{nom} > 100MW$)	ENTSO-E transparency platform
Prices on day-ahead markets	Open Power System Data
Day-ahead consumption forecast Hourly production by production class CO2 emissions by production class	RTE (Eco2Mix platform)
Import costs of coal and oil in France	French Ministry for the Ecological Transition (PEGASE)
Gas market prices	Business Insider

Table 1: Data and associated sources

For comparison's sake, all following results have been obtained with training on 2017 data and testing on 2018 data.

The linear model gives the results described in table 2.

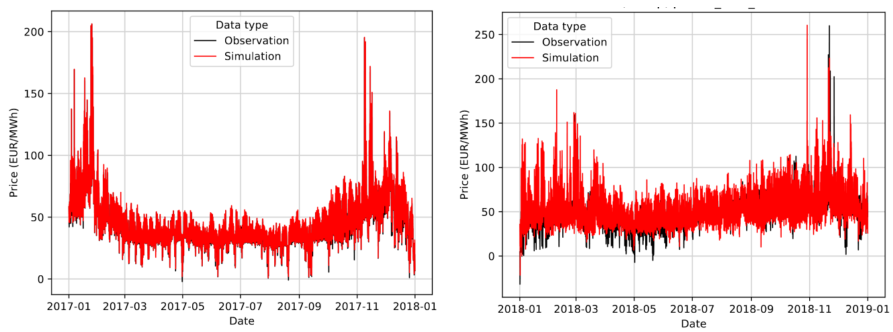
	RMSE	$\Delta(\sigma)$
Train	7.4	3.0
Test	12.2	5.2

Table 2: RMSE and standard deviation difference of linear model

3.3 Local linear models

3.3.1 Spatial local model

The choice of the number of neighbors k drives the results of the model. Similar conditions (in terms of price dependency to features) are prone to happen at the same day and hour of a week, thus around 50 times a year. However, yearly seasonal trend of electricity price (production is logically higher in winter than in summer) weakens this hypothesis. A few more values, not too far (in terms of time) from considered timestamp, should be kept. This has to be balanced with the size of training data sets (one per producer), which is not known in advance. In practice, some data sets have very few values, and sticking to small values of k is more reasonable. The results obtained with $k = 40$ is presented in figure 9.



(a) (b)

Figure 9: Simulated prices with spatial local model ($k = 40$) (a) Train (2017) (b) Test (2018)

	RMSE	$\Delta(\sigma)$
Train	2.9	-0.1
Test	15.9	-0.6

Table 3: RMSE and standard deviation difference of spatial local model ($k = 40$)

Train RMSE is improved but test RMSE is much less accurate. Simulated prices gain volatility at the cost of over-fitting. Temporal variations are, as expected, better evaluated but trend is not improved. Moreover, spike prices on train have great impact (even after deleting extreme values) on test. Tests with other number of neighbors give similar results : less leads to even more over-fitting and signal volatility, more tends to reproduce linear model. The linear model is a better forecaster.

All choices of drivers in nearest neighbors selection have been tested. The results of figure 9 used all selected drivers. As margin is highly correlated with price, using only it for neighbors selection gives very similar results. Consequently, margin seems to be by far the most explanatory feature of price, over oil, gas, coal and CO_2 prices.

A variation of the spatial model with a Gaussian's window (too far neighbors count less) was also tested, but worse results were obtained.

3.3.2 Time local model

In the same way that k drives spatial local model, window size w is the key parameter for time local model. Its choice must be linked to electricity price time periods to avoid asymmetrical training data. Fourier's coefficients of electricity price are shown in figure 10.

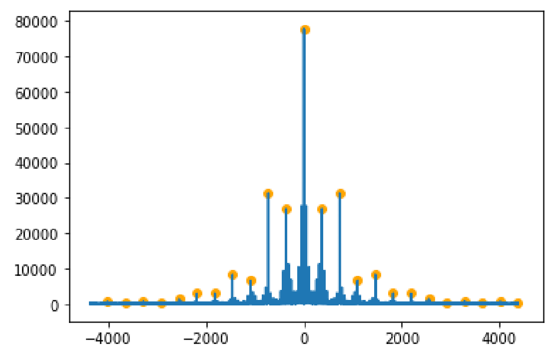
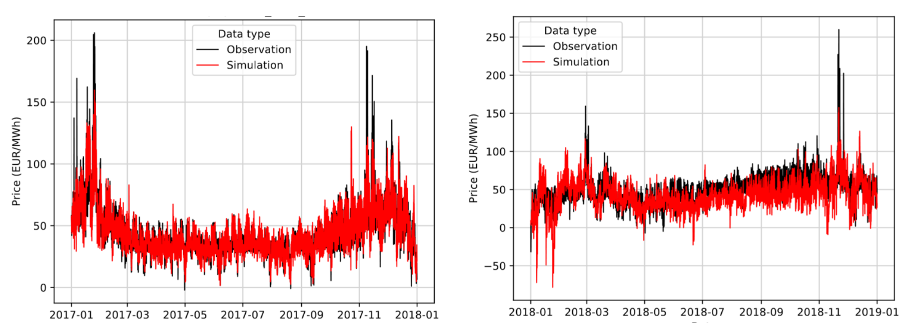


Figure 10: Fourier coefficients of price as a function of frequencies; 1 timestamp = 1 hour ; (starting from 0 forward to the left) yellow dots correspond to the following periods : 5 weeks, 1 week, 1 day, 12 hours, 8 hours, 6 hours

Window size should be chosen carefully though, considering training data sets too, which can contain no larger than a hundred values (which may not be close from each other). Therefore, prices were simulated with a 3-months, 1-month and 1-day window size (respectively 2016, 672 and 24 values). The results obtained with a day window size are shown in figure 11.



(a) (b)

Figure 11: Simulated prices with time local model ($w = 1$ day) (a) Train (2017) (b) Test (2018)

	RMSE	$\Delta(\sigma)$
Train	7.6	0.2
Test	17.8	-2.1

Table 4: RMSE and standard deviation difference of time local model ($w = 1$ day)

As observed with spatial model, resulting simulated prices are more volatile but clearly less precise. Over-fitting, especially of electricity spikes, are observed in testing data. However, even if simulated test prices with time model are less precise (RMSE) than spatial model, they look more appropriate for global trend estimation as the resulting standard deviation is lower.

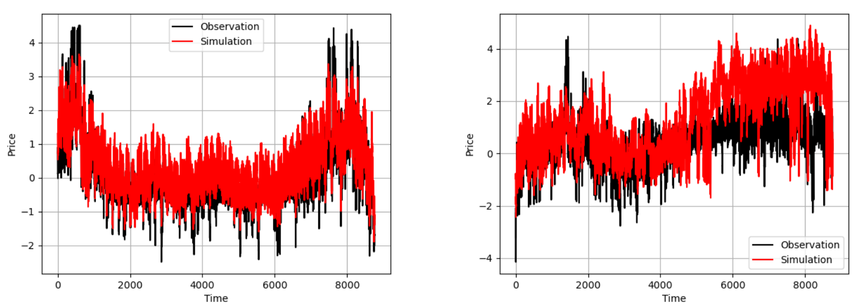
Changing window size has no unexpected effect: larger window size simulations tend to linear model simulations. A Gaussian's window has not improve simulated results in time model neither.

In conclusion, local models do not improve the results. Filled with over-fitting, they are not robust enough to spikes in prices. The presented structural model should not integrate too precise time cuts. It does not seem to perform better in terms of precision, but one may wonder how strong it is in forecasting price trend for long-term foresight.

3.4 Decomposing timescales

As previously explained, price is decomposed between three timescales : trend, seasonality and residual. This decomposition is done with tsa.seasonal.STL (with input parameters period = 3 months and seasonal = 1 week). The period and seasonal parameters were chosen considering Fourier's coefficients of price (see figure 10).

The global results, obtained by simulating prices on trend and on residual with unchanged seasonality are represented in figure 12 and table 5. Contrary to previous parts, price has been standardised.



(a) (b)

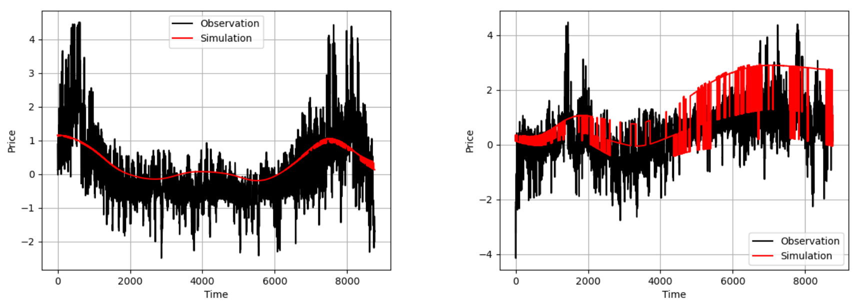
Figure 12: Global forecast (a) Train (2017) (b) Test (2018)

	RMSE	$\Delta(\sigma)$
Train	8.2	1.8
Test	19.5	0.8

Table 5: RMSE and standard deviation difference of global forecast (not standardised)

Results on train are pretty similar to the ones obtained with the linear model. However, due to a lack of precision on second-half of testing data, RMSE is worsened. Signal variability is improved though, which underlines linear model difficulty to follow seasonal variations of electricity price.

An increasing trend looks to incorrectly affect simulated price after 6 months. To have a more precise look at it, simulated trend is shown in figure 13.



(a) (b)

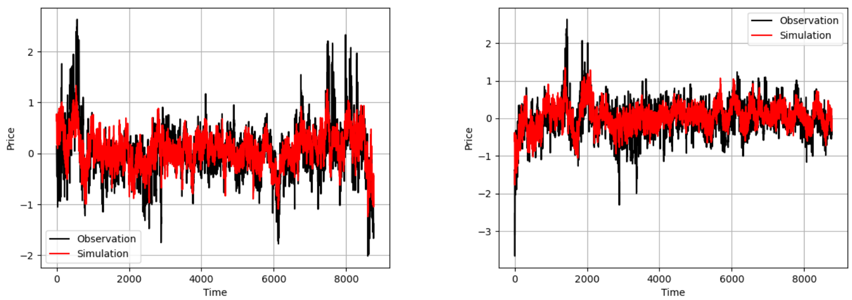
Figure 13: Forecast on trend (a) Train (2017) (b) Test (2018)

Whereas trend prediction on train is satisfying (a weak variability though), trend prediction on test has unexpected jumps. Those leaps actually correspond to marginal producer changes (for example nuclear is marginal at time t and coal is marginal at time $t+1$). The model has difficulty to grasp variability of changes in energy mix from one year to the next.

More globally, the finally retained energy mixes are not very realistic. Following daily periods of price, marginal producers should expect to vary from day to night (less production is needed by night). However, as corroborated by figure 13, there exists too long periods of time with the same marginal producer.

On the other hand, some producers are marginal only a very few time, which makes calibrating their linear parameters inaccurate. In the case the energy mix is similar between train and test, this will not affect too much simulations. But, having the same energy mix from one year to another is a hypothesis our results tend to reject. The model does not seem to be able to adjust correctly training data sets, surely due to a lack of data.

Still, in view of residue forecasts (figure 14 and table 6), the model is sensitive to electricity price drivers. Compared to a random predictor (Gaussian's reduced centered law), the model is three times better (RMSE). Furthermore, the drop and rise of test data just before timestamp 2000 are well predicted, and correspond to a drop and rise in the price of coal. Drivers sudden variations are detected at small scale : an interesting result but not enough to rectify difficult trend forecast.



(a) (b)

Figure 14: Forecast on residue (a) Train (2017) (b) Test (2018)

	RMSE	$\Delta(\sigma)$
Train	6.1	2.3
Test	5.9	1.7

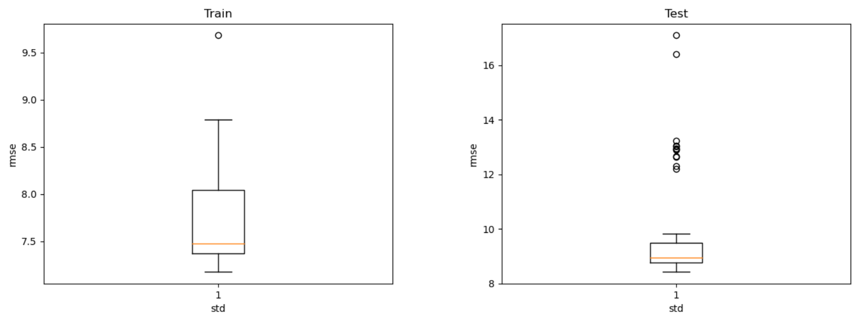
Table 6: RMSE and standard deviation difference of residue (not standardised)

3.5 Robustness

The robustness test method previously described has been applied $N = 60$ times to the linear model. The resulting box plots and statistics on RMSE are shown in table 7 and figure 15.

	mean RMSE	std RMSE
Train	7.72	0.53
Test	9.82	1.95

Table 7: mean and standard deviation of 60 tries RMSEs



(a) (b)

Figure 15: Box plots of 60 tries (a) Train (2017) (b) Test (2018)

As table 7 illustrates, RMSE on train is rather stable with only very few outliers. Standard deviation of RMSEs is 7% of its mean, quite reasonable in prospective analyses. Results get worse on test. Admittedly, mean RMSEs is pretty close to that on train. Nonetheless, standard deviation of RMSEs represents 20% of its mean, and a lot of extreme values appear in figure 15. Furthermore, it seems that a few outliers are gathered around a RMSE of 13, which may be explained by an important change in the energy mix caused by strong uncertainties. As price may vary a lot between producers, the linear model is quite sensitive to uncertainties on the global production infrastructure.

4 Conclusion

A model for forecasting day-ahead electricity spot prices was designed by Mahler and Al and tested on French market [8]. We present a performance analysis of this model by introducing time dependencies and decomposition. Local models for parameters are tested, from a spatial and time viewpoint. Moreover, electricity price is decomposed at multiple timescales (trend, seasonal and residual) with detrending tools.

Our empirical results show the model cannot be improved using more local models. Local models over-fit, probably due to each producer unpredictable training data set and to a lack of data. More precisely, the analysis of time decomposition underlines the model estimates energy mix with difficulty. It has an impact on training data sets and therefore on the model ability to reproduce producers electricity prices. The model actually performs better on shorter timescale (residual) than on more global trend. Lastly, a robustness test on consumption and producers capacities shows a sizeable sensitivity to those parameters.

Concerning the model under study, a mathematical examination could be conducted. Particularly, results on convergence, even on a simplified model, would help know about energy mix changes. Future research could focus on other aspects though.

More data on supply bids exist but useful information has not been extracted yet. Having a precise look at them could avoid gathering producers by mean of production, a strong hypothesis done in this paper. Moreover, interactions between markets are overlooked. Year and trimester markets could bring additional data useful in understanding trend forecasting. Few structural models include real production mix, a point worthy to develop in our opinion. Structural modelling of electricity markets still is an incomplete field and much can be done, especially thanks to access to new data on electricity markets.

5 Acknowledgment

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References

[1] Derek W. Bunn. *Modelling prices in competitive electricity markets.*

[2] Vincent Kaminski. *Energy markets. Risk Books.*

[3] Sergei Kulakov and Florian Ziel. "The Impact of Renewable Energy Forecasts on Intraday Electricity Prices". In: *Economics of Energy & Environmental Policy* 10.1 (Jan. 2021). arXiv: 1903.09641. ISSN: 21605882. DOI: 10.5547/2160-5890.10.1.skul.

[4] Rafał Weron. "Electricity price forecasting: A review of the state-of-the-art with a look into the future". en. In: *International Journal of Forecasting* 30.4 (Oct. 2014), pp. 1030–1081. ISSN: 0169-2070. DOI: 10.1016/j.ijforecast.2014.08.008.

[5] Jesus Lago, Fjo De Ridder, and Bart De Schutter. "Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms". en. In: *Applied Energy* 221 (July 2018), pp. 386–405. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.02.069.

[6] Lion Hirth, Jonathan Mühlenpfordt, and Marisa Bulkeley. "The ENTSO-E Transparency Platform – A review of Europe's most ambitious electricity data platform". en. In: *Applied Energy* 225 (Sept. 2018), pp. 1054–1067. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.04.048.

[7] Philip Beran, Christian Pape, and Christoph Weber. "Modelling German electricity wholesale spot prices with a parsimonious fundamental model – Validation & application". en. In: *Utilities Policy* 58 (June 2019), pp. 27–39. ISSN: 0957-1787. DOI: 10.1016/j.jup.2019.01.008.

[8] Valentin Mahler, Robin Girard, and Georges Kariniotakis. “Data-driven structural modeling of electricity price dynamics”. en. In: *Energy Economics* 107 (Mar. 2022), p. 105811. ISSN: 0140-9883. DOI: 10.1016/j.eneco.2022.105811.