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# Forecasting Nord Pool day-ahead prices with an autoregressive model

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## HIGHLIGHTS

- ▸ Forecasting Nord Pool day-ahead prices with an autoregressive model.
- ▸ The model is based on Weron and Misiorek (2008) but with the set of parameters reduced from 24 to 1.
- ▸ The model includes Nordic demand and Danish wind power as exogenous variables.
- ▸ Hourly mean absolute percentage error ranges from 8% to 11%.
- ▸ Out of sample results yields a WMAE and an hourly MAPE of around 5%.

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## ABSTRACT

This paper presents a model to forecast Nord Pool hourly day-ahead prices. The model is based on Weron and Misiorek (2008) but reduced in terms of estimation parameters (from 24 sets to 1) and modified to include Nordic demand and Danish wind power as exogenous variables. We model prices across all hours in the analysis period rather than across each single hour of 24 hours. By applying three model variants on Nord Pool data, we achieve a weekly mean absolute percentage error (WMAE) of around 6–7% and an hourly mean absolute percentage error (MAPE) ranging from 8% to 11%. Out of sample results yields a WMAE and an hourly MAPE of around 5%. The models enable analysts and traders to forecast hourly day-ahead prices accurately. Moreover, the models are relatively straightforward and user-friendly to implement. They can be set up in any trading organization.



## 1. Introduction

Globalization and democratization of energy markets play an increasingly important role as discussed by Wüstenhagen et al. (2007). Forecasting of energy demand and prices is one of the most important policy tools used by the decision makers all over the world. The ability for particularly medium sized consumers to undertake reliable and independent price forecasting is a significant factor in the democratization of energy trading, and high-quality models with predictable performance levels are therefore bound to become an important factor in developing energy policies in the years ahead. Ediger and Akar (2007) used the autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) methods to estimate the future primary energy demand of Turkey from 2005 to 2020. Strbac (2008) discusses the major benefits and challenges of UK electricity demand side management where price forecasting is a crucial element. Rallapallia and Ghosh (2012) discuss the challenges associated with forecasting monthly peak demand of electricity in India. They point to a number of regression forecasting tools which can help India to forecast demand with better precision.

This paper will focus on accurate forecasting of electricity day-ahead prices. This is critically important for electricity day-ahead trading and its risk management, but also tends to impact the short-term electricity forward curve. A weaker (stronger) than expected day-ahead price often results in a lower (higher) price for the short end of the forward curve because traders extrapolate the recent day-ahead price changes to the short end of the forward curve and possibly longer term contracts.

Therefore, analysts and traders develop models to forecast the day-ahead prices. Analytics service providers such as Point Carbon, NENA and Markedskraft have developed their own day-ahead models for the Nordic power market. However, the models appear as black boxes to the users who do not have access to the inputs and thus are unable to adjust these if necessary.

One solution is to develop an in-house day-ahead model where the user has full access to all input data and can modify the assumptions as desired. There is little literature available on how to develop practical implementable models in a user friendly software environment such as Excel or similar software.

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In this paper, we present an autoregressive (ARX) model with exogenous variables based on Weron and Misiorek (2008) to compute price predictions for all 24 hours of a given day. The model is reduced in terms of estimation parameters (from 24 sets to 1) and modified to include Nordic demand and Danish wind power as exogenous variables. We model prices across all hours in the analysis period rather than across each single hour of 24 hours. Input data are publicly available information and includes historic Nord Pool prices, demand and Danish wind output. We have applied it to more recent data from January 2007 to May 2011 but also included data series from January 2004 to May 2011 for one of the models. The data series was used to estimate the regression coefficients including out of sample testing.

## 2. Day-ahead price forecasting methods

Weron (2006) reviews the approaches to modeling and forecasting of day-ahead electricity prices but finds that only some of them are well suited. Time series models are one of the most powerful model groups. Weron (2006) finds that specifications where each hour is modeled separately present better forecasting properties than model specifications common for all hours. However, both specifications are equally popular. Model specifications include autoregressive (AR) models, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and seasonal ARIMA models (Contreras et al., 2003, Zhou et al., 2006), autoregressions with heteroskedastic (Garcia et al., 2005) or heavy-tailed innovations (Weron, 2008), AR models with exogenous (fundamental) variables–dynamic regression (or ARX) and transfer function (or ARMAX) models (Conejo et al., 2005), vector auto regressions with exogenous effects (Panagiotelis and Smith, 2008), threshold AR and ARX models (Misiorek et al., 2006), regime-switching regressions with fundamental variables (Karakatsani and Bunn, 2008) and mean-reverting jump diffusions (Knittel and Roberts, 2005).

## 3. Autoregressive exogenous models

There are some naive approaches to forecasting day-ahead prices. The similar day approach is based on searching historical data for days with similar characteristics to those of the forecasted day (Weron, 2006). Similar characteristics may include day of the week, day of the year or even weather properties. The price of a similar day is considered as the forecast. Instead of a single similar-day price, the forecast can be a linear combination or a regression procedure that can include several similar days. A simple, yet in some cases relatively powerful implementation of the similar-day or naive method can be as follows: a Monday is similar to the Monday of the previous week and the same rule applies for Saturdays and Sundays; analogously, a Tuesday is similar to the previous Monday, and the same rule applies for Wednesdays, Thursdays and Fridays (Weron, 2006). The similar day approach can be used as a benchmark for more sophisticated models.

Around 60% of Nordic power generation is hydropower. Therefore, the supply side is predominantly weather dependent. A rationale for a Nord Pool forecasting model is that the day-ahead price should reflect all available information discounted in the historic prices. Likewise, the hourly profile of the day-ahead price reflects the demand profile over the course of the day. The demand is typically lower in the off-peak hours (hours 0–8 and 20–24) and in the weekends. Typically the price level is similar to the previous day's price level adjusted for any potential increase or decrease in water values. Hydropower generation has the ability to quickly ramp up production and meet demand. Prices are therefore normally smooth and exhibit smaller differences between peak and offpeak prices compared to those of a thermal system. Thus a regression model is more suitable than a pure thermal power system.

Hydropower producers use different approaches to hydropower scheduling. One approach is to use a model such as the EMPS (Haugestad and Rismark, 1998) or a stochastic dual dynamic programming (SDDP) model (Mo et al., 2001; Pereira, 1989) to calculate water values. These reflect the opportunity cost of storing hydropower. A hydropower producer would prefer to produce when the water value is lower than the day-ahead price. Conversely, it would prefer to save water when the day-ahead price is lower than the water value. Alternatively some market participants use the forward curve as a guide for when to produce. A forward curve in contango (electricity is more valuable in the future) incentivizes producers to save water while a curve in backwardation (electricity is more valuable in the future) incentivizes to produce now rather than in the future.

Weron and Misiorek (2008) used Nord Pool data from 1998 to 1999 (a period with high water reservoir levels) and from 2003 to 2004 (a period with low water reservoir levels) to evaluate their proposed model. In this paper, we use data from 2007 to 2011 and from 2004 to 2011 to test several model formulations. These periods include both dry and wet years. We use historical demand rather than temperatures as utilized by Weron and Misiorek (2008).

The natural logarithmic transformation has been applied to price, $p_t = \ln(P_t)$, load $z_t = \ln(Z_t)$ and wind $w_t = \ln(W_t)$ to attain a more stable variance. We have included Danish wind power and total Nordic demand which were not considered by Weron and Misiorek (2008). However Cruz et al. (2011) have considered wind power in their forecasting approach for Spanish spot prices. Weron and Misiorek (2008) argued that since each hour displays a rather distinct price profile reflecting the daily variation of demand, costs and operational constraints, the modeling should be implemented across all 24 hours and thus leading to 24 sets of parameters (for each day the forecasting exercise was performed). However, we implemented the model across all hours in the analysis period, leading to only one set of parameters.[1] Note that in operational forecasting we use forecasts for demand and wind power for the next day. In the back testing of the model we have applied historic data including out of sample periods.

The weekly seasonal behavior has been captured by a combination of (1) the autoregressive structure of the models and (2) daily dummy variables. The ln-price $p_t$ was made dependent on the ln-prices for the same hour on the previous two days, and the previous week. This particular choice of model variables was motivated by the significance of the coefficients found by Weron and Misiorek (2008). They also used the minimum of all prices on the previous day. The latter created the desired link between bidding and price signals from the entire day. However, our statistical analysis indicated that this variable was statistically insignificant. Therefore, we made one additional regression where the minimum price on the previous day was substituted with the maximum price on the previous day. For comparison, we have included the model with the minimum price on the previous day. Furthermore, four dummy variables (for Monday, Friday, Saturday and Sunday) were considered to differentiate between the two weekend days, the first work day of the week, the last work day of the week and the remaining business days. Note that we have

[1] An implementation across each of the 24 hours yielded the best results for the peak hours while offpeak hours returned poor results.

added an additional dummy variable for Friday compared to the Weron and Misiorek model formulation (2008).

The basic autoregressive model structure used in this study is given by the following formula:

$$p_t = \beta_1 p_{t-24} + \beta_2 p_{t-48} + \beta_3 p_{t-168} + \alpha m p_t + \gamma z_t + \delta w_t + d_1 D_{mon} + d_2 D_{fri} + d_3 D_{sat} + d_4 D_{sun} + \varepsilon_t \quad (1)$$

The lagged ln-prices $p_{t\text{-}24}$, $p_{t\text{-}48}$ and $p_{t\text{-}168}$ account for the autoregressive effects of the previous days (the same hour yesterday, two days ago and one week ago, respectively), while $mp_t$ creates the link between bidding and price signals from the entire previous day (it is the maximum or minimum of the previous day's 24 hourly ln-prices). The four dummy variables —$D_{mon}$, $D_{fri}$, $D_{sat}$ and $D_{sun}$ (for Monday, Friday, Saturday and Sunday, respectively) account for the weekly seasonality. Finally, the $\varepsilon_{t'}$ are assumed to be independent and identically distributed with zero mean and finite variance. The model formulation states that tomorrow's hourly price (forecasted) depends on the hourly day-ahead the previous same 24 hour, 48 hour and 168 hour including the hourly forecasted Nordic demand and Danish wind generation for the day-ahead. In addition there is a link between the day-ahead price and the previous day's price, including links between different weekdays. The most important price forecasting property is the dependence on previous hourly prices. For example the price of hour 11 am on Thursday depends on the price of hour 11 am on Wednesday, hour 11 am on Tuesday and hour 11 am on Thursday in the previous week.

## 4. Case studies

In the performance tests of the model we have calculated the exponential function of the right hand side of Eq. (1) to obtain an hourly price comparable with the actual hourly day-ahead price. We have applied model (1) on data for two periods: from January 2007 to May 2011 and from January 2004 to May 2011. After performing a linear regression on the historical data from January 1, 2007 to May 31, 2011, we obtained the regression results summarized in Tables 1–6. The *R*-square is similar for all regressions, around $R^2 = 0.87 - 0.88$. We note that the price for a certain hour today depends mainly on the same hourly price on the previous day and the previous week (i.e. 168 hours previous price) as these variables have the largest regression coefficients. In regression analysis, the *t*-stat, coupled with its *p*-value, indicates the statistical significance of the relationship between the independent and dependent variable. We observe that all variables except the minimum price on the previous day have a *p*-value less than 0.05. The variable for the minimum price on the previous day has a *p*-value of 0.38.

**Table 1**
Summary statistics regression models.

| Regression statistics | Maximum price on the previous day 2007–2011 | Minimum price on the previous day 2007–2011 | Maximum price on the previous day 2004–2011 |
|---|---|---|---|
| Multiple *R* | 0.9358 | 0.9336 | 0.9414 |
| *R* square | 0.8756 | 0.8716 | 0.8863 |
| Adjusted *R* square[a] | 0.8756 | 0.8716 | 0.8863 |
| Standard error | 0.1525 | 0.1549 | 0.1314 |
| Observations | 38688 | 38688 | 64824 |

[a] The adjusted *R* square is slightly lower than the *R* square but the difference is only for digits beyond the fourth.

**Table 2**
Augmented Dickey Fuller (ADF) test for the two periods 2007–2011 and 2004–2011.

| Time series | ln spot price 2007–2011 | ln spot price 2004–2011 |
|---|---|---|
| Dickey Fuller test statistic | −2.6465 | −5.3239 |
| *p*-value | 0.30 | 0.01 |
| Lag order | 21 | 21 |

Finally, we extended the data series to include data from January 1, 2004 to May 31, 2011 and performed the regression with the maximum price on the previous day. We observe that this dependence is statistically significant. The R square value, $R^2 = 0.88$, is somewhat higher than for the previous presented models.

Table 2 shows the augmented Dickey Fuller (ADF) test for stationary conditions for the two time series. The shorter times series from 2007 to 2011 is non-stationary while the longer times from 2004 to 2011 is stationary.[2] When we apply the ADF on the individual years in Table 3 we find that 2006 and 2007 have *p*-values of 0.33 and 0.27, respectively and thus non-stationary. The year 2008 is a borderline case, while the remaining years are stationary. The characteristics for a stationary time series are a constant mean and a constant variance and thus a time series with trend is non-stationary. Weron and Misiorek (2008) did not test for stationary conditions.

## 5. Model performances

To measure the performance of the models we have used the mean absolute percentage error (MAPE) defined as the average absolute difference between the actual value and the forecast value divided by the actual value:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \quad (2)$$

where *A* is actual value and *F* is forecast value.

The performance and accuracy of the price forecasting models are summarized in Table 7. We note that two of the models have a relatively similar performance with an 11% hourly MAPE and 7% weekly-weighted mean absolute error (WMAE).[3] The 2004–2011 model has a lower hourly MAPE at 8% and WMAE at 6%. The forecasting error is smaller for the weekly prices as they are averaged over more data periods. In terms of deviation between the forecast and the hourly day-ahead price all models forecast lower prices than the out turned hourly day-ahead price. The 2004–2011 model has the best performance with 0.21 EUR/MWh. Weron and Misiorek (2008) achieved a weekly-weighted mean absolute error of 4.66% for4 five week periods (i.e. 20 weeks) from 1998–1999 and 3.37% for 4 five week periods (i.e. 20 weeks) from 2003–2004. Our weekly-weighted mean absolute errors are somewhat larger but we have formulated a different model and included a larger and more recent data period so results are not directly comparable.

In addition we also performed an out of sample test for the maximum and minimum (2007–2011) price models for the period January 1, 2004 to December 31, 2006. The tests results

[2] The critical values for the ADF test based on *F*-statistic are −3.96 for $p = 0.01$ and −3.66 for $p = 0.025$ when the number of observations is greater than 500.

[3] $\text{WMAE} = (1/168 A_{168}) \sum_{t=1}^{168} |A_t - F|$ where $A_t$ is the actual price for hour h, $F_t$ is the predicted price for that hour and $A_{168}$ is the mean price for a given week.

**Table 3**
Augmented Dickey Fuller (ADF) test for years 2004–2011.

| Time series | ln spot price 2004 | ln spot price 2005 | ln spot price 2006 | ln spot price 2007 | ln spot price 2008 | ln spot price 2009 | ln spot price 2010 | Ln spot price 2011 |
|---|---|---|---|---|---|---|---|---|
| Dickey Fuller test statistic | −5.8322 | −5.8582 | −2.5685 | −2.7170 | −3.6560 | −7.4527 | −4.8729 | −5.4915 |
| *p*-value | 0.01 | 0.01 | 0.3362 | 0.2727 | 0.0257 | 0.01 | 0.01 | 0.01 |
| Lag order | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 15 |

**Table 4**
Max price on the previous day 2007–2011.

| | Coefficients | *p*-value |
|---|---|---|
| Intercept | 0.8353 | 0.0000 |
| ln price t-24 | 0.4612 | 0.0000 |
| ln price t-48 | 0.0908 | 0.0000 |
| ln price t-168 | 0.2978 | 0.0000 |
| Mon | 0.0888 | 0.0000 |
| Sat | −0.0427 | 0.0000 |
| Sun | −0.0421 | 0.0000 |
| Fri | −0.0150 | 0.0000 |
| ln demand | 0.0852 | 0.0000 |
| ln wind | −0.0129 | 0.0000 |
| Max price | 0.1458 | 0.0000 |

**Table 5**
Min price on the previous day 2007–2011.

| | Coefficients | *p*-value |
|---|---|---|
| Intercept | 0.7034 | 0.0000 |
| ln price t-24 | 0.5330 | 0.0000 |
| ln price t-48 | 0.1175 | 0.0000 |
| ln price t-168 | 0.3115 | 0.0000 |
| Mon | 0.0799 | 0.0000 |
| Sat | −0.0449 | 0.0000 |
| Sun | −0.0545 | 0.0000 |
| Fri | −0.0184 | 0.0000 |
| ln demand | 0.0872 | 0.0000 |
| ln wind | −0.0126 | 0.0000 |
| min price | −0.0019 | 0.3835 |

**Table 6**
Max price on the previous day 2004–2011.

| | Coefficients | Standard error | *t* stat | *p*-value |
|---|---|---|---|---|
| Intercept | −0.6692 | 0.0282 | −23.7211 | 0.0000 |
| ln price t−24 | 0.4660 | 0.0040 | 117.8678 | 0.0000 |
| ln price t−48 | 0.1028 | 0.0036 | 28.8764 | 0.0000 |
| ln price t−168 | 0.2875 | 0.0028 | 101.2457 | 0.0000 |
| Mon | 0.0766 | 0.0016 | 46.8272 | 0.0000 |
| Sat | −0.0383 | 0.0016 | −23.5002 | 0.0000 |
| Sun | −0.0370 | 0.0017 | −22.1779 | 0.0000 |
| Fri | −0.0168 | 0.0016 | −10.5545 | 0.0000 |
| ln demand | 0.0721 | 0.0030 | 44.9298 | 0.0000 |
| ln wind | −0.0135 | 0.0027 | 26.6101 | 0.0000 |
| max price | 0.1346 | 0.0004 | 30.7801 | 0.0000 |

are presented in Table 8. The model performance results are better than for the in sample periods with a daily MAPE and WMAE of around 5%.

For a given stochastic process one is often interested in the connection between two random variables of a process at different points in time. One way to measure a linear relationship is with the autocorrelation function (ACF), which measures the correlation between these two variables. We have applied the ACF with various time lags on the residuals and the squared residuals in Figs. 1–3. For the max price model, the ACF residual tails off to 0 after 28 lags while the ACF squared residual tails off to 0 after 29 lags. For the min price model the ACF residual tails off to 0 after 47 lags while the ACF squared residual tails off to 0 after 28 lags. For the max price 2004–2011 model the ACF residual tails off to 0 after 48 lags while the ACF squared residual tails off to 0 after 30 lags.

**Table 7**
Hourly MAPE and WMAE and absolute price deviation (EUR/MWh).

| | MAPE/ WMAE | Deviation day-ahead and forecast price (EUR/ MWh) |
|---|---|---|
| Maximum price on the previous day | 11%/6.8% | 0.26 |
| Minimum price on the previous day | 11%/6.8% | 0.33 |
| Maximum price on the previous day for the time series from 2004 to 2011 | 8%/5.9% | 0.21 |

**Table 8**
Hourly MAPE and WMAE and absolute price deviation (EUR/MWh) for the out of sample period 2004–2006.

| | MAPE/ WMAE | Deviation day-ahead and forecast price (EUR/MWh) |
|---|---|---|
| Maximum price on the previous day | 5%/5% | −0.03 |
| Minimum price on the previous day | 6%/5% | 0.34 |

## 6. Practical considerations

The model requires access to historic Nord Pool hourly day-ahead prices and demand and Danish wind power to enable estimation of the regression coefficients. Historic Nord Pool hourly day-ahead prices and demand can be downloaded from the Nord Pool web-page (http://www.nordpoolspot.com). Danish wind power can be downloaded from Energinet.dk (http://www.energinet.dk).[4] Energinet.dk also has historical data for Nord Pool hourly day-ahead prices. A future modification of the model could involve an inclusion of total Nordic wind power. The amount of wind power is expected to increase in the coming years with the inception of trading of green certificates in Norway. When the model is used in practical forecasting the user must specify a Nordic demand forecast and a Danish wind forecast.

[4] http://energinet.dk/_layouts/Markedsdata/framework/integrations/markedsdatatemplate.aspx?language=en

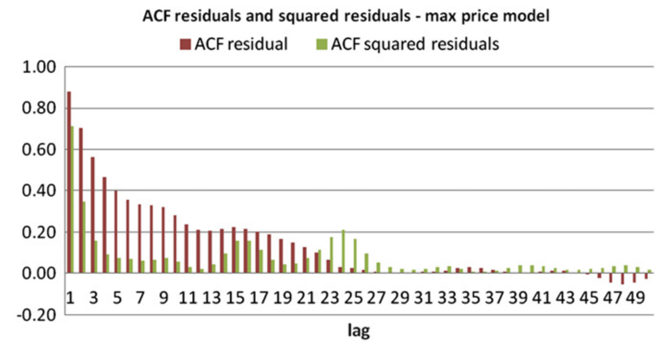


**Fig. 1.** The autocorrelation function for the residuals and squared residuals for the max price model.

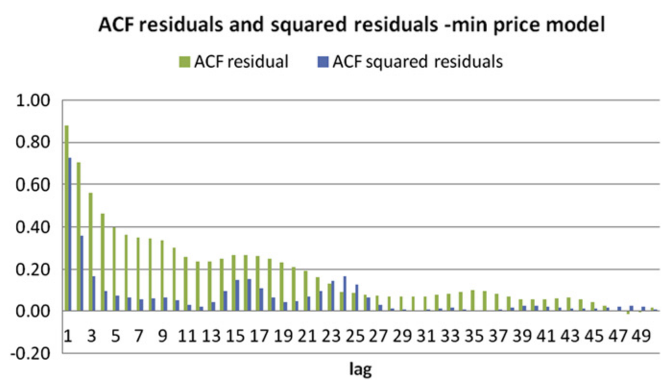


**Fig. 2.** The autocorrelation function for the residuals and squared residuals for the min price model.

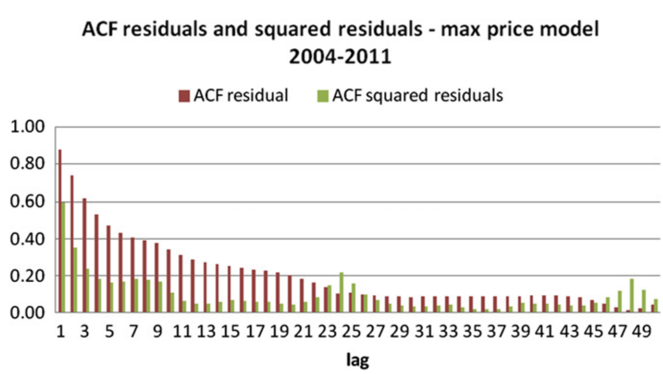


**Fig. 3.** The autocorrelation function for the residuals and squared residuals for the max price model 2004–2011.

## 7. Conclusions

This paper develops a relatively simple and user-friendly regression model for the Nord Pool power market. It is based on Weron and Misiorek (2008) but with the number of parameter sets reduced from 24 to 1. Furthermore we have included Danish wind power and Nordic demand as additional exogenous factors in the model. To apply the model in operational forecasting runs we must specify a Nordic demand forecast and Danish wind forecast. These forecasts can either be from external providers or supplied in-house. We introduced a dependence on the maximum price on the previous day rather than the minimum price as proposed by Weron and Misiorek (2008). This modification improved the accuracy of the model for out of sample tests. In terms of performance the models including data from 2007 to 2011 have a WMAE of 7% and hourly MAPE of 11%. The model with a dependence on the maximum price on the previous day has the lowest deviation with 0.26 EUR/MWh and forecasted a lower hourly day-ahead price than the out turned price. A similar model with dependence on the maximum price including data from 2004 to 2011 on the previous day achieved a lower WMAE of 6% but an hourly MAPE of 8%. The model's deviation between the hourly day-ahead price and the forecast is 0.21 EUR/MWh. Out of sample tests for the min and max price models yielded even better results with a WMAE and an hourly MAPE of around 5%.

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