# Effects of increasing wind power penetration on the physical operation of large electricity market systems

Bernd Klöckl, *Member, IEEE*, and Pierre Pinson

***Abstract*—This contribution describes indirect coupling effects between wind power infeed and physical operation of power market systems by means of qualitative hypotheses, backed by suited exploratory data analyses. As an example, the case of a central European TSO located in the vicinity of a control block with high wind penetration is demonstrated. It shows, based on established methods of computational statistics, considerable nonlinear effects on cross border power flows and transmission system flows of that control block, conditional on increasing wind power penetration in an interconnected market system. The observed effects are theoretically explained through the influence of the wind infeed on the behaviour of market participants and attributed to indirect coupling between wind power and conventional generation in adjacent control blocks.**

***Index Terms*—Wind power, energy market, cross border flows, principal component analysis.**

## I. Introduction

THE rapidly increasing share of wind generation in the European energy markets, together with further progress in their liberalization has led to a number of direct and indirect effects of wind power injection on flow patterns in the transmission systems and has increased the operational challenges for TSOs. The developments throughout the last years have shown that increasing the share of wind generation beyond certain levels has created the need for further investigations on the following issues:

1) connection issues and grid codes (technical)
2) high concentrations of volatile infeeds in certain areas, e.g. close to windy coast lines, leading to the need for infrastructure reinforcements, especially in the transmission system (technical)
3) implications of day-ahead wind forecasts on the wholesale electricity prices in a given market area (economic)
4) coupling of these implications to adjacent markets and TSOs (economic)
5) increasing wide-scale influence of wind generation on the behaviour of conventional generation (economic)
6) thus increasing operational challenges for TSOs beyond the effect of the wind infeed itself (techno-economic).

The first two points above are currently being extensively treated by planning and operation staff of DSOs and TSOs, and the last point is experienced more and more by the grid operation staff. In this paper, the authors elaborate on the points 3 to 5, which is a simplified functional chain creating a feedback loop between technical and economic issues of wind generation.

The remainder of the paper is structured in the following way: First, a general overview of the EU transmission system with respect to the market operation and a glimpse on the most obvious effects of wind infeed is given. Then, a suited statistical analysis method for the problem set is derived. This analysis is exemplified on the measurements taken from the system of a central European TSO being indirectly affected by large wind power penetrations in adjacent markets. The conclusions attempt to relate the observed effects to future investigation needs.

## II. Effects of wind power on market prices

### A. The EU market and transmission system

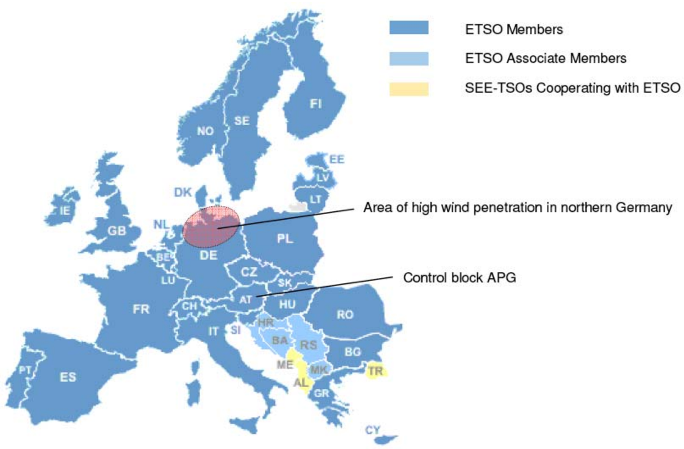


Fig. 1. Overview of the ETSO member states and the related EU market zones. The geographical distance between northern Germany and the APG block as indicated is approximately 750 km.

The European transmission system operators are organized in ETSO [1], which is an association that covers five different synchronous zones. The largest zone of the EU transmission network is the UCTE grid, that links all national transmission systems of continental Europe except for the Baltic states (Fig. 1). It is one of the largest synchronous systems in the world with an installed generation capacity of approximately 650 GW [2]. For the time being, the different national transmission networks represent market zones that are technically

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connected by sets of tie lines and commercially linked by allocation mechanisms for the cross-border transmission capacities.

### B. Observed interaction of wind generation and spot prices

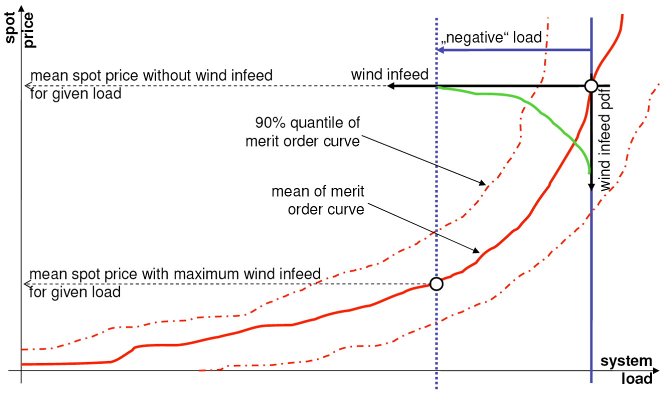


Fig. 2. Potential shift of the market settlement price on the aggregated merit order curve of a price zone in dependence on wind generation. Quantiles of the merit order curve (e.g. a 90% quantile) are indicated as an illustration of the uncertainty of the market settlement prices as a consequence of market imperfections and other factors.

Recently, the effect of wind power on market prices has been discussed for the cases of market areas with high wind penetration. Generally, there seems to be an agreement that wind generation lowers the spot market prices, while the mechanisms behind are not entirely clear. For a first general treatment of the effect, see e.g. [3]. In [4], the reduction of price in dependence on wind generation is described. This does not come as a big surprise since wind generation in the German system is prioritized in the dispatch and can thus be regarded as a negative load. In [5], this is interpreted as an effect on the activation of the merit order curves of the GENCOs, meaning that in the presence of wind there is increased probability that expensive power plants will not settle the spot prices. This effect is then opposed to the costs of the renewable energy support scheme[1]. See Fig. 2 for an graphical illustration of the mechanism. Jóhnsson [6] provides detailed modeling recommendations for the price reduction effect applied to the Danish case and states that the decisive variable for the reduction effect is clearly the wind power prediction, rather than the actual production at the time of delivery.

In addition to the findings cited above, it can be shown that there is a second effect of high wind generation on the market prices which has not yet been discussed in the literature. One would assume that, especially for market zones with priority wind dispatch, the variable to look at is simply a fictitious expected system load,

$$L_{fic} = L - \hat{P}_w, \tag{1}$$

[1]However, the reduction of energy price for the end consumers must not be confused with the calculation of the total socio-economic benefit, which has to take into account also the financial impact on the GENCOs, the wind turbine manufacturers etc.

where $L$ is the system load (the consumption within the market area), and $\hat{P}_w$ is the predicted wind generation. Fig. 3 shows the German EEX spot prices for 2006-07 in a logarithmic scale plotted against $L_{fic}$. It can be observed that for equal $L_{fic}$, the mean prices at high wind generation are still slightly lower and that price spikes virtually do not occur in periods of high forecasted wind penetration

$$\hat{r}_w = \hat{P}_w / L. \tag{2}$$

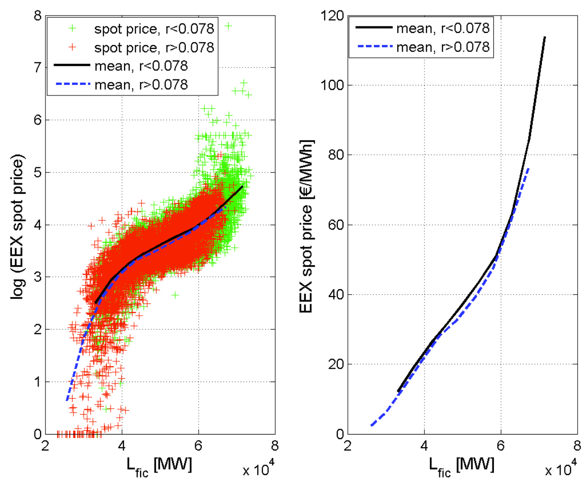


Fig. 3. EEX market prices for 2006 and 2007 in dependence on different levels of $L_{fic}$ (Sources: [2], [7], [8], [9], [10]), plotted for events with a wind penetration below 7.8% (red) and above 7.8% (green), where 7.8% is the mean of the wind penetration in the period. The logarithmic scale for the spot price is depicted on the l.h.s., while the plot on the r.h.s. shows the mean values in a linear scale. It can be observed that for the region in which the resulting loads to be covered by the market are equal, the price is still always lower for high $\hat{r}_w$. This might be caused by price expectations of the traders or by the fact that not the entire volume of energy consumed in Germany is traded at the power exchange.

There is little doubt that this general price damping effect of predicted wind infeed has an influence not only on the affected market zone itself, but also on adjacent interconnected areas with correlated market prices. In the following, we would like to explain how this can be detected from observed data.

## III. Methodology: Conditional Multivariate Data Analysis

Analysing the operation of a complex system may translate to simultaneously studying the behaviour of a large number of possibly redundant variables in a multivariate data analysis framework. At a given time $t$ the measured values for this set of $m$ variables are gathered in a single vector $\mathbf{X}_t$. For the example of the present study, these variables may be cross-border flows or flows on transmission systems. Owing to the instantaneous nature of electricity transmission, flow data recorded at different points in the horizontal network may often cloud the true underlying mechanisms by containing redundant information and noise components that arise from mechanisms other than the one that is subject to investigation. A possibility to alleviate this problem is to employ Principal Component Analysis (PCA) for dimension reduction. This will be described in a first part below. One can then work in a reduced basis defined by principal components, and develop conditional parametric models for capturing the nonlinear effects of the influential variables of interest, e.g. forecasted wind power penetration, on the flows.

### A. Dimension reduction with Principal Component Analysis (PCA)

PCA is a classical method in multivariate data analysis, which allows one to reduce the dimension of the problem at hand, and to potentially work in a reduced orthonormal basis defined by the set of (uncorrelated) principal components. For a nice introduction to multivariate data analysis and PCA, the reader is referred to [11], while more extensive mathematical developments may be found in e.g. [12]. Consider a number $N$ of measured flow values $\mathbf{X}_t$ (being of dimension $m$), and define $\tilde{\mathbf{X}}_t$ the centered and standardized version of $\mathbf{X}_t$. This simply means that for each dimension of $\tilde{\mathbf{X}}_t$ one has

$$\tilde{X}_{t,j} = \tau_j(X_{t,j}) = \frac{X_{t,j} - \bar{X}_j}{\sigma_j}, \quad j = 1, \ldots, m \qquad (3)$$

where $\bar{X}_j$ and $\sigma_j$ are the mean and standard deviation of the $j^{\text{th}}$ flow variable. We will denote by $\tau$ the simultaneous application of the $\tau_j$ transformations to all components of $\mathbf{X}_t$.

Finding the principal components for the dataset considered may be performed by diagonalizing the covariance matrix of the data, given as

$$\mathbf{R} = \frac{1}{N} \sum_{i=1}^{N} \tilde{\mathbf{X}}_t \tilde{\mathbf{X}}_t^\top \qquad (4)$$

By arranging the eigenvalues in decreasing order and identifying the corresponding eigenvectors, one obtains the set of principal components. Using the average eigenvalue method [12, pp. 348], the set of retained principal components are those for which the related eigenvalue is larger than the mean eigenvalue of $\mathbf{R}$. By writing $\mathbf{Y}_i$ $(i = 1, \ldots, n, n < m)$ these principal components, one then obtains an orthonormal basis in which $\tilde{\mathbf{X}}_t$ can be written as linear combination of the principal components,

$$\tilde{\mathbf{X}}_t = \sum_{i=1}^{n} \alpha_i \mathbf{Y}_i + \epsilon_t, \quad \forall t \qquad (5)$$

plus $\epsilon_t$ which is a $m$-dimensional centered noise of finite variance. By comparing the eigenvalues corresponding to the retained principal components to the trace of $\mathbf{R}$ (i.e. the sum of all eigenvalues), one can determine the degree of explanation of the variance in the data, giving a hint on the information content of the remaining noise. Note that the principal components $\mathbf{Y}_i$ can be seen as orthogonal modes explaining the interrelated variations of the flows considered, while

$$\mathbf{P} = [\mathbf{Y}_1 \ \mathbf{Y}_2 \ \ldots \ \mathbf{Y}_n] \qquad (6)$$

can be seen as the projection matrix allowing to project standardized flow values $\tilde{\mathbf{X}}_t$ in the basis defined by the principal components.

### B. Conditional parametric models for local smoothing

The model in Eq. (5) permits one to express the flows as a linear combination of the principal components $\mathbf{Y}_i$. Such models can be extended in order to account for the potential nonlinear effects of influential variables on the flows. Denote by $\mathbf{u}_t$ the values of these influential variables at time $t$. They may include forecast wind power penetration, fictitious load or the spot price on the EEX market for instance. The dimension of $\mathbf{u}_t$ should be kept low (say, lower than 3) owing to the so-called curse of dimensionality. The model of Eq. (5) is then extended to

$$\tilde{\mathbf{X}}_t = \sum_{i=1}^{n} \alpha_i(\mathbf{u}_t) \mathbf{Y}_i + \epsilon_t, \quad \forall t \qquad (7)$$

where the $\alpha_i$ coefficients are not constant anymore, but instead coefficient functions of the set of influential variables $\mathbf{u}_t$. $\epsilon_t$ is still a $m$-dimensional centered noise of finite variance.

We do not describe here the detail of the method for estimating the coefficient functions. In general, the challenge is to define a fitting procedure for the coefficients $\alpha_i(\mathbf{u}_t)$ that allows to consistently eliminate $\epsilon_t$ in Eq. (7) (i.e. to regard it as noise component). The basis for their estimation can be found in e.g. [13]. No assumption is made about the shape of the coefficient functions, except that they are continuous and suffiently smooth for being locally approximated. The method for their estimation consists of approximating them locally at a number of fitting points with first order polynomials, and of using weighted least squares for determining the polynomial coefficients. Different variants of the method for their estimation can be found in e.g. [14], [15].

### C. Identifying trend surfaces

There may be different ways of using the estimated coefficient functions in Eq. (7) for analysing the impact of the defined influential variables on the flows. One can in a first stage analyse the estimated $\hat{\alpha}_i$ functions themselves in order to see how influential variables act on the contribution of the various identified modes to the observed flows. Alternatively, it may be easier to go back to the original flow variables and to show what is the mean effect of the influential variables in the variations of the various flows considered. It is this alternative that will be preferred in the following. Indeed, by simply discarding the noise term in Eq. (7), projecting the $\hat{\alpha}_i$ functions back to the basis in which $\tilde{\mathbf{X}}$ is defined, and using the inverse $\tau$ transformation for getting back to the original $\mathbf{X}$ variables, one obtains

$$\hat{\mathbf{X}}(\mathbf{u}) = \tau^{-1} \left( \mathbf{P} \hat{\alpha}_i(\mathbf{u}) \right) \qquad (8)$$

which defines the mean flows as a function of the influential variables $\mathbf{u}$. Variations in such mean flows as a function of $\mathbf{u}$ can be seen as trends induced by $\mathbf{u}$, which can be for instance a trend induced by forecast wind power penetration. Examples of such trend surfaces will be given and discussed below.

## IV. Methodology application example

### A. *Influential variables in the analysis*

For this study, a closer look is taken at the control block of Austria, operated by the TSO APG (Fig. 1). The installed generation capacity in Austria is more than 19 GW (12 GW in hydro power units), while the maximum load is less than 10 GW [2]. In spite of this excess of installed generation capacity, the block has shifted its overall characteristics from export to import throughout the last years, which can be caused by a number of factors. The block is physically linked to six different control blocks and a total of nine control zones. The complexity of such structures is demanding a concise top-down approach based on recorded data. Effects caused by the following influential variables were subject to detailed investigations:

1) fictitious load (Eq. (1)) in Germany, and
2) forecasted wind power penetration in Germany (Eq. (2)),

both together generating an indirect effect on generation and trading within the APG block via market-related effects. The trends of cross-border flows and APG system flows were subsequently analysed for 2006-07 data according to the methodology outlined in Sec. III above. The vector $\mathbf{u}_t$ as introduced in Eq. (7) then includes the measured values for these 2 influential variables at time $t$. In parallel, the vector $\mathbf{X}_t$ of flow values measured at time $t$ may either relate to the overall block balance (being one-dimensional in this case, thus not needing the PCA step of the methodology introduced above), or gathering the set of cross-border flows ($m = 6$), or finally the flows on transmission lines ($m = 23$).

### B. *Flow patterns as a result of wind power*

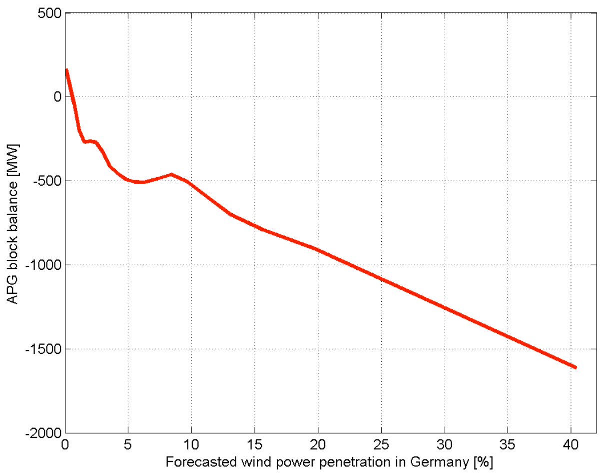


Fig. 4. Trend of the block balance of APG in dependence on the wind power penetration in Germany.

*1) Control block balance:* The control block of APG is closely linked to the control block of Germany, due to high transmission capacities and mutual benefits in the generation mixes the two block are able to share. In particular, the pumped hydro facilities within the APG area serve as buffer for low price energy injected into the German block. The question is if a general tendency for a relation between the wind penetration in Germany and the export/import balance of APG can be found. Since there are many different simultaneously relevant influential variables, the method described in Sec. III has been used for the identification of the influence of the wind power penetration alone. The result is depicted in Fig. 4 and shows an interesting feature: The general trend indicates that for zero wind penetration in Germany, there is even a slight export to be expected from the APG block. For higher penetrations, the sign turns to negative, that is, the consumers and pumped hydro plants clearly start to import “green” energy. Disintegrating this information to the influence of the wind power penetration and the ficititious load in Germany separately results in the trend surface plot shown in Fig. 5. It shows the trends of the export/import balance of APG in dependence on the wind power penetration and the fictitious load in Germany at the same time.

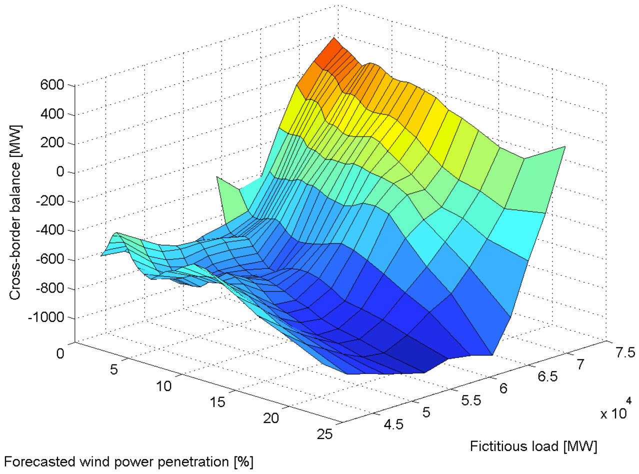


Fig. 5. Trend of the block balance of APG in dependence on the wind power penetration and the fictitious load in Germany. Due to computational reasons, the three-dimensional fitting procedure cannot be applied with suffcient numerical reliability up to the full measured wind power penetration of 40%.

*2) Physical cross border flows:* The cross-border flow trends of the APG block have been identified following the methodology outlined in Sec. III. The dimension reduction part of the methodology has led to the identification of 2 modes explaining 60% of the variations in the data. The resulting trend computations are shown in Figs. 6, 7 and 8. The analysis indicates that for high wind penetration and low load in Germany, the northern flowgates of APG (Germany and Czech Republic) are importing considerably more energy than in periods of low wind penetration and high load in Germany. For the export flow at a southern flowgate to Switzerland (and then further to Italy), the opposite is the case, which is a clear indication of wind energy transit through the APG block.

*3) Unintended cross border flows:* The unintended cross-border flow at a flowgate is defined as the difference between the physical flow and the scheduled flow. It turns out that the level of wind power penetration influences the probability of unintended exchanges on APG’s borders. Again, the dimension

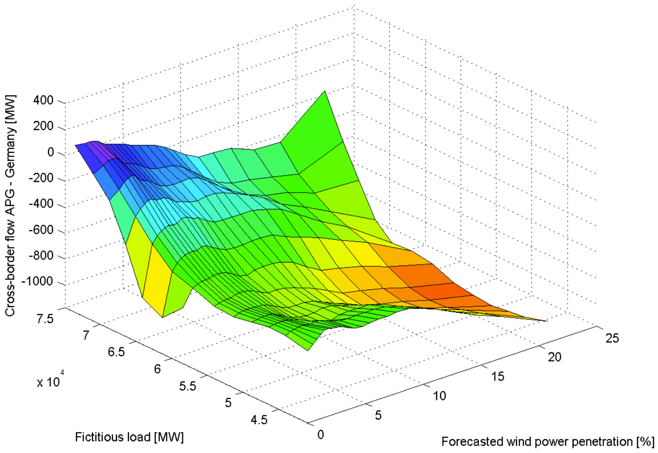


Fig. 6. Trend of the physical cross-border flow at the border between APG and Germany dependent on the wind power penetration and the fictitious load in Germany.

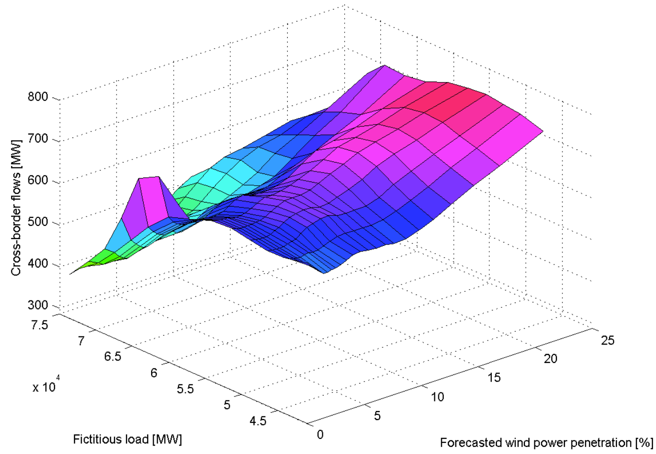


Fig. 8. Trend of the physical cross-border flow at the border between APG and Switzerland dependent on the wind power penetration and the fictitious load in Germany.

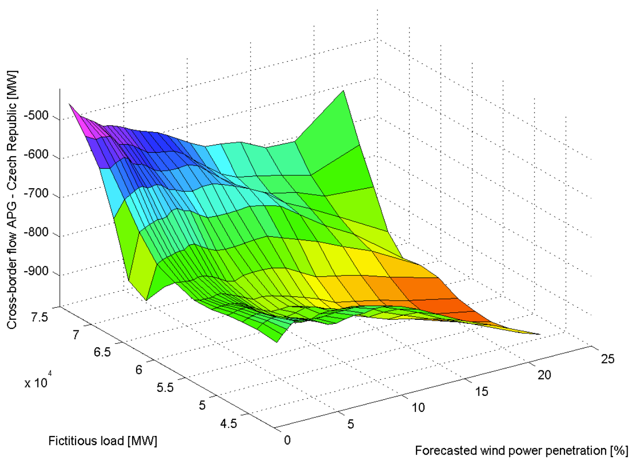


Fig. 7. Trend of the physical cross-border flow at the border between APG and Czech Republic dependent on the wind power penetration and the fictitious load in Germany.

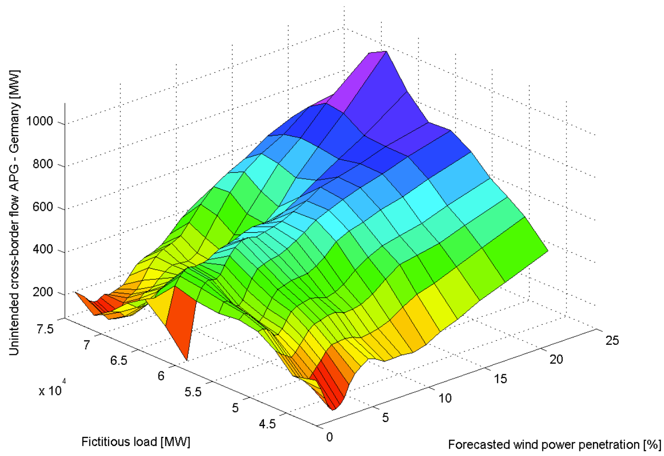


Fig. 9. Trend of the unintended exchange at the border between APG and Germany dependent on the wind power penetration and the fictitious load in Germany.

reduction part of the methodology has led to the identification of 2 modes, which explain here 67% of the variance in the data. As an example, Fig. 9 shows the trends at the German border. There is a nonlinear dependence on the fictitiuos load, showing a peak at a certain value, and a roughly linear and clearly positive dependence on the German wind power penetration. Here, it should be noted that a part of such effects comes from the zonal market model and is influenced by the impedance relations in the horizontal network. That is, the overall unintended exchange of the APG block is widely unaffected by the wind power penetration.

*4) Transmission line flows:* The 4 identified modes (explaining 75% of the variance of the original data) of some important 400-kV-systems have been analysed in order to distinguish between more and less volatile flow patterns. In Fig. 10, these modes are plotted for 23 systems. Following the introduction of PCA in Section III-A, most of the variations of the flows on the 400-kV-systems can be explained and expressed as a linear combination of these 4 modes. Visual inspection can already tell which systems have more flow variations. It can be seen that e.g. system No. 15 shows distinguished volatile behaviour, since exhibiting larger magnitude of variations in the various modes. Fig. 11 reveals that the flow on this line shows a clear nonlinear dependence on the wind power penetration and the fictitious load in Germany.

## V. Conclusions

The market-related indirect influence of high local wind penetration on physical variables in other locations of large transmission systems has been demonstrated for an EU control block. The theoretically suspected effect has been separated from other influences by means of a classical multivariate data

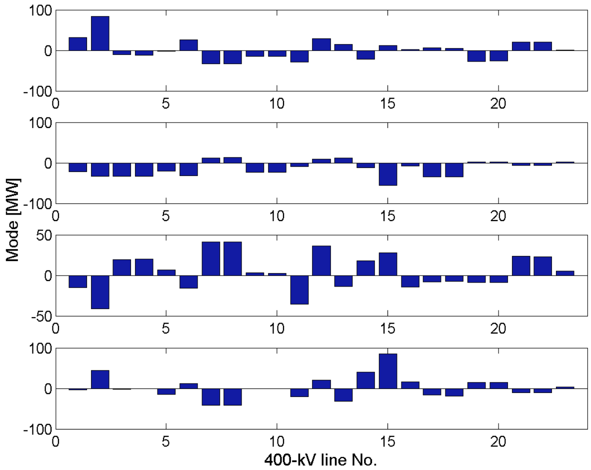


Fig. 10. Modes of 23 400-kV-systems in the APG block identified by PCA as described in Sec. III.

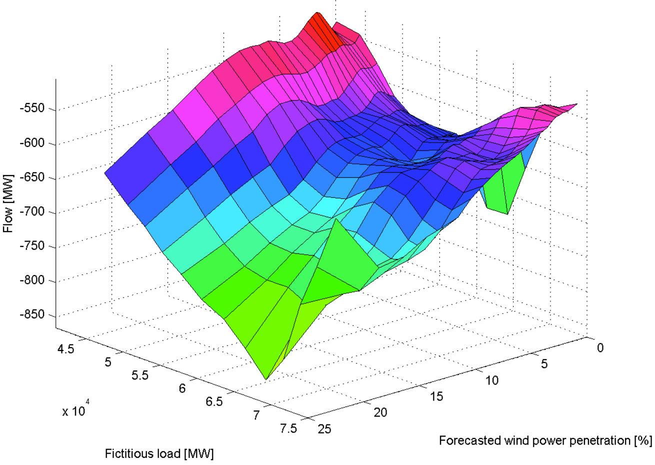


Fig. 11. Trend of the flow on one selected APG system (No.15) dependent on the wind power penetration and the fictitious load in Germany.

analysis method. Since the future development of renewables in the EU is highly ambitious, there will be the need for a projection of the observed nonlinearities to future renewables penetrations. Top-down approaches based on measured data as the one outlined in this paper seem to be a practical and reliable way to approach this problem. In the light of the demonstrated statistical evidence for still relatively small wind power penetrations incorporated into the market via a simple mechanism, future research activities should increasingly focus on smart market design for renewables and other new energy technologies.

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