Dynamic Data Driven Dimensioning of Balancing Power with k-Nearest Neighbors

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***Abstract*—This paper proposes a novel dynamic design for control reserve dimensioning. In contrast to the current statistical analytic design we present a data driven approach with methods of computational intelligence. The chosen k-nearest neighbor algorithm is one of the most sucessfully used methods in machine learning. The model is able to predict complex nonlinear behavior by assuming that similar observations have similar outcomes. A condition for the success of this method is to determine the salient features. Therefore the core of this paper is to show the dependencies of the influencing parameters. Numerical experiments on the basis of freely available data for the years 2011 until 2013 show that there are time and space patterns as well as inter dependencies with the active power market.**

***Index Terms*—Control Power, k-Nearest Neighbor**

I. Intruduction

To ensure a constant power frequency and thus a stable quality of supply, the permanent balance of power demand and supply is the most crucial constraint in an electrical power system. Therefore time series modeling and prediction of the power demand and supply is an important task. In recent years machine learning algorithms have drawn attention and have established themselves in the forecasting community. Especially for wind power and electricity demand the machine learning algorithms improved the prognosis accuracy. But due to the increasing share of generation from renewable resources the need for reserve and balancing power to cover these prognosis faults is still increasing.

In contrast with dynamic machine learning approaches, the current design for the dimensioning of these necessary reserves and its reliable provision is still an analytically statically method. It is based on the former hierarchical and centralized structure of the European electricity sector, where the need for reserve was primarily caused by unpredictable power plant outtakes or load and generation noise, which were random and stochastically independent. Today both the reserve dimensioning and its activation critically depend on the actual state of generation and supply, the current network characteristics and also generation and load forecasts. A simple attractive method to predict such complex nonlinear behavior with many influencing parameters is the k-Nearest Neighbor regression method. In this paper we propose a multivariate multistep k-NN Regression to dynamically predict the demand of balancing power. Contrary to established approaches for wind generation and demand, the prediction of the balancing power implies some challenging differences. First there is the effect of periodicity. Whereas the time series for electricity demand are highly time-sensitive with daily, weekly and annual patterns, the time dependency of the activation of balancing power is ambiguous, so that established filter mechanisms cannot easily be extended. Second there is the task of feature selection. The objective is to find the optimal subset of features which minimizes the prediction error. For predicting wind and PV generation the main influencing parameters are mostly known and primarily state specific [1], so that the accuracy of the predicted value (power output) can be globally optimized. In contrast, the influencing features for demand of balancing power are time- and space-dependent - heavily depending on generation structure, demographic effects etc. - and therefore bound to the system state. So the challenge is not to find the global optimum model to predict the balancing power demand for every time and space, but to find the locally optimal setting. To tackle this challenge the k-NN model is multistep, which means that the regression model is split into the k-NN model itself and a meta-model, which both optimizes the model parameters, and the feature selection for each system state. And the third discrepancy is the accuracy metric. Whereas for generation and demand the predicted curve must coincide with the real curve, for balancing power the provided (maximum and minimum) power over a given time period is critical, thus over- and underestimation must be avoided at all costs. This paper focuses on the first two aspects of the ambiguous time and space dependency of balancing power and its influencing parameters. The remainder of this paper is organized as follows: first we introduce the k-NN algorithm and review related approaches in the energy domain. Second we discuss the time and state dependency and the statistic inference of the features based on the experimental results of the factorial design.

II. Modeling

A. *Design of Control Reserve*

Depending on its activation time, three different types of control reserve are distinguished, primary, secondary and tertiary. Whereas the primary reserve (frequency-response reserve) is fixed to 3000 MW (outtake of two power plants) and is activated by autonomous f/P-droop controllers, the design and activation for secondary and tertiary reserve (minute reserve) falls to the transmission system operators (TSO). To prevent a contrary activation of operating power in different areas, the German TSOs coordinate their operation reserve in a network called Netzregelverbund (NRV). Within this NRV the actual demand of reserve control is determined and tendered on the common internet platform[www.regelleistung.net]. The dimensioning of the control reserve to be provided is based on a probabilistic approach which convolutes the individual probability density functions of the influencing parameters into one density function and then determining the amount depending on the given loss of load probability (LOLP). The current deficit probability is 0.1%, which means that in 0.1% of cases (9 hours a year) a lack of reserve is accepted.

But due to the change from the former randomly caused power plant outtakes to today stochastic prognosis faults, the actual applied method for dimensioning by convoluting the individual probability density functions is not adequate anymore. On the one hand the influencing parameters are no longer statistically uncorrelated (see section II) and on the other hand the given LOLP is originated from large capacity power plant blackouts, implying that the provided reserve power is oversized in the majority of cases. Recently, besides the probabilistic method also simulative approaches are used. According to the method of Graf-Haubrich, a Monte-Carlo-Simulation-based approach for probabilistically dimensioning of the demand of operating reserve by distinguishing the probability density function for each form of control power has been introduced by Brueckel [2]. Many of the following studies aim at DER integration in the power markets through economic optimizing [3], [4], [5]. Besides these studies to integrate single technologies, there is already related work dealing with the overall control power market. [6] examines an adaptive control power market with capacitive reserve. The objective of this research is to extend the approach of a flexible tendering for tertiary reserve on the principals of a capacity market. Flexible Dimensioning of Control Reserve for Future Energy Scenarios is examined in [7]. Therefore a model is developed which is capable of calculating the control reserve within future energy scenarios by the hour.

In contrast of the aforementioned studies, this paper will focus on computational intelligence methods to predict the demand for operating reserve dynamically and is not based on probabilistic convolution-based calculation methods. In addition the aim of prior examinations was to predict the expected demand in future energy scenarios [8], [9], whereas this approach concentrates on the prediction of control reserve today. As a model we choose the nearest neighbor algorithm as one of the most popular techniques in nonlinear time series analysis. This method is already used in the energy domain for prediction of wind and PV generation [10], [11], [12] or energy demand, [13], [14].

B. k-Nearest Neighbor Algorithm

Prediction problems can be considered as a problem of supervised learning , where we have to infer from historical data the possibly nonlinear dependence between the input (feature vector) and the target output (future value) [15]. The basic process of a k-nearest neighbor prediction model is shown in Figure 1. Given a query feature vector $x_q \in \mathbb{R}^d$ and a set of N d-dimensional vectors $X = x_1, ..., x_N$, the nearest neighbor search algorithm aims to find the subset of k items $N_k(x_q)$ from X such that its distances to the query vector are minimum. Assuming that similar observations will lead to similar outcomes of the target value, the target value $\hat{y}_q$ for a query feature vector (new observation) can be calculated as follows:

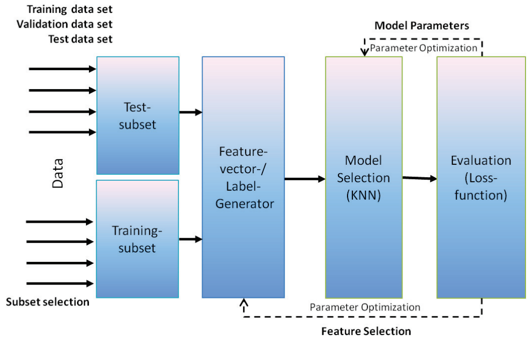


Fig. 1: k-NN model

$$\hat{y}_q = f_{kNN}(x_q) = \frac{\sum_{i \in N_k(x_q)} w_i y_i}{\sum_{i \in N_k(x_q)} w_i} \tag{1}$$

w_i is the weight given to each neighbor x_i and therefore the contribution of its target value y_i is also weighted with w_i. This can either be done with a uniform weight, i.e. the formula (1) can be simplified to $f_{kNN}(x_q) = \frac{1}{k}\sum_1^k y_i$ or with a distance weighted kernel function. The precise weight given to each neighbor depends on the weighting function employed. The normal distribution is one option. That is, the weights form a bell-shaped curve centered on x_q that declines with distance from x_q. Another common distance weight function, which decreases quadratically with the distance is

$$w_i = \frac{1}{1 + \alpha d(\mathbf{x}, \mathbf{x_q})^2} \tag{2}$$

Weighting with a kernel function has the advantage that it can be applied to the whole training set, because the weight of points with high distance tend to zero. Particularly when the samples are not uniformly distributed a fixed k would entail that too much weight is given to distant samples. However, defining the neighborhood both by choosing the k and the α is essential, because of the bias-variance dilemma. That is, larger neighborhoods will tend to make the smoothed values less variable but likely more biased. For $k \to N$ the target value becomes the average. Smaller neighborhoods will tend to make the smoothed values more variable but will likely be less biased and less stable. So defining the optimal neighborhood by selecting the optimal k respectively the optimal kernel weight function is one major goal. The other objective is the

TABLE I: Describtion of the parameters for the year 2012 in the NRV

minor	balance		Wind generation		Wind_Err_rel		PV generation		PV_Err_rel		Vertical netload		Phelix Base	
	2011	2012	2011	2012	2011	2012	2011	2012	2011	2012	2011	2012	2011	2012
count	33128	33304	33128	33304	33128	33304	33128	33304	18970	19049	33128	33304	33128	33304
mean	-438	-71	5212	5220	0.28	0.23	2132	3175	0.94	0.50	35546	32794	51.12	42.60
std	933	941	4558	4444	0.39	0.33	3284	4884	6.62	2.30	8400	8374	13.60	18.68
min	-5340	-4587	91	115	0.00	0.00	0	0	0.00	0.00	10472	-11681	-36.82	-221.99
25%	-902	-574	1714	1988	0.07	0.06	0	0	0.07	0.06	29192	26857	43.90	34.06
50%	-350	-87	3667	3918	0.16	0.13	42	69	0.18	0.13	35648	32604	51,85	42.08
75%	104	425	7434	7102	0.32	0.27	3497	5098	0.44	0.31	42346	39181	60.63	52.88
max	3997	4135	22929	24086	5.48	6.47	34800	22402	597	113.12	56121	54507	117.49	210.00

weighting of the different features. That leads to the issue of Feature Selection which implies three big challenges [16].

First, there is the curse of dimensionality. As the number of features increases, the space that needs to be filled with data goes up as a power function. So, the demand for data increases rapidly, and the risk is that the data will be far too sparse to get a meaningful fit. Second regarding more than one feature raises some difficult issues about how to best define the neighborhood. For example, how is the neighborhood near x_q to be defined when features are correlated or one feature has much more variability than another. But also due to the units of measurement, one feature could dominate the definition of the neighborhood. Third, there are interpretative difficulties. When there are more than two features one can no longer graph the fitted surface. The second aspect leads to the feature weights and distance metric, which are both important for selecting the salient neighbors. Solving this the features are first normalized and then scaled (by multiplying them with their weights w_i) according to their importance before the distance is calculated. Applying the euclidean distance the weighted distance is calculated as follows

$$d_w(\mathbf{x},\mathbf{y}) = |\mathbf{x}-\mathbf{y}| = \sqrt{\sum_{i=1}^{d} w_i(x_i-y_i)^2} \qquad (3)$$

For evaluation of the chosen model function the empirical risk of the prediction is calculated which is the expected value of the Loss function.

$$E_{emp}(f) = \frac{1}{N}\sum_{i=1}^{N} L(y_i, f(x_i)) \qquad (4)$$

Common used loss functions for regression are the proportional loss function $L(y_i, f(x_i)) = |y_i - f(x_i)|$ or the quadratic loss function $L(y_i, f(x_i)) = (y_i - f(x_i))^2$. Then the empirical risk is given by the MAE (mean absolute error) or by the RMSE (root mean squared error).

The goal is to find the function $f^* = argminE_{emp}(f)$ so that the empirical risk is minimal. Therefore the hyper parameters have to be optimized, i.e. the model parameters like the distance metric $d(x_i, x_q)$ and the neighborhood (k or α), the loss function $L(y_i, f(x_i))$ and the feature subset selection (FSS).

But because both the feature values x and the target realizations are random variables, the real risk of the prediction is given as the structural risk which factors in their distributions.

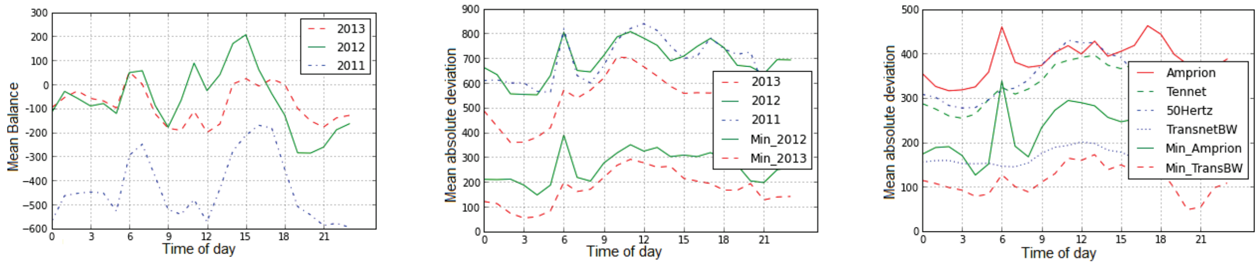
$$E_{struc} = E(E_{emp}) = \int\int L(y, f(x))p(x,y)dxdy \qquad (5)$$

In order to avoid the so called overfitting, the task is not to minimize the error on the training set but on the test set. Therefore the training set is divided into a training set and a validation set and the hyper parameters like the features weights and the neighborhood definition are optimized within a cross validation.

For our purposes, perhaps the major weakness of nearest neighbor methods is that they are not derived as a way to represent how y is related to $\mathbf{x}$; they are not explicitly linked to some $f(\mathbf{x})$. One consequence is that when there are more than two features, there is little guidance on how to represent the manner in which the predictors are related to the response [16]. So in the following section a sensitivity analysis is conducted to identify the relationships among the features.

III. Simulation

Prediction results of k-nearest neighbor nonparametric regression depend directly on the quality of the sample database and the chosen features. Therefore a sensitivity analysis of the main influencing parameters is made for the years 2011 to 2013. As a database we take the freely available data from the internet platforms of the four German TSOs and the common NRV. To analyze the demand for control reserve the characteristic number is the joint balance of the four German TSO areas, whose geographic location can be seen in figure 5. The control area balance of each TSO is defined as the sum of all deviations of balance groups/areas within the control area (e.g the EEG balance group) and it is equivalent to the receipt of balance power in this control area, i.e. positive balance will lead to positive balance power to counterbalance an underestimated control area and vice versa. These balances are then summed up and adjusted both among themselves and with the import and export of balance power to associated countries. The remainder has to be covered with balance power from the tendering platform. Due to the REMIT (Regulation on wholesale Energy Market Integrity and Transparency) since 2011 the TSOs have to publish different operating figures. Out of these figures the following time series were extracted; the



(a) Mean: years 2011 to 2013

(b) MAD: years 2011 to 2013

(c) MAD : four control areas (2012)

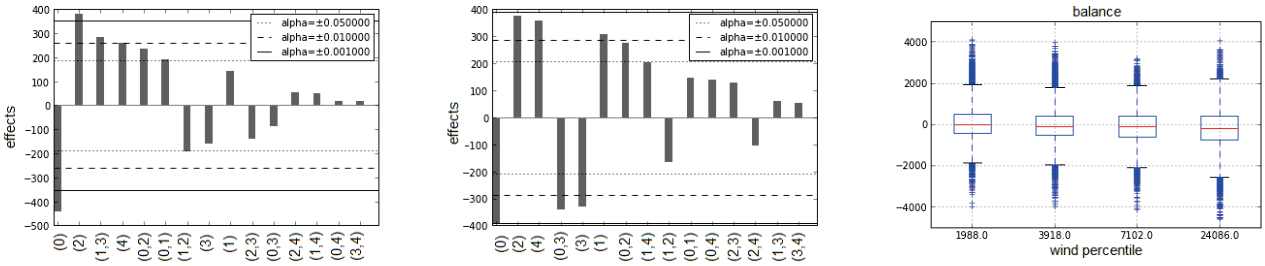
Fig. 2: joint balance aggregated by hour for the years 2011 to 2013(a/b) and for the different control areas(c)

wind and PV generation and prediction, the vertical net load and additional to the TSO figures the phelix base price at the EEX (since the introduction of the reBAP (standard price) in the year 2010 the price for balance power is related to the EEX). The description of the parameters for the NRV are given in table I. For each feature the mean, the standard deviation, the max, min values and the 25% and 75% percentiles are calculated. The percentiles are the values below respectively above which 25 percent of the observations may be found. Count is the number of observations in each year, given in 15 min intervals. In sum there are 33128 intervals for 2011 and 33304 intervals for 2012, because intervals with power plant deficiencies (1912 intervals in 2011 and 1832 intervals in 2012) were filtered out. For the generation and the vertical net load the single values of the four areas are added. To quantify the prognosis faults, the relative error of wind and PV is calculated as Wind_Err_rel and PV_Err_rel. That is the difference between the forecasted and the realized generation in relation to the latter. With respect to the relative errors it can be seen, that the errors are decreasing, especially the maximum error had been reduced from 0.16 to 0.13 for wind and from 0.18 to 0.13 for PV. But for wind as well as for PV there are still big slopes, so in 25 % (that are the 75% percentiles) of the cases the error was about 0.30 (30%), that is an absolute value of 700 MW for wind and 402 MW for PV. The maximum absolute deviations in the year 2012 were 5448 MW (-4871 MW) for wind and 6614 MW (-6005 MW) for PV, which all led to high balances of 2527 MW (-1511 MW) and 2720 MW (-1039MW), with the influence of the positive deviations dominating. Another thing that can be noticed is the 50% increase in PV generation from 2132 MW (mean) to 3175 MW (mean). This affects the vertical net load; so it is conspicuous that in 2012 the minimum vertical net load turns negative, which means that there were intervals where more energy was generated in the underlying net areas than have been consummated, yielding a slight decrease in the mean and the maximum vertical net load. For the balance the effect is the other way around. The overall mean of the balance increased from -438 MW to -71 MW. So there was a shift in the balance time series with an offset of approx. +300 MW which can also be seen in figure 2a, where the curve of the year 2011 has a negative offset to the other two curves in the years 2012 and 2013. To detect patterns that can be used with our machine learning algorithm we made two different analysis. First we analyzed the time and state dependency of the power balance and second we analyzed the influence of the wind, PV, price and net load on that balance.

A. *Time and State dependency*

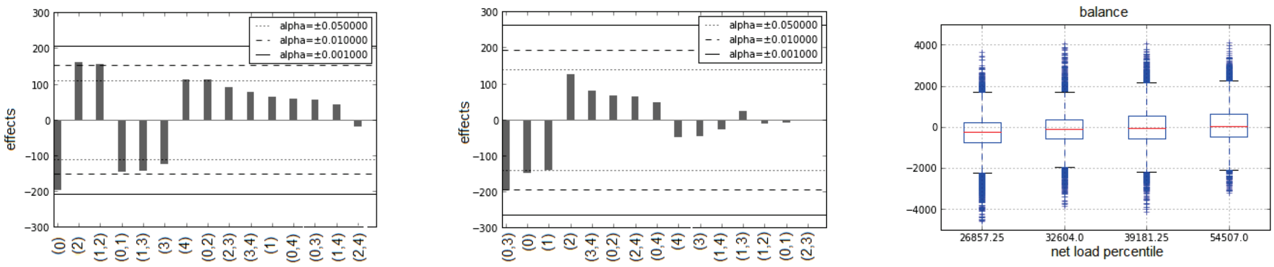
Fig. 5: control areas in Germany[www.netzregelverbund.de]

To detect a time and state dependency the mean of the joint balance was aggregated by hour. Regarding the results for the years 2011 to 2013, which are plotted in figure 2a, a trend can be noticed in the shape of the curves. Especially in the morning there is a positive peak in the balance as well as in the afternoon. In the evening a negative peak is noticeable. But for the activation of control reserve in particular for minute reserve not the mean of the balance is crucial but the deviations. Therefore the mean absolute deviation (MAD) of the balance is plotted for the years 2011 to 2013 in figure 2b. For an univariate data set, the MAD is defined as the median of the absolute deviations from the data's median. For large normal distributed samples the standard deviation is approx 1.48 times the MAD. For the year 2012 the MAD is 658MW and the standard deviation σ of the balance is 944MW, what reconfirms the assumption that the balance has a normal distribution and leads to the statement that approx. 70% of the time the balance is kept within this limit. Noticeable is a conspicuous peak at 6 am. This peak as well as the whole shape of the MAD curve are reflected in the activation of minute reserve, which is plotted in the lower lines (number of instances with activation of positive or negative minute



(a) NRV in 2011 (b) NRV in 2012 (c) inference of the wind in 2012

Fig. 3: Inference of the parameters wind (0), pv (1), vert. load (2), price (3) and weekday (4)



(a) 50Hertz in 2012 (b) Amprion in 2012 (c) inference of the net load in 2012

Fig. 4: Inference of the parameters wind (0), PV (1), vert. load (2), price (3) and weekday (4)

reserve for the year 2012 (solid) and 2013 (dashed). Regarding figure 2c, where the MAD for the year 2012 is plotted for each control area, it can be seen that this effect is mostly derived from the Amprion area. So the balance is not just related to the hour of the day but also to the control area. In the TransnetBW area the dotted curve is very flat, so the standard deviation in the TransnetBW area is just 250 MW. In the following regression analysis we will see, that also the different influencing parameters have a time and state specific weight in determining the balance. The reason for the Amprion peak is still under investigation, but one assumption is, that it is related to the spot market, so e.g. from 5 am to 7 am there is the highest rise in prices from 30 Euro up to 47 Euro (hourly mean for 2012). But, whether it is the direct cause or both facts have another source, this is no fortuitous event and therefore can not be explained with randomness.

B. Inference of the features

The k-NN method is very sensitive to feature weights given with the distance metric (see equation 2). Therefore the Feature Subset Selection is import preliminary work. To detect first trends a sensitivity analysis based on regression analysis from Design of Experiments [17], [18] is made before the feature weights are optimized within the k-NN-algorithm. Prior examinations draw ambiguous conclusions about the influencing parameters for control reserve. On the one hand many studies [19] state, that the rising share of renewable energies would lead to a higher amount of reserve control, which would imply a high correlation between the wind and PV generation and the control balance. A recent study [20] estimates an increase of control reserve of 30-70 Megawatt for each Gigawatt of added installed capacity of renewable resources and a decrease of control reserve if the prognosis could be revised. On the other hand, [21] found in their regression analysis for tertiary control for the years 2008 to 2011 that no direct correlation between the installed capacity of fluctuating energy sources and the activated amount of control reserve could be observed. Nevertheless they argued that situations with low amount of wind power production require a lower amount of control reserve.

To investigate these hypothesis, a statistical design was generated to analyze the effects of the different parameters. Therefore a full-fractional design with two levels for each feature was generated, so that for n features the full fractional experimental design with two levels has 2^n steps of combinations. For the analysis of the NRV, the levels (-1/+1) were set according to the 25% (-1) and 75% (+1) percentiles from table I. To populate the samples both boundaries were enlarged by 10% - the upper boundary is set at 1.1 times the 25% percentile and the upper bound at 0.9 times the 75% percentile - so that 25% of the samples were considered. The resulting levels for the chosen parameters and mean balances for the two levels are plotted in table II. So for the two steps when all levels are set to +1/ -1, all the intervals are selected where the parameter values are greater/ lower than the values given in table II. As target value the mean of the joint balance is calculated. In figure 3 and 4 the effect of the wind (0), PV (1), load (2), price (3), weekday (4) and its interaction is plotted. The bar represents the effect when the setting of the parameter turns from -1 to +1. For the interactions between the parameters this is when the sign turns from negative to positive. Negative sign

TABLE II: levels (-1/+1) set for the NRV

feature		level (-1) 2011	level (-1) 2012	level (+1) 2011	level (+1) 2012
wind	[MW]	1894	2187	6718	6392
PV	[MW]	0	0	3147	4586
net load	[MW]	32111	29543	38075	35263
PHB	[€]	48.29	37.40	54.57	47.37
weekday		weekend	weekend	weekday	weekday
mean balance	[MW]	-181	59	-423	-405

means, that the parameters have different levels, positive sign vice versa. The horizontal lines are the levels of significance for 95% (dotted), 99% (dashed) and 99.9% (solid). So in the NRV in both years 2011 and 2012 the effect of the wind generation on the balance is significant, i.e. that in times with high wind generation the balance is approx. 400 MW lower than in times with very low wind generation. The effect of the net load is quite opposite, here the mean of the balance turns positive with high level of net load. To emphasize this effect the boxplots for the balance according to the percentiles of wind (fig. 3c) and load (fig. 4c) are plotted. In other words in each figure the boxes represent each 25% of the intervals. Whereas the most negative mean of balance and its highest negative deviations occur in times with high wind feed in, in times with very high vertical net load the balance has its most positive mean and especially the negative deviations are more tight. Also noticeable is the influence of the weekday, so during week the balance is rather positive than during weekends. The significant difference between the year 2011 and 2012 is the increasing influence of PV (1) and price (3). The PV influence could be derived from its increased share, whereas the price could be derived from a new calculation of the balance power price introduced (08/2011). The bar (0,3) represents the interaction between the wind generation and the price, i.e. in times when the wind generation and the price are both very low/high, the balance is more likely to be negative as when they are in the opposite direction. That could of cause also be argued with the day and night difference, which would state the thesis of [21] that during night (PHB = -1), the demand for control power is less, during wind calms (wind = -1). In figure 4 the effect of the parameters is shown for the two most characterized German control areas. In the 50Hertz area with the highest amount of generation from wind and PV related to the vertical net load, the wind generation has the highest influence and the PV generation has a noticeable share. In contrast in the Amprion area with the highest net load and the lowest share of renewable generation no direct influence of a single parameter can be determined. Just the interaction (0.3) is slightly significant, but this could also be derived from day/night difference as carried out before. For that reason a dynamic model to dimension the demand of control reserve is aimed to be designed, with respect to the time and state specific requirements based on local learning respectively local optimizing.

IV. Conclusion

In this paper we introduced a new methodology for predicting the amount of balancing power with methods of machine learning, namely with a two step k-nearest neighbor regression. The machine learning approach has the advantage to the current convolution-based method, that it is more suitable to adapt the dimensioning of the balance power to the current system state. The importance of the time and space specific influence on the balance was illustrated in section III. The regression results reinforced the hypothesis that the weight of the influencing parameters vary as well among the control areas as between different hours of the day or years. Therefore a locally optimized non parametric approach like the k-NN algorithm is feasible.

References

[1] Mangalova, E. ; Agafonov, E.: Wind power forecasting using the k-nearest neighbors algorithm. In: *International Journal of Forecasting* Bd. 30, S. 402–406

[2] Brückl, Oliver: *Wahrscheinlichkeitstheoretische Bestimmung des Regel- und Reserveleistungsbedarfs in der Elektrizitätswirtschaft*, Technische Universität München, Dissertation, 2008

[3] Speckmann, Markus ; IWES (Hrsg.): *Regelleistung durch erneuerbare Energien - Herausforderungen und Lösungsansätze*. Köln/Aachen, 2011

[4] Klobosa, Marian: *Dynamische Simulation eines Lastmanagements und Integration von Windenergie in ein Elektrizitätsnetz auf Landesebene unter regelungstechnischen und Kostengesichtspunkten*, ETH Zürich, Dissertation, 2007

[5] Burger, Andreas et a.: Zusammenschluss von dezentralen Erzeugern zur Netzregelung. In: *Bulletin* (2011), Nr. 12, S. 12–15

[6] Kippelt, Stefan ; Schlüter, Thorsten ; Energiewirtschaft ie3-Institut f. (Hrsg.): *Ausgestaltung eines adaptiven Regelleistungsmarktes mit Kapazitätsreserve*. 2012

[7] Kippelt, Stefan ; Schlueter, Thorsten: Flexible Dimensioning of Control Reserve for Future Energy Scenarios. In: *IEEE Power Tech Grenoble France*, 2013

[8] Consentec: *Gutachten zur Dimensionierung des Regelleistungsbedarfs unter dem NRV*. 17.12.2010

[9] dena - Deutsche Energie Agentur ; DENA (Hrsg.): *Integration EE: im Auftrag der RWE*. 15.08.2012

[10] Ren, Ye ; Suganthan, P. N.: *Empirical Mode Decomposition-k Nearest Neighbor Models for Wind Speed Forecasting*

[11] Treiber, Nils A. ; Heinermann, Justin ; Kramer, Oliver: Aggregation of Features for Wind Energy Prediction with Support Vector Regression and Nearest Neighbors. In: *ECML*, 2013

[12] Wolff, Björn ; Lorenz, Elke ; Kramer, Oliver: Statistical Learning for Short-Term Photovoltaic Power Predictions. In: *ECML*, 2013

[13] Al-Qahtani, Fahad Crone S.: *Multivariate k-Nearest Neighbor Regression for Time Series Data*. ISF 2013 and Seoul and Korea, 11.07.2013

[14] Paparoditis, Efstathios ; Sapatinas, Theofanis: *Short-Term Load Forecasting: The Similar Shape Functional Time-Series Predictor*

[15] Bontempi, Gianluca: *Machine Learning Strategies for Time Series Prediction*. 2013

[16] Berk, Richard A.: *Statistical Learning from a Regression Perspective*. 1. s.l : Springer-Verlag, 2008. – ISBN 0387775005

[17] Kleppmann, Wilhelm: *Versuchsplanung*. 1. s.l : Carl Hanser Fachbuchverlag, 2013 http://ebooks.ciando.com/book/index.cfm/bok_id/902242. – ISBN 978–3446437524

[18] Box, George E. P. ; Hunter, W.G ; Hunter J.S.: *Statistics for Experimenters*. Wiley, 2005

[19] DENA ; DENA (Hrsg.): *DENA Netzstudie II*. 26.11.2010

[20] Hirth, Lion ; Ziegenhagen, Inka: Wind, Sonne und Regelleistung. In: *Energiewirtschaftliche Tagesfragen* 63 (2013), Nr. 10

[21] Kays, Jan ; Schwippe, Johannes ; Waniek, Daniel ; Rehtanz, Christian: Multidimensionales Verfahren zur Bestimmung des Regelleistungsbedarfes unter Berücksichtigung von Unsicherheiten. In: *Zeitschrift für Energiewirtschaft* (2010), Nr. 4