The influence of the switch from fossil fuels to solar and wind energy on the electricity prices in Germany

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Abstract

Germany is actively pursuing a switch from fossil fuel to renewables, the so-called Energiewende (energy transition). Due to the fact that the supply of wind and solar energy is less predictable than the supply of fossil fuel, stabilizing the grid has become more challenging. On sunny and windy days the supply in Germany substantially exceeds demand, and the surplus needs to be exported to the neighboring countries. In this study we analyze data from the German day-ahead market in the period 2009 through 2015 and show that the realized day-ahead price experiences significant downward pressure from high predictions for the day-ahead solar and wind supply. This conclusion is based on a regression analysis using the singular value decomposition (SVD) method. SVD decomposes the time series as a sum of data-determined profiles.

During the observed period the market share of solar and wind energy in the total energy supply increased in Germany. The larger the market share, the more impact solar and wind energy have.

Key words: solar energy; wind energy; electricity price, day-ahead market

1. Introduction

In Abudaldah, Dorsman, Franx and Pottuijt (2014), hereafter ADFP (2014), we looked at the influence of wind and solar energy on the electricity prices in Germany. In that article we found for the period January 1 2011 through December 31 2012 strong evidence that solar energy and wind energy have a negative impact on the electricity price in Germany. Before the energy switch we saw that prices during peak periods (8.00 - 20.00 hours) are higher than during off-peak periods (20.00 - 8.00 hours). However, a substantial supply of solar and wind energy can push the peak price below the off-peak price. In recent times we have

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occasionally seen negative energy prices in Germany caused by the exceptional high supply of solar and wind energy. The switch from fossil fuels to renewables in Germany has continued unabatedly since the period reported upon in ADFP (2014) and at the time of writing this (May 13 2016) 33% of the energy supply in Germany is sustainable. The German minister of Finance has indicated that this percentage will increase to 45% in 2025. Therefore it is interesting to see whether a growing penetration of renewables in the total energy supply has an increasing impact on the electricity price, not only in Germany but also in neighboring countries. A main disadvantage of solar and wind energy is volatility in supply, caused by the difficulties of storing the occasional surplus of electricity. However, the last years have witnessed a considerable evolution in storage technologies (see for example Papaefthymiou et al. (2014)).[2] Nevertheless, the cost of storing electricity supplied by solar and wind energy is not negligible and can cause additional volatility in electricity prices. In this paper we will look at the influence of the predicted supply of renewables on the realized day-ahead electricity prices on the German day-ahead market. This research has clear practical implications. Indeed, if an abundance of German renewables impact the price and volatility of the electricity in Germany substantially, it effects the position of fossil fuel suppliers. In addition, the price volatility will increase, causing additional market risks for suppliers and consumers on the German electricity market. It is also conceivable that it would negatively impact the reliability of the electricity grid. Due to the integration of the European grids the problems will not be limited to the German grid. Increasing instability on the German grid means also a higher instability on the neighboring grids.

The research question in this study is: Is there a correlation between the day-ahead predictions for solar and wind energy supply on the one hand, and the day-ahead electricity price in Germany on the other?

In section 2 we will give an overview of the literature, followed by section 3 that focuses on the data description and analysis for Germany. Electricity is a commodity and not a virtual product likes stocks or bonds. We start this section with a descriptive analysis of the time series for the electricity price, and the supply of both solar and wind energy. Next we use a regression analysis to quantify the impact of the predicted supply of renewables on the predicted day-ahead price. Section 4 concludes and outlines possibilities for further research.

[2] The US company UniEnergy Technologies (UET) and the Chinese company Rongke Power will jointly develop the largest battery up to now (June 2016). The maximum storage capacity of this battery is 800 MWH. The battery has to absorb the volatility in the supply of wind energy (http://www.duurzaambedrijfsleven.nl/industrie/15265/grootste-batterij-ter-wereld-wordt-game-changer-voor-energiesysteem).

2. Literature

The power market faces substantial changes. Large power companies like E.ON and RWE are planning to break up in two independent companies, namely in a company that produces electricity with renewables and in a company that produces electricity with fossil fuel. The German government is hesitating to give permission for such a split up because the second company may face high losses caused by large depreciations on fossil fuel plants.

The move from fossil fuel to renewables can also mean a switch from centralized to decentralized power generation. The next step is that decentralized produced electricity can also be consumed decentralized. The access to a grid is no longer a necessity. Instead of one (national) grid, a set of decentralized markets will develop. It will be the role of traders to avoid (large) price differences between the decentralized markets. In other words the role of the transmission system operator (TSO) will change or even disappear.

The switch from central to decentralized markets is also important for areas where national grids are facing problems with the security of delivery. In Europe we have mostly a central grid with several sidelines. When there is a problem on the grid it is mostly possible to deliver electricity to the demanders by using alternative lines. However, this is not always the case. For example, Italy has the mountain chain the Apennines. The grid exists of two main lines at both sides of the mountain chain. In the Netherlands, we have the same problems in the province of Zeeland, with its islands and peninsulas. Decentralized markets can in that case be an advantage.

After the liberalizations of the electricity markets at the end of the last century, we saw a tendency towards integration of various markets. Interconnectors linked the markets and as long as the capacity of the interconnectors was not fully used, the deviations of the prices between the linked markets was very limited. The general idea was that bringing all the demand and all the supply together on one market, the best price was guaranteed. The volatility of the electricity prices should be reduced and the price differences between the markets should be reduced. See for example Dorsman, Franx and Pottuijt (2012).

Integrated markets created the possibility to transform additional supply from one market to another. In case every country tries to keep its own grid in balance this system works well. However, the energy switch (Energiewende) in Germany makes the German grid less stable due to the unpredictable supply of solar and wind energy. The German Transmission system operator (TSO) cannot always handle this unexpected additional supply which not only causes negative prices from time to time, but also the necessity to export the additional supply to the neighboring grids. In other words, the integrated markets gives Germany the possibility to export its grid problems for free.

Gullberg et al. (2014) conclude that German actors see Norwegian electricity as a means for enhancing the stability of their electricity system. In other words, a cooperation with Norway can compensate the higher volatility in electricity supply due to the higher percent of wind and solar energy. However, Gullberg et al. also conclude that Norwegian state-owned electricity producers and grid operators are interested in cooperation largely out of profit motives and expect that Germany creates a favorable environment for investors. In the discussions about a new connector between the grids of Norway and Germany (more than 600 km underwater cable, price more than € 2 billion), the Norwegian state-owned partner has some doubts about the profitability of this project due to the (increasing) supply of wind and solar energy in Germany (Financieele Dagblad, March 28 2014).

Swift-Hook (2010) argues that grid-connected intermittent renewables like wind energy will never be stored unless nothing else is available and that storage is counterproductive for fuel saving. Due to the fact that the marginal costs of wind (and solar) energy are (nearly) zero, wind (and solar) energy will be used first, if it is available. Only in the case wind (and solar) energy is 100% of the total supply, you will store it. In other words, a shift in energy supply to renewables like wind energy are increasing the instability of the energy system on the grid. A switch in supply to more wind and solar energy means that you are driving out other alternatives with higher marginal costs and therefore are reducing the storage capacity of the system. However, Grant Wilson et al. (2011) show that for the United Kingdom there is evidence that grid-connected intermittent renewables have been, and will continue to be stored. If so, the shift to renewables is less destabilizing than was previously assumed. In his reply Swift-Hook (2013) argues that Grant Wilson et al. made some erroneous denials. Storing on a power system will normally takes place during night time when the electricity price will be low. Solar energy therefore is not compatible with storing. Supply of wind energy can take place during day- or nighttime. However, in all cases it is better to use the wind energy for direct consumption because - as we already mentioned - the marginal costs are very low.

We disagree with Swift-Hook. It is not only the price, but also the risk that counts. The certainty of supply is an essential element to get the grid in balance. Storing electricity generated by solar and wind energy can reduce the volatility of the supply of renewables energy and is therefore valuable. The last years several initiatives have been started to store the electricity generated by solar and wind energy. For example the energy company Wemag AG opened in 2014 in Germany a storage facility for solar and wind energy using batteries with a capacity of 5 MWh. Wemag claims that due to this installation the stability on the grid has been approved.

Jensen and Skytte (2002) were among the first who argued that due to the low marginal costs of renewable energy a shift from traditional energy sources (gas, oil, coal, nuclear energy) with higher marginal costs to renewable energy will cause lower electricity prices. Gelabert et al. (2011) show that for the observed period 2005-2009 an increase of 1 GWh of electricity production using renewables and cogeneration gives a reduction of almost € 2 per MWh in the electricity price. Due to the difference in marginal costs we will see higher renewable energy supply will cause the turn off of energy sources with higher marginal costs. As we earlier argued, this development leads to a higher instability of the electricity system on the grid.

Barnham et al. (2013) conclude that in Germany and Italy the exponential growth in solar energy leads to substantial lower peak electricity prices in both countries. They show that the demand on the German grid can be met by solar and wind energy with back-up from biogas and (pumped hydro) storage. However, the last years we see in Germany an enormous growth in the supply of wind and solar energy and it is questionable whether the backup from biogas and (pumped hydro) storage can follow this speed growth. Nevertheless the backup cannot eliminate a high supply in solar and wind energy when the weather conditions are sunny and windy, causing negative electricity prices. We have doubts about the backup capacity from biogas and hydro power. Real time balancing with biomass plants is very difficult. The flexibility with hydro power is much higher.[3] However, in Europe the capacity is relative low and due to the limited capacity of the connectors the possibility to transfer the (additional) supply of hydro power is not large enough to play a substantial role as back up for wind and solar energy.[4] The main benefit of gas plants is that they can be located at the best places for keeping the grids in balance. In that respect is the development: Power to Gas very interesting, because gas has the benefit of storing, easy transfer possibilities and therefore can be very helpful as backup for wind and solar energy.[5]

Winkler et al (2016) write that rising renewable shares influence electricity markets in several ways: among others prices are reduced and price volatilities increases. Wozabal et al. (2014) argue that there is not always a direct relationship between renewable shares and price volatility, for example when the renewables share is low and photovoltaics produce mainly during the midday demand peak.[6] During our observed period we see an increasing in the market share of renewables and we will test whether for the German market the influence of solar and wind energy on the electricity price increases.

However, the earlier described development to one central market with one universal price has been changed by the increasing supply of wind and solar energy. More and more households have solar panels (and wind mills). An excess of their supply can be delivered to the grid. Alanne and Saari (2006) wrote that more and more we will see that local generated supply will be locally used. The role of central grids is weakening and decentralized markets are developing.

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[3] see http://www.sciencedirect.com/science/article/pii/S0960148104000928
[4] See http://www.iea.org/publications/freepublications/publication/impact_of_wind_power.pdf
[5] http://en.wikipedia.org/wiki/Power_to_gas)
[6] Referral from Winkler et al (2016).

In this paper we will look at the influence of day-ahead predicted solar and wind energy on the realized day-ahead electricity price in Germany. In case we find that the supply of German solar and wind energy is a crucial factor in the price forming process. Extending this research to other countries is desirable to quantify the effects of the German energy switch on the stability of the grids in the neighboring countries.

3. The influence of predicted supply of renewables on the realized price in the German day-ahead market

3.1 Data

In our research we use the realized German day-ahead prices and the expected day-ahead supply of wind and solar energy. The period of observation started on January 1, 2009 and ended on December 12, 2015. On the day-ahead power exchange, spot prices are fixed for every hour of the next day. The data of the wind and solar energy are the expected data for the next day. For every quarter of an hour the next day the database contains an estimation for the expected solar and wind energy supply (in total: 96 estimations for each day.) This means that for every day we have 24 hourly day-ahead prices for the electricity prices and 96 day ahead solar and wind supplies. To make the data comparable we calculated for every hour the unweighted average of solar and wind supplies of the relevant quarters. Our database contains 60,684 observations (2536 days x 24 hours).

On the day-ahead power exchange, the prices for day *t+1* are fixed at 11.00 hours on day *t*. By doing so, the TSO (Transmission System Operator) - who is responsible for balancing demand and supply on the grid - is able to manage the positions on the grid the following day. To facilitate the price formation process, detailed predictions for solar and wind energy production for day *t+1* are released on day *t*. These predictions for day t+1 are collected in the morning of day t and released at 16.00 hours in the afternoon at day t. Strictly speaking this information is not available at the moment the day ahead prices for day t+1 are settled. Nevertheless we will assume that "the market" has access to this information about solar and wind energy for day t+1.

3.2. Descriptive statistics: daily and weekly patterns for predicted day-ahead price

As explained above, in this paper we are interested in three different data time series for the day-ahead market: the electricity price, supply of solar and supply of wind energy. In this section we decompose the time series of electricity prices to get a better understanding of the price-forming process. This information will be used in the subsequent regression analysis (section 3.3) where we explore how day-ahead electricity prices correlate with the day-ahead predicted supply of renewables (wind and solar). Not surprisingly, all three time series show clear daily and seasonal periods.

Fig. 1 gives the predicted day-ahead price for every day at the week, starting with the first timeslot on Sunday (0:00-1:00 hrs) and ending with the last timeslot (23:00-24:00 hrs) of the next Saturday 24.00 hours. During the weekend the price is lower than during the working days and during the day the price will be higher during day-time than during night-time. On Sunday we see a peak in the beginning of the evening which is different from the other days of the week.

Leaving the seasonal cycle aside for the time being, we can get a better idea of the daily and weekly profile by averaging the data out over the periods of interest. In fact, we will opt for a slightly more versatile analysis which decomposes the time series as a sum of data-determined profiles. Apart from its intrinsic interest, this decomposition will also be re-used in the regression analysis later on (see section 3.3).

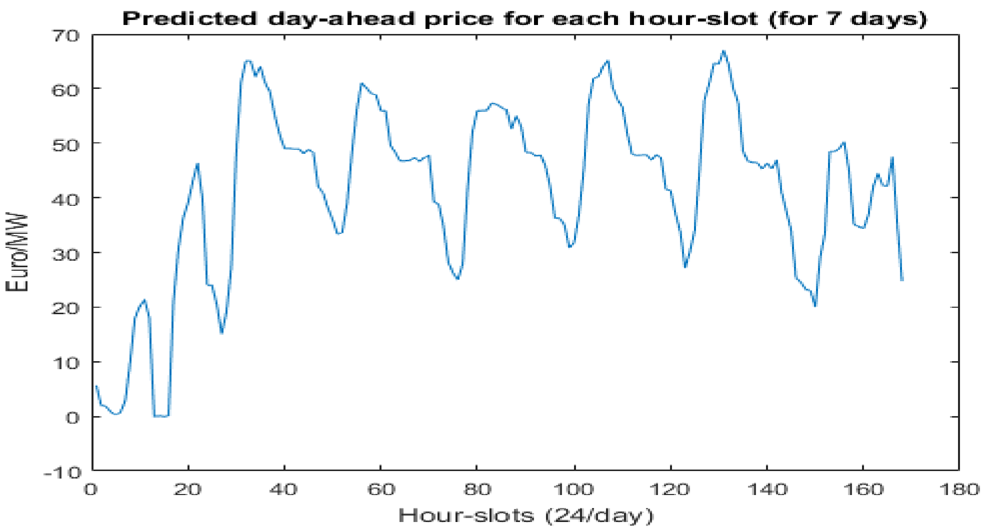


Fig. 1: Detail from the predicted day-ahead price showing 168 values (corresponding to one week of hourly values). The daily peaks during the work week are clearly visible.

The technical insight that allows us to explore this possibility is based on a mathematical technique called singular value decomposition (SVD for short). The idea is straightforward and can easily be explained using a concrete example. Since this analysis will be used throughout the rest of the paper we will spend some time expounding the underlying principles in the next paragraphs.

Suppose we have a time series covering hourly observations (24/day) during a year (365 days). We can now re-write this time series as a matrix by taking the first 24 observations and using them as the first row of the matrix, the next 24 observations go into the second row and so on, resulting in the time series being represented as a matrix with 365 rows and 24 columns. If the time series happened to be perfectly periodic, then all the rows would be identical. Such a matrix could be more economically expressed as the product of a column matrix (size = 365x1) and the row matrix with the day profile (size = 1x24). If, on the other hand, the day-profiles still had identical shape but different amplitudes, the column matrix would no longer be a column of ones, but a column filled with values proportional to the amplitudes of the profile.

Generalizing even further, if there were slight intra-day variations in the shape of the profile, then the product of a simple column and row matrix would no longer suffice to recover the original matrix. Instead it would be the first (and dominant) term in the sum of similar products, each of which providing additional corrections on the first order approximation detailed by the first term in the decomposition. Put differently, the SVD-based expansion yields a decomposition analogous to the well-known Fourier decomposition of periodic signals, except in this case the basis functions are not specified upfront (trigonometric function in case of Fourier analysis) but are determined by the data.

Fig. 2 illustrates the above by providing some examples from the actual price data (for the period 2013-2015).

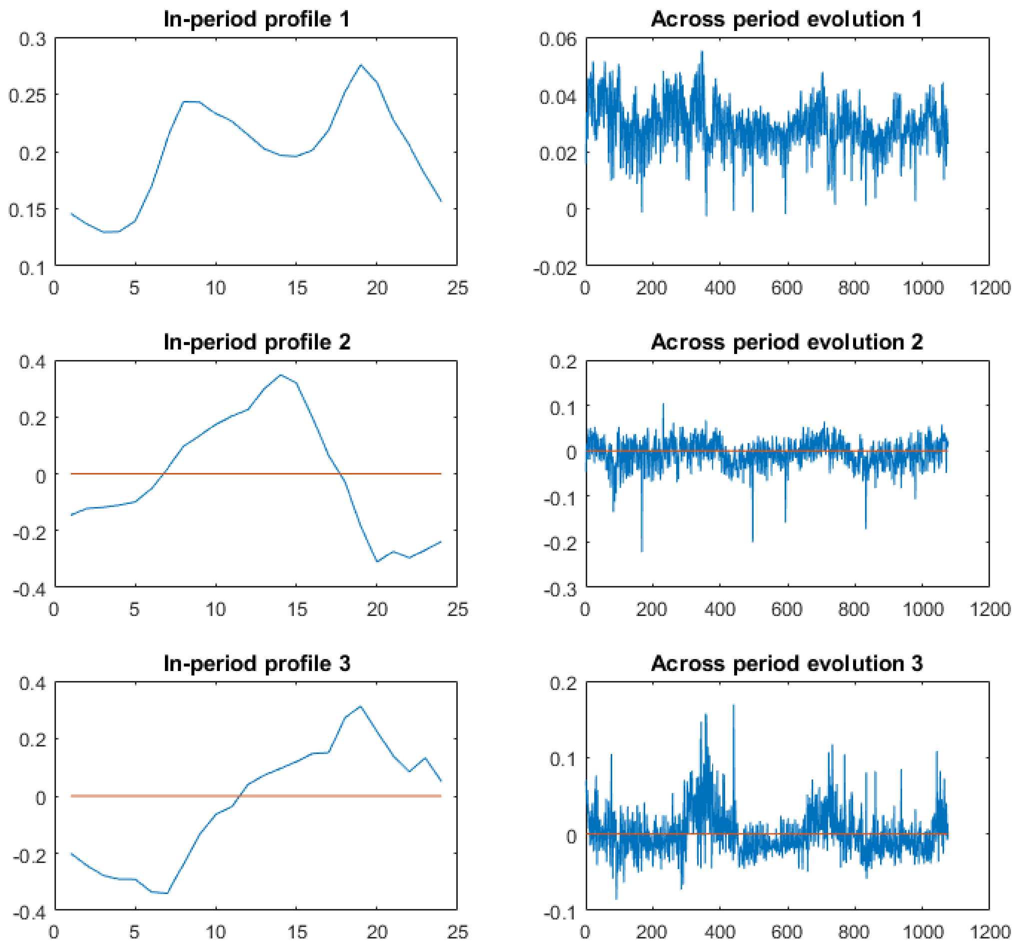


Fig. 2: First three components in the SVD decomposition of the price timeseries (using the timespan of a day as the fundamental period).

In the left column we get the first three (i.e. most dominant) daily price profiles (one data point for each of the 24 hour slots). The first component (top-left) is the daily average, showing the expected bi-modal appearance corresponding to high prices at peak times in the morning and afternoon. The flanking time series on the right specifies the amplitudes (one data point for each day) by which the profile needs to be scaled to obtain a first approximation for the data on the actual day. However, not every day in the year has the same predicted day-ahead price. The price depends on several variables, such as time of the year, holiday on no holiday and possible - but that is the research question in this study - the supply of solar and wind energy. In other words, there is not a predicted day-ahead price which is for every day the same.

We decompose the data series in components and try to label the components to factors like weekend, season etc. To make a good prediction of the electricity price during the day, we have to correct the predicted price on the first graph for additional factors, for example the components 2 and 3.

The next profiles (rows 2 and 3 in the left column) attempt to capture this intra-day variation. More specifically, the second component (Fig. 2, 2^{nd} row, left column) attempts to increase the value in the middle of the day (peak times) while simultaneously decreasing the values in the evening and night period (for which it shows negative values). Flanking on its right hand side, we find the corresponding coefficients (one per day) which we need to apply to the profile in order to find the appropriate correction for each day. Notice that when this coefficient is positive, the correction will result in a less pronounced bi-modal profile, while a negative coefficient will give rise to a more pronounced bi-modal profile. The explanation for the last row is similar: this time the correction (at least in combination with a positive coefficient) will increase the price in the afternoon, while lowering it in the morning. The ordering of the component profiles is such that successive terms have corresponding lower impact, hence truncating the series after k terms results in the best possible approximation with at most k terms.

The effect of the approximation is further illustrated in the Figure 3:

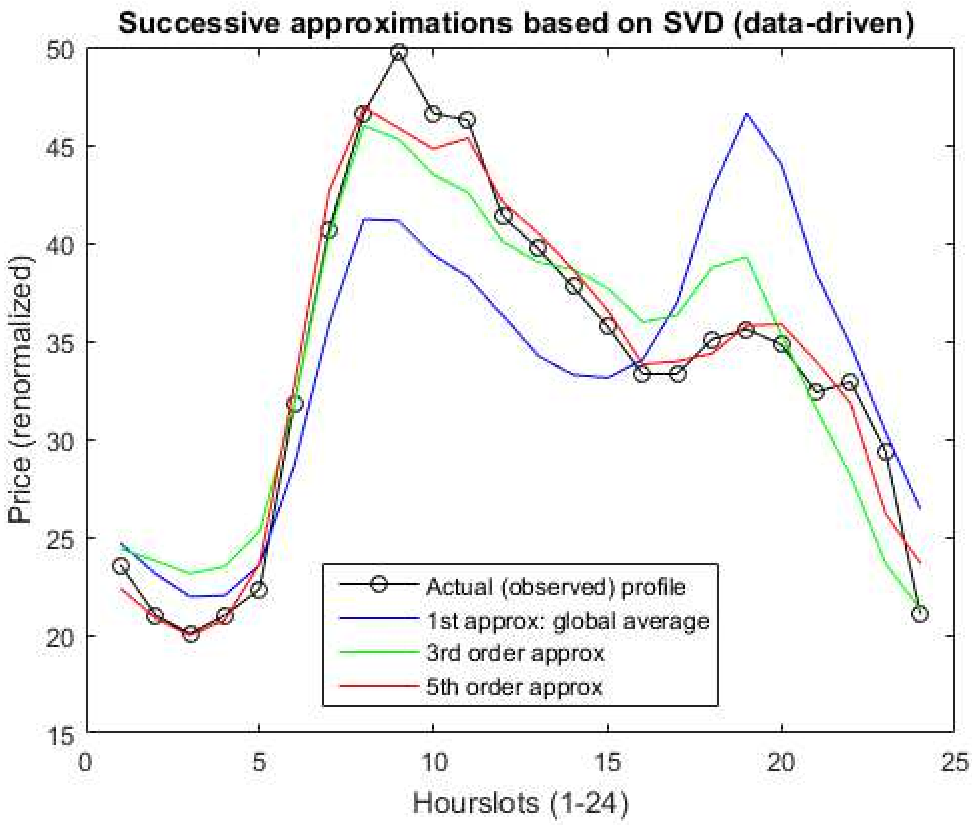


Fig. 3: Illustrating the effect of adding successive components in the SVD expansion for the predicted day-ahead price for one particular day.

The actual price values for a single day are shown in black. The first approximation based on the globally averaged day-profile is shown in blue. Two further approximations are also shown (3rd order in green, and 5th order in red). It is clear that (at least in this case) the 5th order approximation (based on the blue global approximation to which 4 successively smaller correcting profiles have been added) is already fairly accurate.

In summary (see Fig. 4): Because of the strong periodicities in the time series we use the SVD algorithm to decompose the observed data into a sum of periodic components (of decreasing importance). Truncating this expansion at the k-th term results in a data-driven approximation the residuals for which are now a (mean) stationary time series. Because of the stationarity of the residuals, identifying outliers can be done by straightforward thresholding.

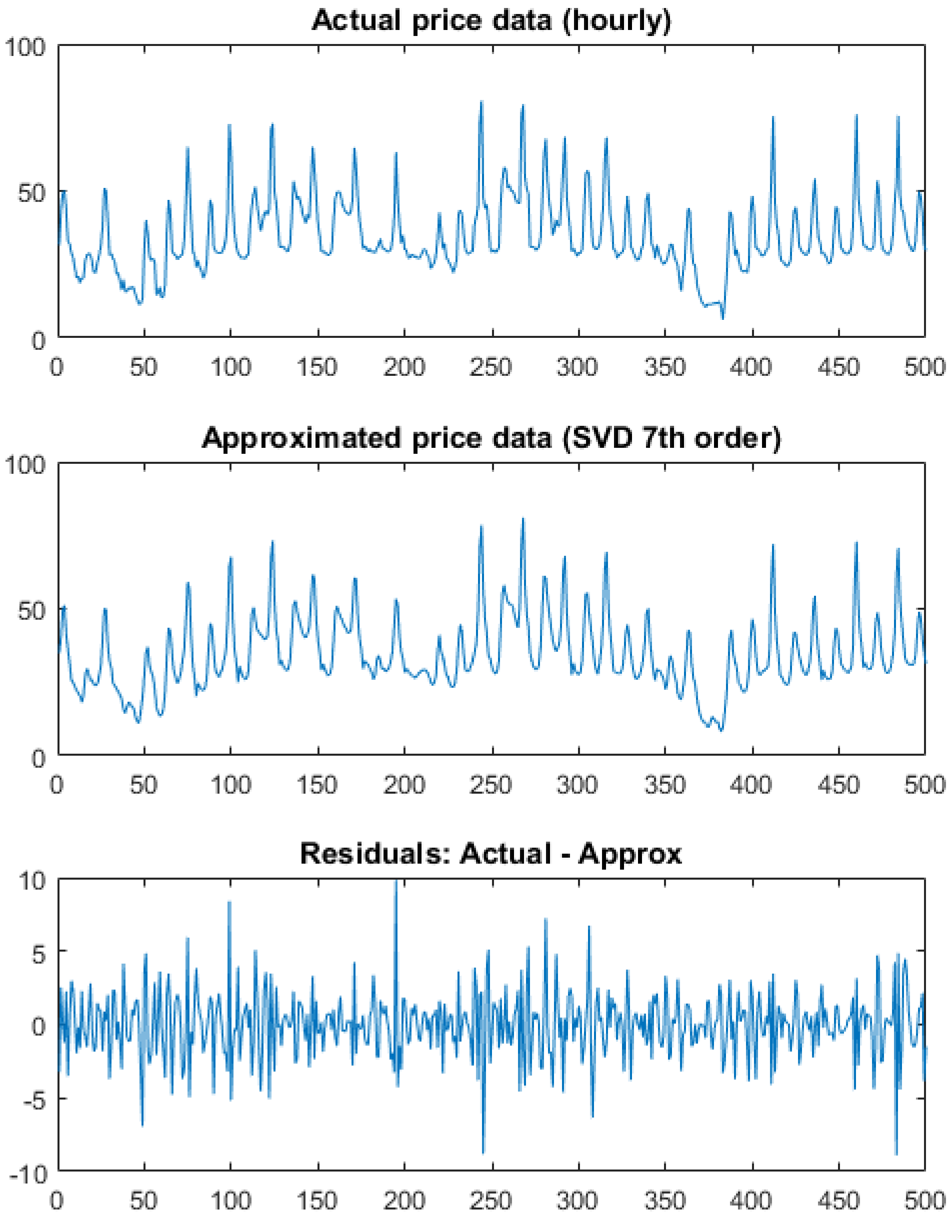


Fig. 4: Top: Actual time series. Middle: Approximation based on the first seven SVD components. Bottom: Residuals (stationary time series).

3.3 Daily and weekly pattern for realised price on day-ahead market

Daily pattern: The top graph in Fig. 5 shows the averaged day profile obtained from the SVD analysis (which in fact is equivalent to averaging out over all days in the time series). The electricity price during peak hours is - as expected - higher than during off-peak hours. The bottom panel in Fig. 5 graphs the inter-day variability between the day averages. It is basically a down-sampled version of the original time series. Put differently, we can get a first order approximation of the original data by multiplying the day profile (top panel) by the amplitude of each point (one per day) in the time series depicted in the bottom panel and concatenating all the results (to reconstruct a time series that has the same length as the original one).

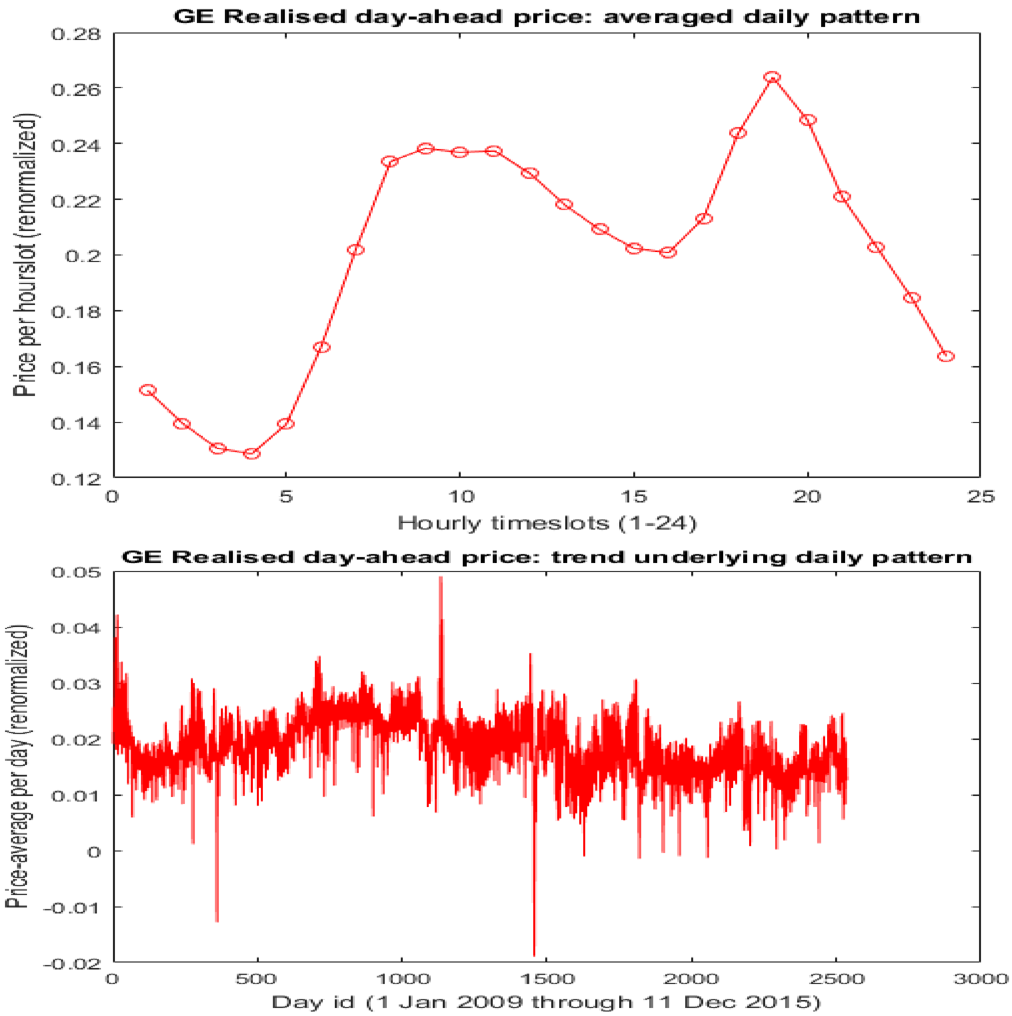
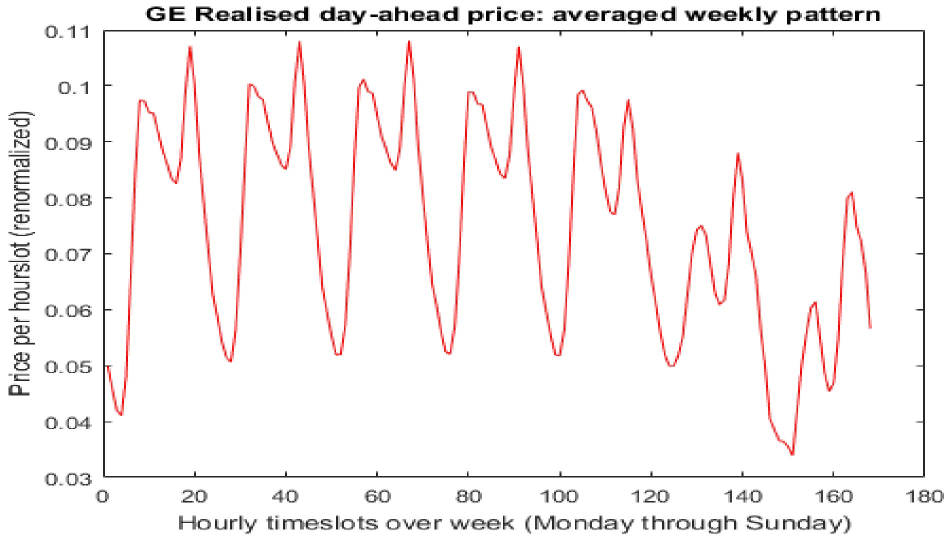


Fig. 5: SVD (Rank-1) approximation of the realized day-ahead price for Germany during the observed period 1 Jan 2009 through 11 Dec 2015. Top: Averaged daily profile (24 values per day). Bottom: Inter-day variability for the averaged day-profile.

Weekly pattern: All of the analysis in the preceding paragraphs focused on the daily patterns. Of course, since price depends on human activity, it also exhibits a weekly periodicity. Fig. 6 gives the weekly pattern of the German electricity price. On the horizontal axis we have the 7x24 =168 hour-slots (ranging Monday through Sunday). The graph (average over the week) clearly shows the seven days. The influence of the weekend (last two days) is already noticeable on Friday afternoons which is in line with expectations. The accompanying plot shows the scale factors that need to be applied to this weekly profile account for the inter-week variation (at least to a first approximation).



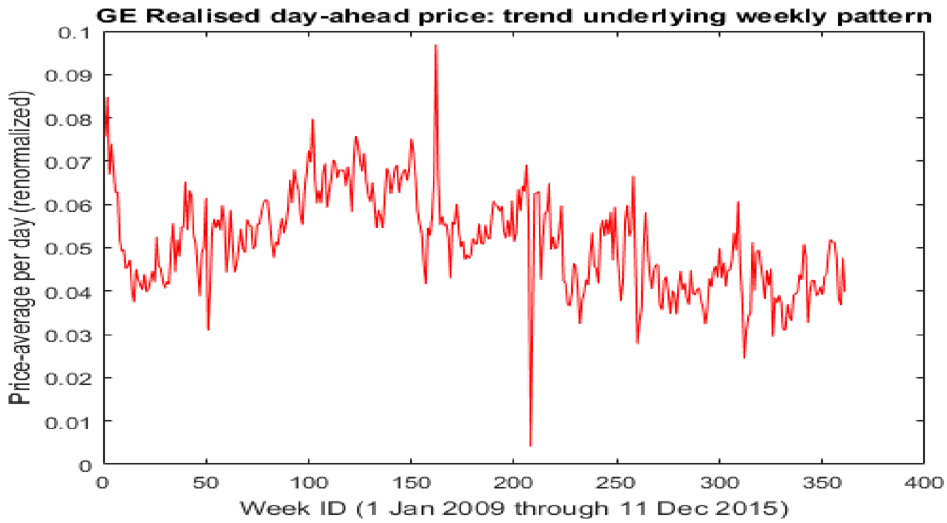


Fig. 6: SVD (Rank-1) approximation of the realized day-ahead price for Germany during the observed period 1 Jan 2009 through 11 Dec 2015. Top: Averaged weekly profile (24 values per day). Bottom: Inter-week variability for the averaged week-profile.

3.4. Periodic patterns in day-ahead forecasts for solar and wind energy

Obviously, the supply of solar and wind energy varies across days and seasons, which is going to be reflected in the day-ahead predictions. However it is important to notice that the predictions for solar and wind show very different volatility.

Solar: In Fig. 7 we have plotted the day-ahead prediction for solar energy during one particular week, i.e. a sample of seven successive days.

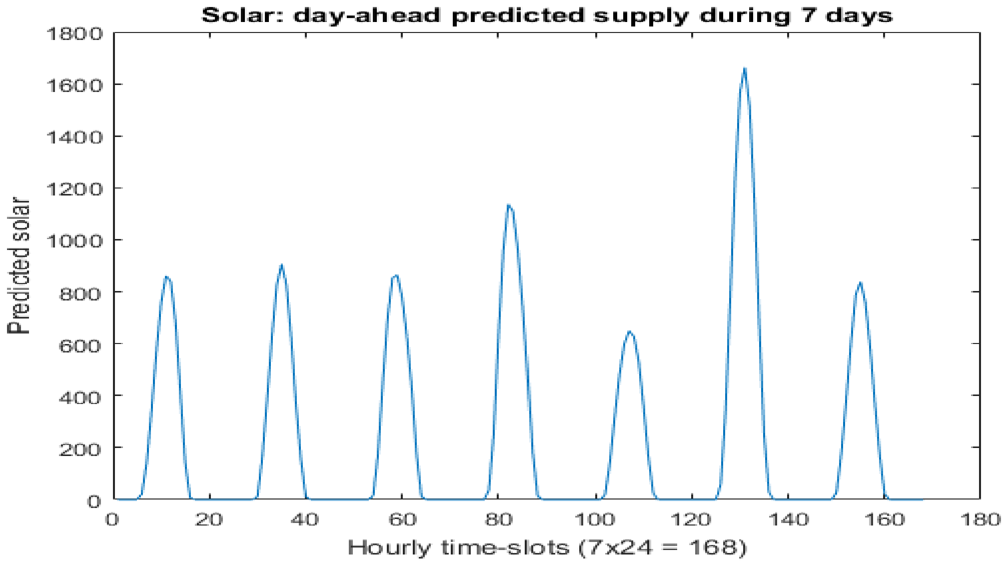


Fig. 7: The solar day-ahead prediction during seven successive days.

From the sample figure above it is clear that prediction of solar is relatively rough: it is basically rectified sine wave, of which the amplitude is scaled up or down (depending on weather forecasts). Using the SVD-based rank-1 approximation to get a daily profile we obtain the following results:

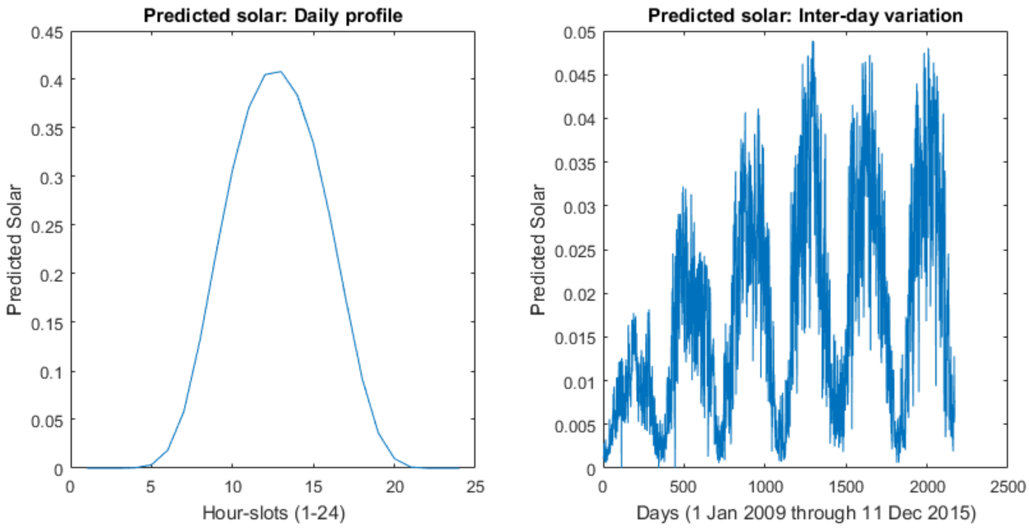


Fig. 8: LEFT: Average daily profile for predicted day-ahead solar supply. RIGHT: Inter-day variation in predicted solar supply during 6 years.

Repeating the same analysis but this time taking the period to be equal to one year, yields an annual profile that clearly peaks in the summer (middle months, see Fig 9). The horizontal axis of the left graph of fig. 9 gives the hours of the year 8760 (= 24 * 365) and starts with 0.00 hours on January 1 and ends on December 31 24.00 hours. For every day in the year we calculated the unweighted averages of the expected solar energy during that day in the several years during the observed period. For example the predicted solar energy for June 8 18.00 -19.00 hours is the unweighted average of predicted solar energy during that time frame of the June 8 in 2009, 2010, ..., 2015. In the right graph of fig. 9. we look ath the predicted solar energy as function of the time. During the observed period we see that the supply of solar energy increases very rapidly during the first years (2010-2013), but after that period there seems to be a marked leveling off.

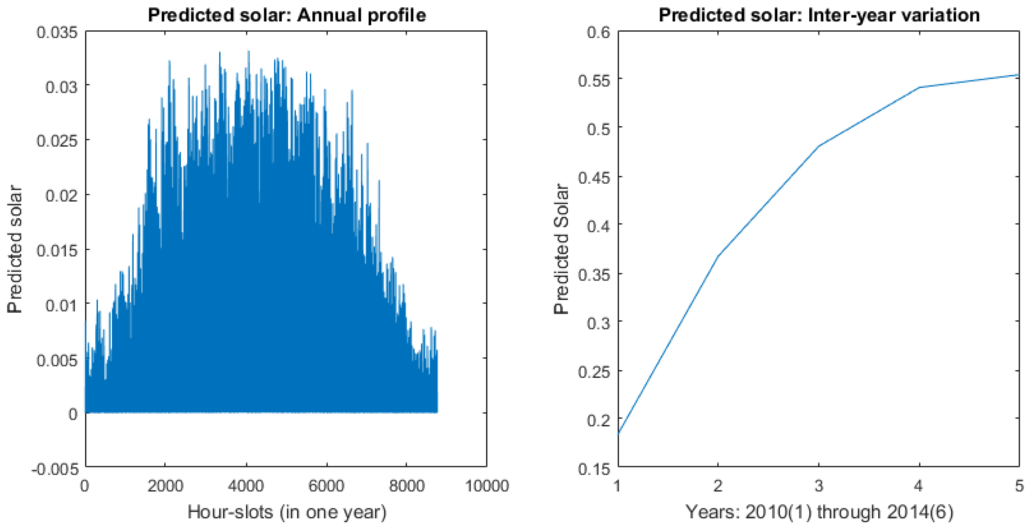


Fig. 9: Solar supply, annual pattern. LEFT: Predicted pattern averaged over several years. RIGHT: Inter-year trend from 2010 through 2015.

Wind: The forecasts for wind energy are more sophisticated and consequently show a higher volatility as can be seen in the figure 10 which again charts the predicted wind for each hour-slot in a particular week (i.e. a sample of seven consecutive days).

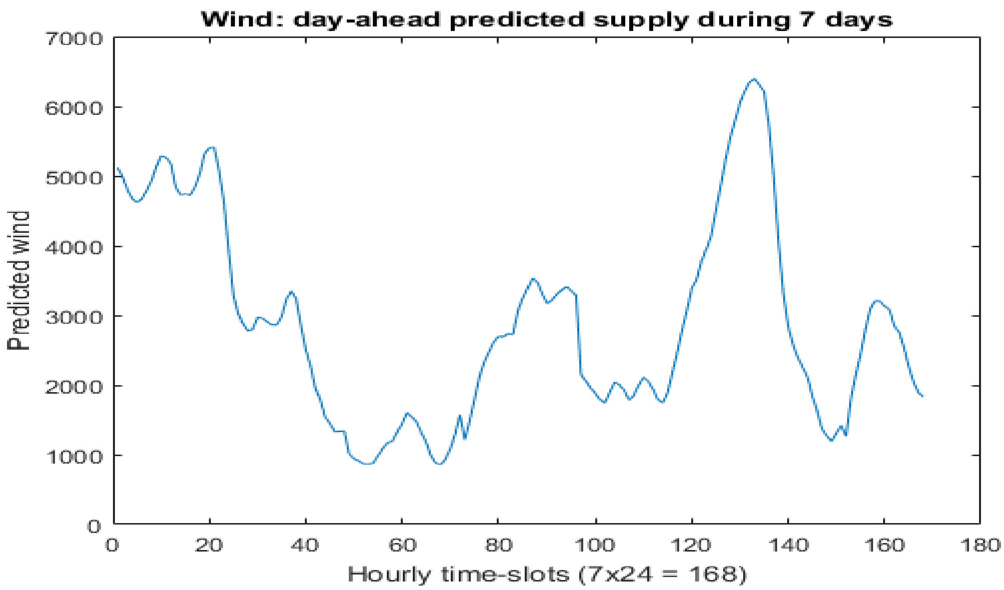


Fig. 10: Day-ahead prediction for wind supply for one week (168 hourly values).

Although the wind data look erratic it is interesting to apply the SVD-based rank-1 decomposition to the dataset (covering 2009 through 2015) to extract the average daily profile. The result can be seen in Fig. 11:

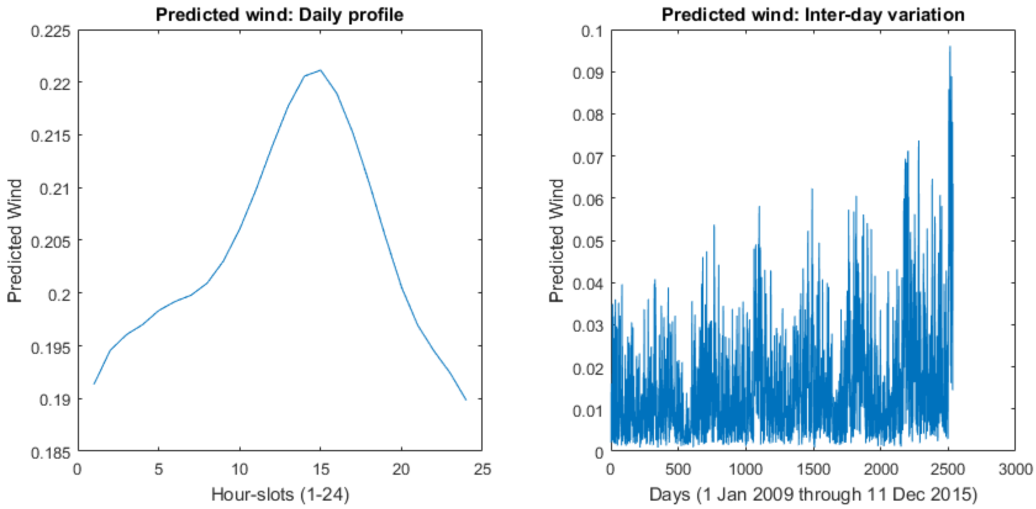


Fig. 11: WIND: SVD-based rank-1 approximation. LEFT: Averaged daily profile. RIGHT: Inter-day variation.

The daily profile shows a marked peak during the early afternoon (around 15.00 hours). The inter-day variation on the other hand shows the steady increase in the total wind supply over the course of the seven year period. It is not surprising that the supply of wind energy is the highest during that period of the day. Wind is the flow of air from places with high air pressures to places with low air pressures. During the day the sun warms the air, more above land than above see. The air pressures decreases and a (see) wind will start or increase in power. A first indication that the supply of wind energy influences the electricity price is that the graph of the electricity price (see fig. 3) shows a price decrease after the morning peak and the local minimum is around 15.00 hours, exactly the time when the supply of wind energy is at its highest.

To highlight this trend more clearly we conduct the same analysis as above, but this time we take a year (365*24 obs) as the relevant period. This result in the following profiles (see Fig. 12) :

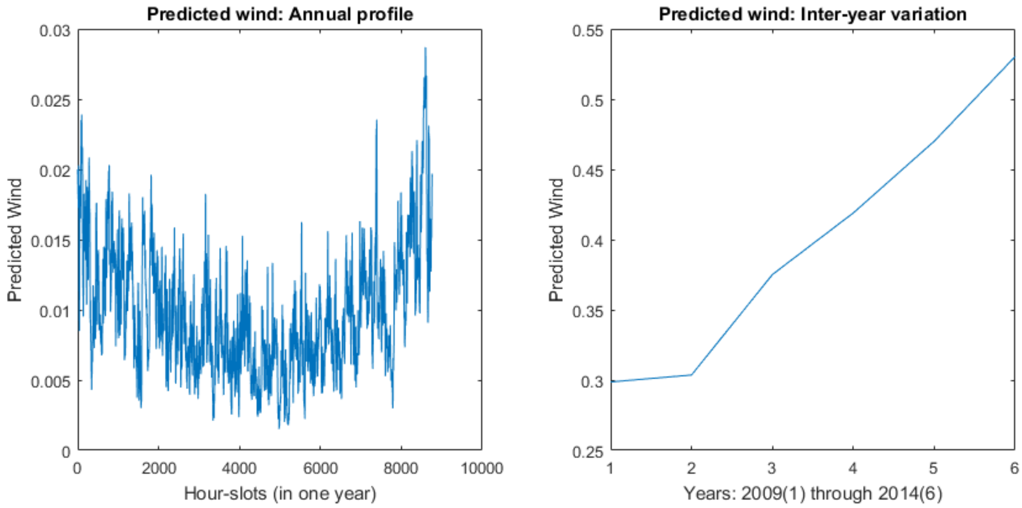


Fig. 12: WIND, LEFT: Averaged annual profile. RIGHT: inter-year trend.

The horizontal axis gives the 8760 hours of the year, starting with 0.00 hours of January 1 and ending with 24.00 hours December 31. Our observed period encompasses nearly six years, which means that every value of the predicted wind energy in the annual profile is the unweighted average of seven individual observations (with exception of the period December 12-December 31; they are the unweighted average of six observations). The annual profile on the left clearly shows that wind is expected to be stronger in the winter than in the summer months (middle of the year). Furthermore, the inter-year variation clearly shows that the total capacity grows approximately linearly starting in 2010. The right graphs of fig. 9 and fig. 12 show a decreasing growth of supply of solar energy and a continuous growth of supply of wind energy. Comparing to wind energy solar energy is losing market share in the supply of energy.

3.5 The influence of solar and wind energy on the electricity price

In this section we return to question considered in an earlier publication (ADFP,2014) in which the authors investigate the influence of the (day-ahead) predicted supply of wind and solar on the realized day-ahead spot price in each hourly timeslot. The complicated nature of the regression function found in (ADFP,2014) is not surprising in view of the fact that (at least on average) wind and solar input shows a clear pattern throughout the day. These patterns have been discussed extensively in the previous sections. Loosely speaking, all variables are connected through their (non-linear) dependence on the time of day. As a consequence, the regression function proposed in (ADFP,2014) turns out to be complicated, involving non-linear effects and interaction terms.

In this paper we propose to proceed along different lines by looking at the SVD-based representation of the data. Recall that all the predicted data are issued as a batch (of 24 hour values) on the previous day. Hence, rather than focusing on individual hour-slots it makes sense to investigate whether, for example, the predicted *day-profile* for wind has an influence on the corresponding predicted *day-profile* for price. Since we intend to look at day-profiles, the SVD-decomposition provides us with exactly the sort of information that we need.

This is illustrated in the fig. 13 where we regressed the amplitude coefficient for the predicted price on the amplitude coefficient for predicted wind (including all the data ranging from 2009 through 2015).

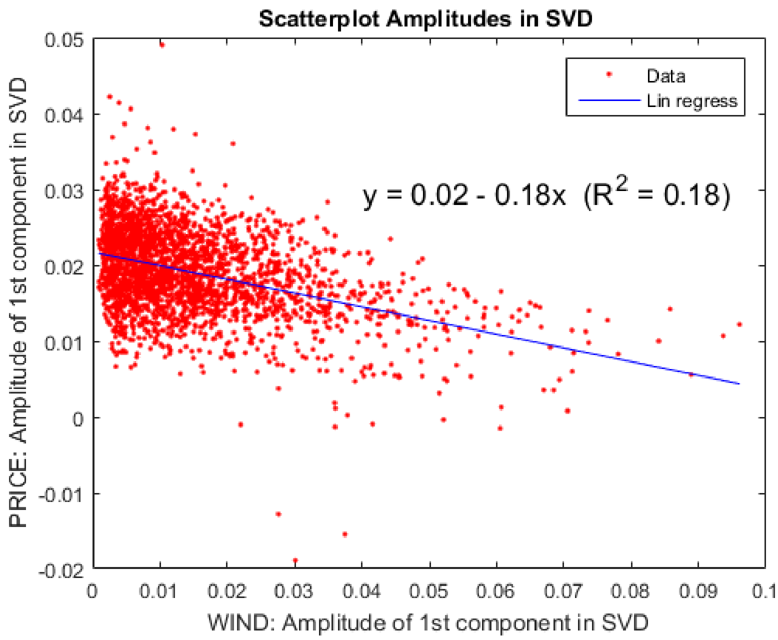


Fig. 13 The electricity price as function of the wind energy for the whole observed period

There is a clear negative correlation between the two variables (with correlation coefficient = - 0.42) resulting in a regression line with highly significant coefficients (significance above 99%). Intuitively, this makes sense: high values for the first component in the SVD-expansion for wind, means that the average value for predicted wind is high, resulting in a lower averaged price. In the next paragraph we will look in more detail at these data, and we make a distinction between the more recent period (2013-2015) and the data from earlier period (2011-2012) as supply of wind and solar is quite different in these periods.

Period 2013-2015:

We first focus on the influence of wind on the price. By regressing the first component of the SVD expansion of the predicted price on the first component of the predicted wind we get the following results (also see Fig. 14):

Price_comp_1 = 0.03 - 0.20 Wind_comp_1 (with R^2 = 0.21),

confirming the expected inverse relationship between price and predicted wind supply. Indeed, the negative coefficient (-0.20) indicates that higher averaged expected wind supply tends to be associated with a reduction in the averaged predicted price.
Motivated by this result we investigate other relations between the observed amplitudes in the SVD expansion.

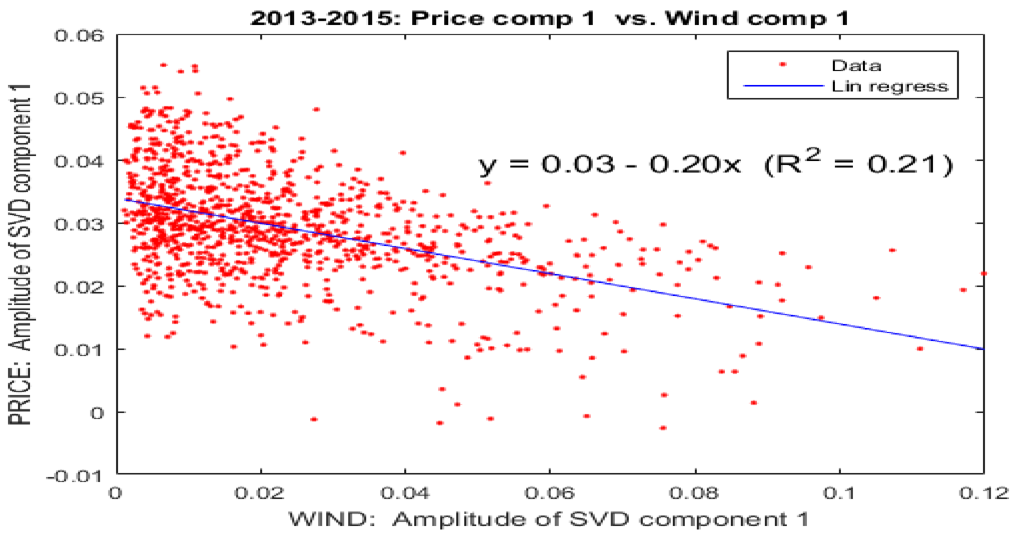
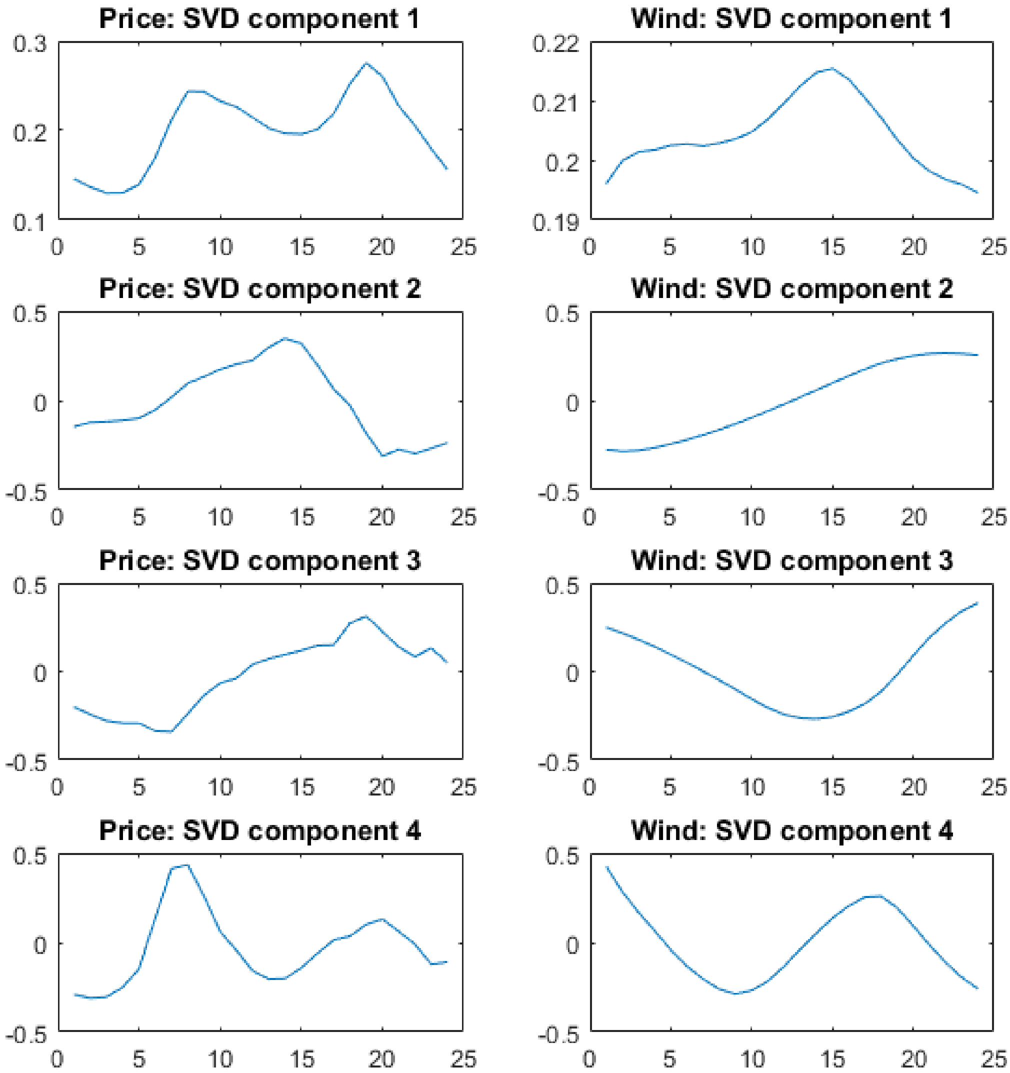


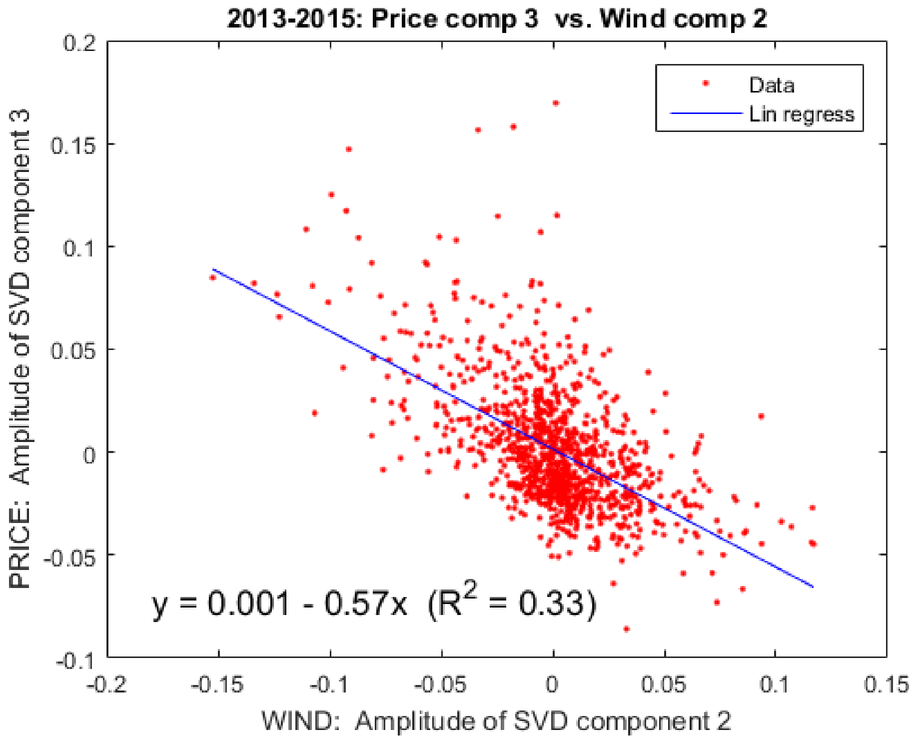
Fig. 14 The electricity price as function of the wind energy for the sub period 2013-2015

In Fig. 15 we have plotted the first four components of the SVD expansion of both the predicted price (left column) and wind (right column). The relations between the day-averaged profiles have been discussed above.

By comparing the shapes of the successive components, the (rough) equivalence between the second and third components of both columns becomes apparent. More specifically, if the high (predicted) wind yield should have dampening impact on the price we expect a strong negative correlation between the 2^{nd} wind component and the 3^{rd} price one, and also the 3^{rd} wind component and 2^{nd} price one (after flipping its sign). This is confirmed by the detailed regression analysis as illustrated in Fig. 16:



Figuur 15: First four components in the SVD expansion of price (left) and wind (right). Notice the similarity in shape between the 3rd price component and the second wind component.



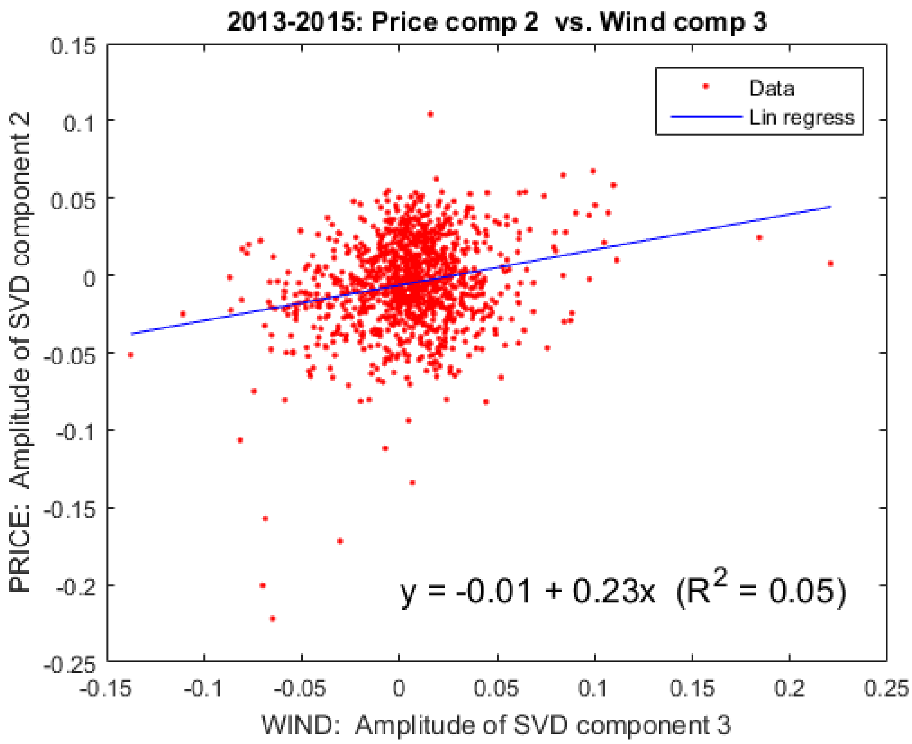


Fig. 16: Regression of different components of wind and price.

From the above it can be concluded that it makes sense to predict the first five (say) components in the SVD expansion of the price using the first five SVD components in for the wind data.

Based on the considerations above, we propose the following regression strategy to investigate the impact of the predicted wind supply on the predicted price. Rather than regressing the predicted price in each hourly timeslot on the predicted wind supply in that slot (the approach that was adopted in ADFP,2014), we regress the whole price profile for the next day on the day-profile for predicted wind. More precisely we proceed as follows:

1. For each day (d) expand the predicted price and wind supply in terms of the SVD components:

$$Price(d) = a_1(d)\phi_1 + a_2(d)\phi_2 + \ldots a_{24}(d)\phi_{24}$$

$$Wind(d) = b_1(d)\psi_1 + b_2(d)\psi_2 + \ldots b_{24}(d)\psi_{24}$$

   In the above expansion the basic functions on the right hand side or the SVD components, the first four of which are represented in Fig. 15 (Price in left column, Wind in right column).
2. Now use linear regression to predict the price-coefficients (a's) based on the knowledge of the wind-coefficients (b's). We refer to Fig. 16 where the regression is performed to compute an estimate for a3 in terms of b2 (top) and a2 in terms of b3 (bottom).
3. Once we can predict all (or most of) the a-coefficients in terms of the b-coefficients, we can reconstruct the predicted profile for the price. Put differently, this means that we have predicted the price starting from the wind supply.
4. Restricting our attention to the first 10 coefficients in both expansions, the regression-based estimates about 44% of the variation (R2 = 0.44). Fig 17 below shows both the realized day-ahead price and the approximation based on the wind information.

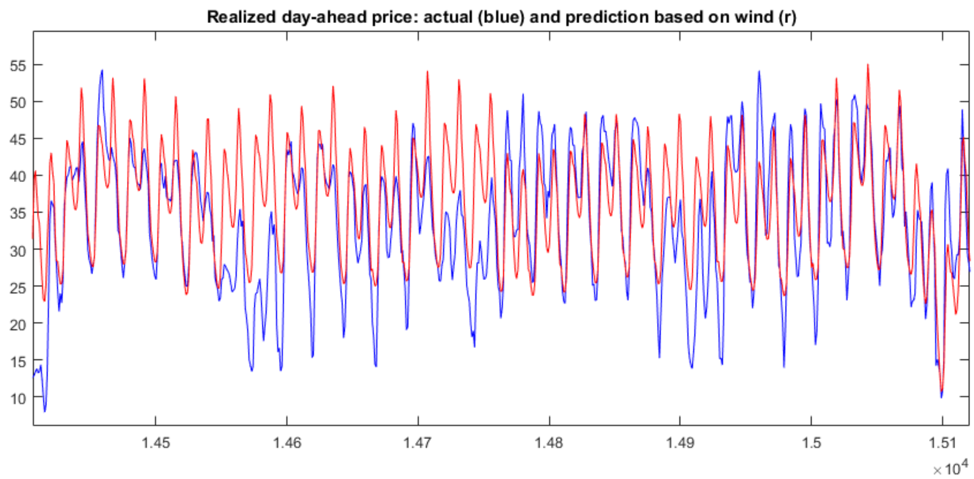


Fig. 17: Realized day-ahead price: actual (blue) and prediction based on predicted wind (red).

The above results can also be illustrated by looking at the scatter plot of the realized day-ahead price versus the predicted day-ahead price using the predicted wind supply as predictor (see Fig 18 below)

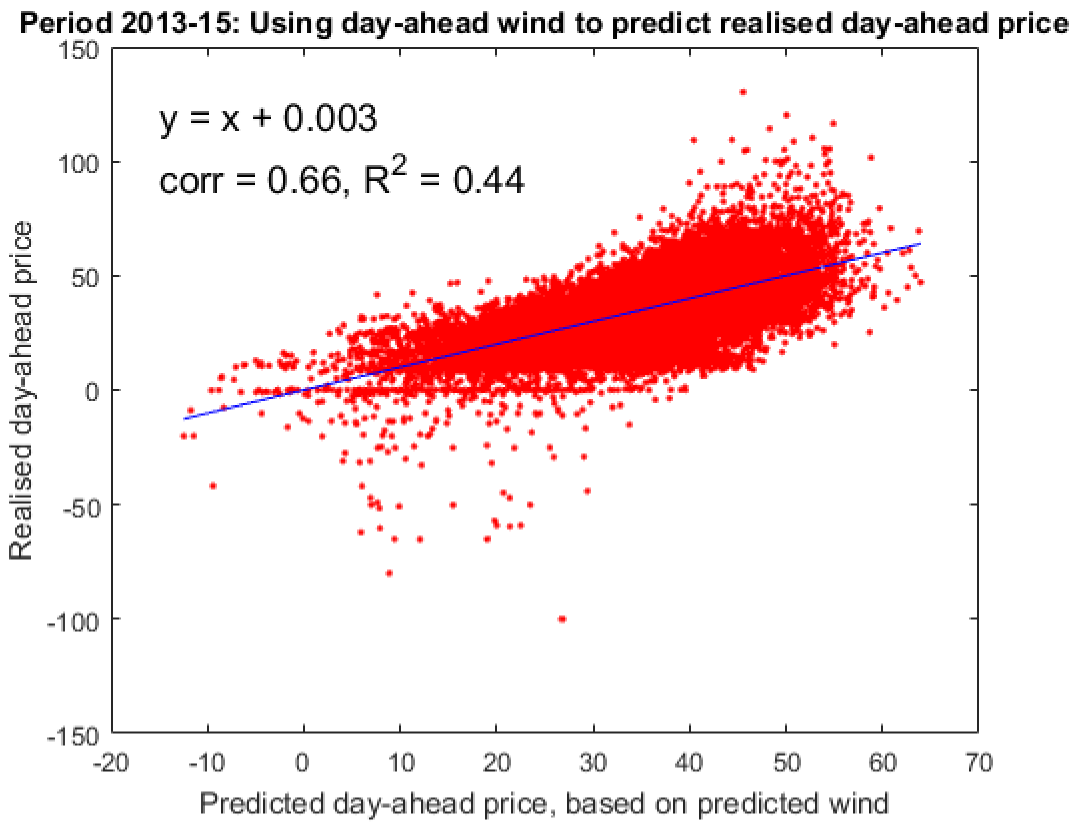


Fig. 18 Predicted day-ahead price, based on predicted wind energy

This plot is informative because it confirms the numerical results reported above:

- Fitting a regression line through the scatter plot, essentially coincides with the first bisectrix (y = x), indicating that the predicted price is correct on average.
- However, the considerable width of variation of scatter plot about the regression line means that only part of the variation has been explained confirming the value R2 = 0.44 reported above.

Periods 2009-2010 and 2011-2102

We redo the above analysis for the earlier periods 2009-2010 and 2011-2012, we get similar results, with slightly different values for the amount of explained variation:

- 2009-2010: R2 = 0.38,
- 2011-2012: R2 = 0.43
- 2013-2015: R2 = 0.44

The modest increase in explained variation might reflect the increase in wind-energy penetration and its subsequent impact on the price.

Repeating the analysis for solar
Repeating the analysis but this time using the day-ahead prediction for solar supply yields similar results, summarized in Fig.19 below. Again we see that the regression plot coincides with the first bisectrix (y = x) indicating that the prediction is correct on average. However, the width of the scatterplot about the regression line shows that only part (40%) of the variation has been explained (as can be expected).

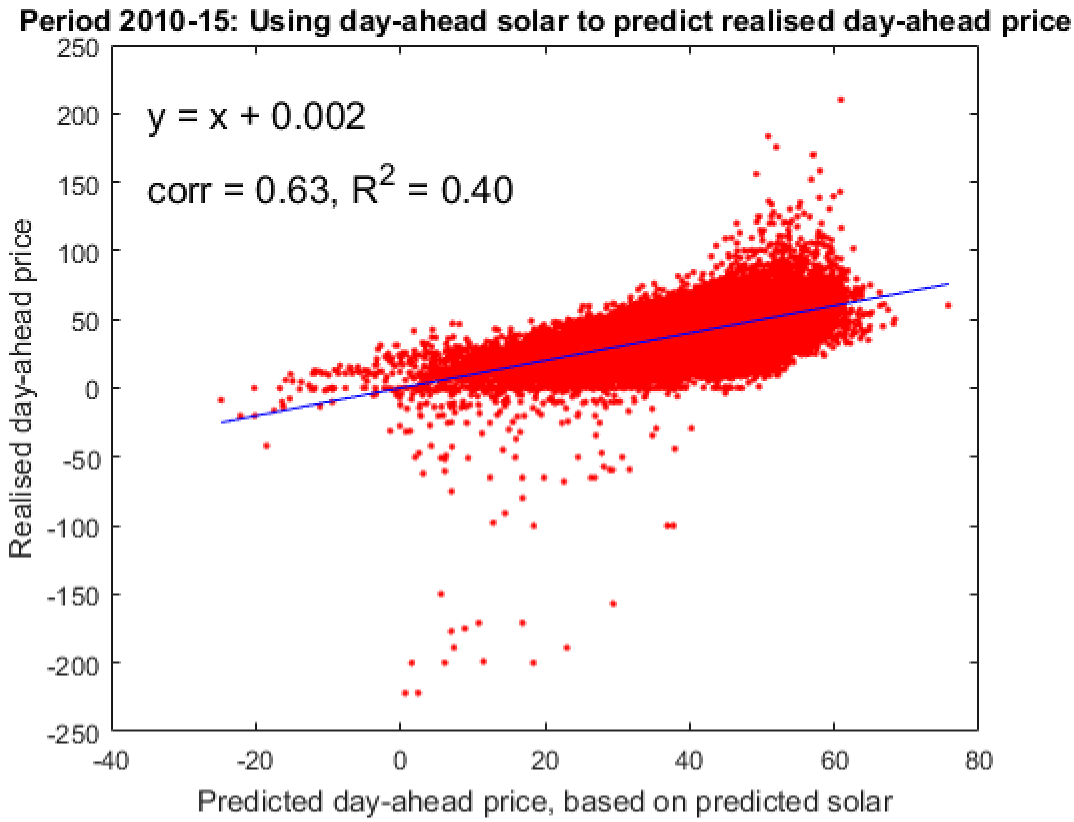


Fig. 19 Predicted day-ahead price, based on predicted solar energy

4 Summary

In this paper we looked at the influence of the German solar and wind energy in the electricity prices in German day-ahead market. During the observed period (January 1 2009 - December 12 2015) the energy policy of Germany changed very rapidly. The German government decided to close down nuclear energy in a couple of years, to reduce the dependency of gas and oil supply and fully supported the production of solar and wind energy. These energy switch (in German: Energiewende) has several causes. Firstly, the marginal costs of solar and wind energy is (nearly) zero. The construction costs of solar panels and wind turbines are high, but when the production facility starts to produce, the costs are very low. The low marginal costs means that solar and wind energy drive the oil and gas suppliers out of the market. Secondly, because the volatility of solar and wind energy is much higher than the supply of electricity generated by gas and oil, the instability of the grid increases. The need for batteries to create storage capacity for solar and wind energy is high.

In this study the research question is: What is the influence of solar and wind energy on the electricity price in Germany? Before answering this question we first looked at the time series of electricity prices, supply of solar energy and supply of wind energy. Clearly daily, weekly and annual patterns could be elucidated by applying and SVD-based approximation. Furthermore, these profiles could be used in a regression analysis to highlight the impact of predicted solar and wind supply on the day-ahead price. We show that both solar energy and wind energy has a significant negative influence on the electricity price in Germany. We also showed that the supply of solar energy is reaching a certain level, while the supply of wind energy is still growing.

The several European grids (electricity networks) are linked to each other by so-called interconnectors. The impact of an imbalance on a certain market can be reduced by transporting it to other grids. TSO's (Transmission System Operators) that have the task to keep the grid in their area in balance can help each other. However, due to the energy switch in Germany, the grid in Germany became less stable. Imbalances on the German grid can cause imbalance on the grids of the neighboring countries. How to reduce the imbalance caused by a higher market share of solar and wind energy is the main topic in the energy sector the coming years.

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