Forecasting Spanish electricity prices

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Motivation and importance.

What did we do?

- Forecast to short, medium and long term the electricity prices in Spain.
- Using SVM, ARIMA models, TBATS and dynamic factor models.
- Create an App where can be visualized and downloaded these predictions.

Why did we do it?

- It is very useful for portfolio managers, producers and utilities companies.
- Forecasting in real time.
- No user intervention.

Law of supply and demand.

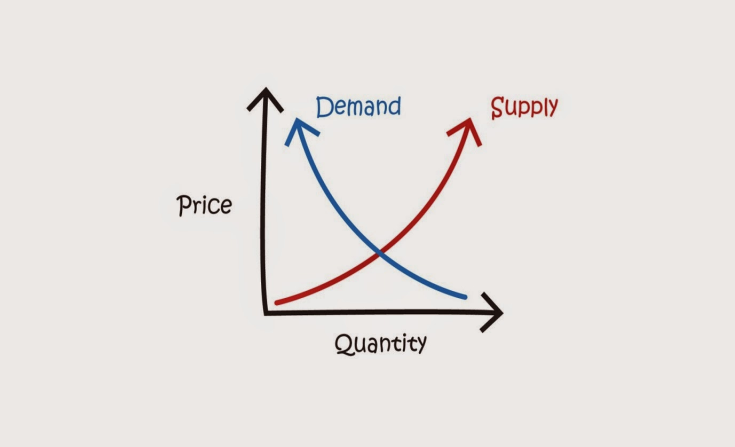

Figure: The Law of Supply and Demand.

Similar researches.

Short term.

- ARMA models in the German EEX market.
- AR models in the California market.
- ARMAX models in the PJM market.

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- VAR models in the Iberian market.
- Forward price models in the Nordic markets.

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Medium term.

- VAR models in the Iberian market.
- Forward price models in the Nordic markets.

Long term.

- ANN in the Spanish market.

Software tools

R's packages

- jsnolite
- httr
- lubridate
- MLmetrics
- forecast
- caret
- shiny
- cronR

How can we download the data?

REE has developed an information system known as E-SIOS. Where we can access to non confidential information through the ESIOS-API.

Table: Variables downloaded from E-SIOS website.

Variable	Id	By Month	By Day	By Hour
Price	600	Yes	Yes	Yes
Demand Forecast	460	No	No	Yes
Wind Power Generation Forecast	541	No	No	Yes
Solar PV Generation Forecast	542	No	No	Yes
Solar Thermal Generation Forecast	543	No	No	Yes

Methodology in order to select the best models.

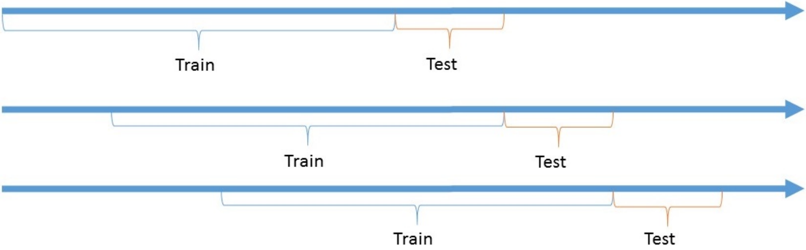

Figure: Illustration of the rolling forecasting origin procedure.

Methodology in order to select the best models.

Forecasting Accuracy Measure

- $MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{y_t - \widehat{y}_t}{y_t} \right|$
- $MAE = \frac{1}{n} \sum_{t=1}^{n} |y_t - \widehat{y}_t|$
- $MDAE = median(|y_t - \widehat{y}_t|)$

where y_t is the real price and $\widehat{y}_t$ is the corresponding forecast

Forecasting 24 hours.

Regression Formula

$$\begin{aligned} Price \sim & DailyPeninsularDemandForecast \\ & + PeninsularWindPowerGenerationForecast \\ & + SolarPVGenerationForecast \\ & + SolarThermalForecast. \end{aligned}$$

Period under study.

From January 1st, 2016 to June 30th, 2017

Forecasting 24 hours.

Algorithms for forecast 24 hours

- SVM with linear kernel.
- SVM with polynomial kernel.
- SVM with radial kernel.
- KNN.
- Gaussian Process with polynomial kernel.
- Gaussian Process with radial kernel.
- Dynamic Factor Model.

Number of days for train.

- 7, 14, 21, 42, 84 days.
- 100, 200, 300, 400 and 500 days for DFM.

Forecasting 24 hours.

Hyperparameter tuning

- SVM with linear kernel $\Rightarrow$ C.
- SVM with polynomial kernel $\Rightarrow$ degree, scale, C.
- SVM with radial kernel $\Rightarrow$ sigma, C.
- Gaussian Process with polynomial kernel $\Rightarrow$ degree, scale.
- Gaussian Process with radial kernel $\Rightarrow$ sigma .
- KNN $\Rightarrow$ kmax, distance, kernel.

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Algorithms for forecast 24 hours

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Number of days for train.

- 7, 14, 21, 42, 84 days.
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Measure	Min	Q1	Median	Mean	Q3	Max
MAE	0.57	2.13	2.94	3.39	3.96	18.26

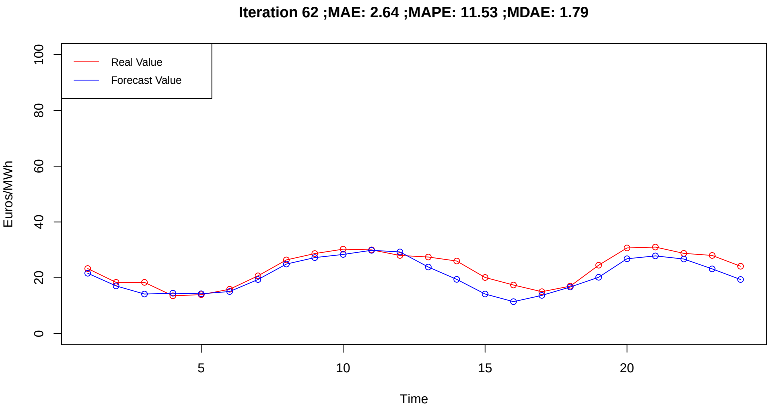

Figure: Real and predicted prices when a low MAE is obtained using SVM with linear kernel for the next 24 hours.

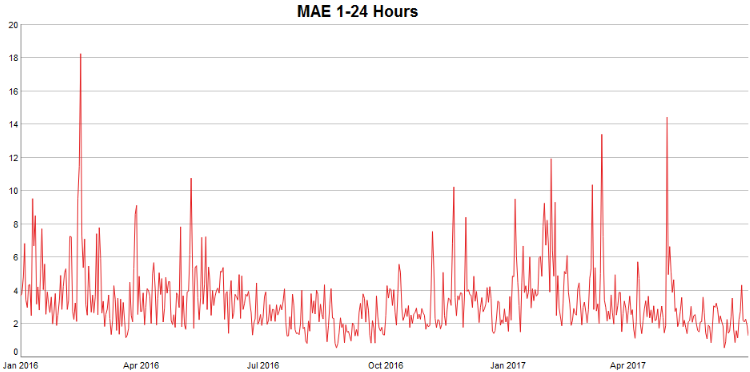

Figure: Daily MAE for 1-24 Hours from January 1st, 2016 to June 30th, 2017.

Forecasting 144 hours.

Formula regression

$$Price \sim DailyPeninsularDemandForecast$$

Period under study.

From January 1st, 2016 to June 30th, 2017

Forecasting 144 hours.

Algorithms for forecast 144 hours

- Dynamic Factor Model with 2 factors.
- Dynamic Factor Model with 3 factors.
- DFM with 2 factors + Linear Regression.
- DFM with 3 factors + Linear Regression.

Number of days for train.

- 100, 200, 300, 400 and 500 days.

Forecasting 144 hours.

Algorithms for forecast 144 hours

- SVM with linear kernel.
- Dynamic Factor Model with 2 factors.
- Dynamic Factor Model with 3 factors.
- DFM with 2 factors + Linear Regression.
- DFM with 3 factors + Linear Regression.

Number of days for train.

- 100, 200, 300, 400 and 500 days.

Measure	Min	Q1	Median	Mean	Q3	Max
MAE	1.98	3.63	4.92	5.72	6.65	20.59

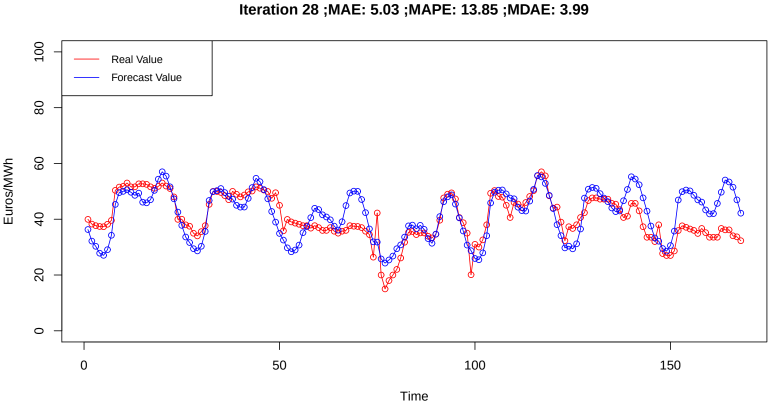

Figure: Real and predicted prices when a low MAE is obtained using LR+DFM with r=3 for the next 144 hours.

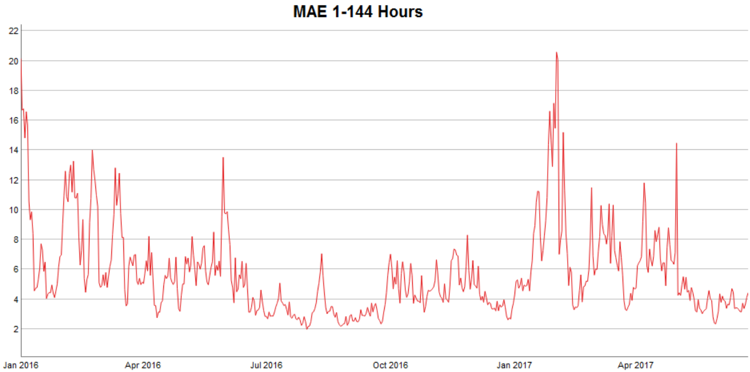

Figure: Daily MAE for 1-144 Hours from January 1st, 2016 to June 30th, 2017.

Forecasting 30 days.

Algorithms for forecast 30 days

- $ARIMA(p, 1, q)(P, 1, Q)_7$
- $TBATS_7$

Number of days for train.

- 100, 20, 300, 400 and 500 days.

Forecasting 30 days.

Algorithms for forecast 30 days

- $ARIMA(p,1,q)(P,1,Q)_7$
- $TBATS_7$

Number of days for train.

- 100, 20, 300, 400 and 500 days.

Measure	Min	Q1	Median	Mean	Q3	Max
MAE	2.18	4.14	5.39	6.75	8.41	25.33

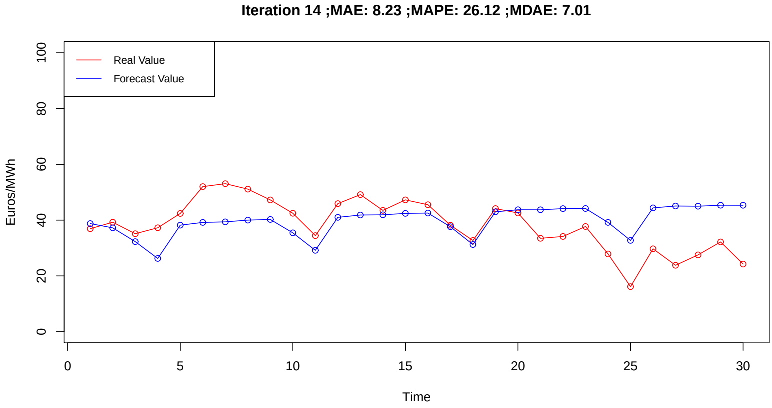

Figure: Real and predicted prices when a low MAE is obtained using $TBATS_7$ for the next 30 days.

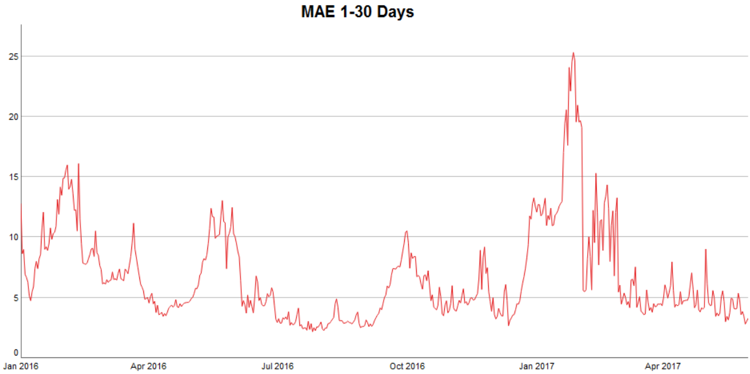

Figure: Daily MAE for 1-30 Days from January 1st, 2016 to June 30th, 2017.

Forecasting 12 months.

Algorithms for forecast 12 months

- $ARIMA(p, 1, q)(P, 1, Q)_{12}$
- $ARIMA(p, 1, q)(P, 1, Q)_{12}$ with automatic BoxCox transformation.

Number of days for train.

- 60, 80, 100, 120 and 140 months.

Forecasting 12 months.

Algorithms for forecast 12 months

- $ARIMA(p, 1, q)(P, 1, Q)_{12}$
- $ARIMA(p, 1, q)(P, 1, Q)_{12}$ with automatic BoxCox transformation.

Number of days for train.

- 60, 80, 100, 120 and 140 months.

Measure	Min	Q1	Median	Mean	Q3	Max
MAE	2.53	5.36	8.23	9.22	10.90	30.00

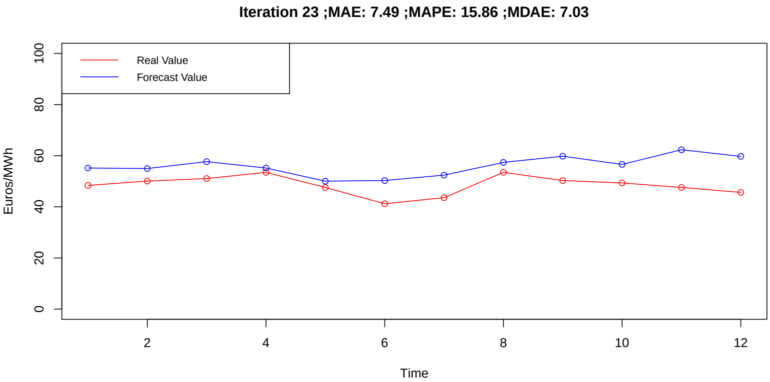

Figure: Real and predicted prices when a low MAE is obtained using *ARIMA* for the next 12 months.

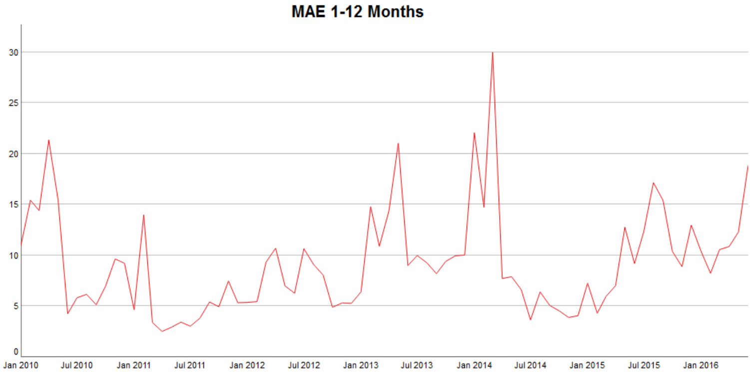

Figure: Monthly MAE for 1-12 Months from January, 2010 to June, 2017.

Automatization and Visualization

AWS and cron

- AWS instance with RStudio and Julia server.
- cronR package.

Appication

App

THE END!!!!