

Analysis of the correlation behavior between local available information to the overall reactive power of a medium-voltage grid group

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Abstract— The initiated energy transition leads to extensive changes in the supply of energy. The increasing use of renewable energy causes a shift of the produced power from centralized conventional power plants to decentralized energy plants. Because of this redistribution and the related change of load-flows, new challenges and problems for distribution system operators appear. This includes the integration of new loads and plants into the existing power grid and the guarantee of a high supply security and quality. It also includes strengthened requirements for the use and provision of reactive power. The project “SyNErgie” (“Systemoptimierendes Netz- und Energiemanagement für Verteilungsnetze der Zukunft”) deals with the development of a new reactive power management, which gets embedded in grid planning and controlling processes. One focus of the project is on the integration of decentralized energy plants (DEPs) to the reactive power management. The aim is to develop a decentralized and self-sufficient reactive power control system, which only works with local available information (measures). Therefore is no necessity of a complex communication system to the grid control center. Self-controlled Q-controller in the DEPs get characteristic curves and control the reactive power sources with local measurements (e.g. current, voltage, effective power). This new reactive power control management aims for the reactive power compensation in order to increase the integration capacity of loads and plants in a grid [2]. In order to generate characteristic curves for DEPs, it is necessary to analyze the correlation behavior between the local available measurements at the DEPs and the overall-Q-behavior of the grid group at the transformer. In that regard, influencing quantities should be considered. The aim is to involve and evaluate all relevant influencing quantities in order to determine energy plants and certain operating points, in which the correlation behavior and the prediction for the overall-Q-behavior are sufficient. The next step is to develop a model that fits these correlation behaviors and generate characteristic curves. One method to generate characteristic curves for the Q-controllers is regression analysis. The developed Q-control-system with the characteristic curves will be tested, evaluated and optimized in a following field test in cooperation with distribution system operators.

Keywords— energy transition; correlation; regression; medium-voltage; integration of renewable energy; electrical grid; reactive power; distribution system operators

I. INTRODUCTION

Due the initiated energy transition in Germany, the number of conventional power plants has been decreasing while the number of decentralized renewable energy plants has been increasing. This redistribution causes bidirectional load-flows, volatile feed-in of the power from renewable energy plants and higher power gradients [1]. New challenges and problems for distribution system operators appear, e.g. for the integration of new plants and loads, for the delivery of system services and at the guarantee of a high supply security and quality.

A. Motivation

The development of new control concepts can help to fix the problems and are key technologies of avoidance of a cost-intensive grid expansion. The project “SyNErgie” (“Systemoptimierendes Netz- und Energiemanagement für Verteilungsnetze der Zukunft”) is supported by the Federal Ministry of Economics and Energies and deals with the development of a new reactive power management, which gets embedded in grid planning and controlling processes. The aim is to improve the utilization of the existing grid infrastructure to increase the reactive power capability and the integration capacity of loads and plants in the grid [2].

One focus of the project is on the integration of DEPs to the reactive power control system. In rural grid topologies with widespread DEPs the development of a self-sufficient decentralized control system, which only works with local information (measures), is strived. Therefore is no necessity of a complex communication system to the grid control center. The Q-controller at the DEPs get characteristic curves and control the feed-in of reactive power with the aid of local reference variables (e.g. effective power, voltage or current) [2].

B. Objective

The aim of this work is to identify and interpret correlations between local available information to the overall reactive power of the grid group at the transformer. In that regard, temporal influencing quantities (time of day, season of year, type of day) were considered and in terms of their relevance analyzed.

The focus of this work is the determination of energy plants and operating points, in which the correlation behavior and the prognosis for the overall reactive power is sufficient for the functionality of decentralized reactive power management.

II. TECHNICAL BASICS

The correlation and regression analysis are important tools for statistical studies of dependencies and relations. This chapter is about the introduction of these calculation methods and the presentation of the regarded grid group.

A. Basics of correlation and regression analysis

1) Correlation analysis

Correlation is generally understood as a relation or a coherence of occurrences or processes. Besides the detection of stochastic relationships, the aim of correlation analysis is to quantify the intensity of a relation [3].

A measure of correlative connections is the correlation coefficient according to Bravais-Pearson r_{xy} . Its value is dimensionless which enables a comparability of relations [3].

$$r_{xy} = \frac{cov_{xy}}{s_x \cdot s_y} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \cdot \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (1)$$

This correlation coefficient requires linear relations between the variables. It is necessary to examine the violation of the linearity with a scatter diagram visually. The rank correlation coefficient according to Spearman is suitable for non-linear correlations to quantify general monotonous or ordinally scaled relations [3, 5]. In this work, only the coefficient of Bravais-Pearson is used, because there were no discernible non-linear relations in the analyses.

Correlation coefficients can assume values between +1 (direct proportionality) and -1 (reversed proportionality) [3]. For a better interpretation, the coefficient can be classified. TABLE I shows exemplary value classes. Factual justifications must be always considered in order to exclude spurious correlations [3].

TABLE I. POSSIBLE CLASSIFICATION OF CORRELATION COEFFICIENTS FOR A BETTER INTERPRETATION [5]

Amount of the correlation coefficient	Possible Interpretation
$ r \leq 0,2$	Very low correlation
$0,2 < r \leq 0,5$	Low correlation
$0,5 < r \leq 0,7$	Medially correlation
$0,7 < r \leq 0,9$	High correlation
$0,9 < r \leq 1,0$	Very high correlation

An existing correlation doesn't always come along with a relation, it is just an indication for an existence of a relation [3].

2) Regression analysis

Regression is the description of a unilateral directed stochastic dependency. It is possible to approximate a dependency of a variable \hat{y} on other variables x_k ($k = 1, \dots, m$)

by using a regression function. Having established a relation with correlation analysis, the aim of regression analysis is to describe this relation mathematically. In case of a multiple linear regression, the following term is used.

$$\hat{y} = b_0 + b_1x_{i1} + b_1x_{i2} + \dots + b_mx_{im}, \quad i = 1, \dots, n \quad (2)$$

b_0 is the regression-constant. The regression parameters b_1, \dots, b_m show the medial partial influence of the variables and are chosen to get the lowest medial quadratic deviation [3].

B. Topology of the regarded grid group

This subsection presents the regarded grid group in which the correlation analysis is applied. Figure 1 shows the operating points with a P-Q-cloud.

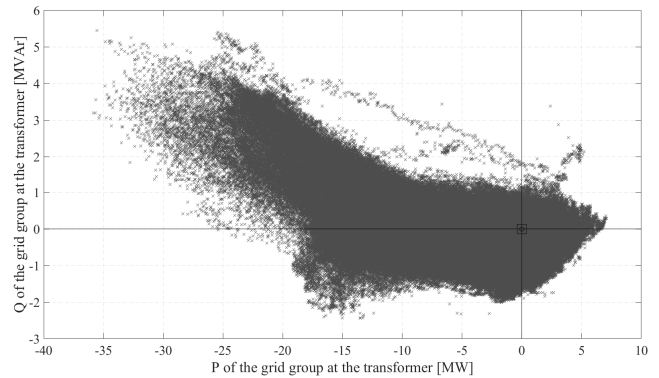


Figure 1: P-Q-cloud of the regarded grid group over the observation period from March 2016 to March 2017

The dominance in the second quadrant and the high power feedback of a maximum effective power of 35,8 MW shows a grid group in a rural area with less industry and a high proportion of DEPs. Another characteristic of the grid group is the high proportion of installed PV-power, as is shown in Figure 2.

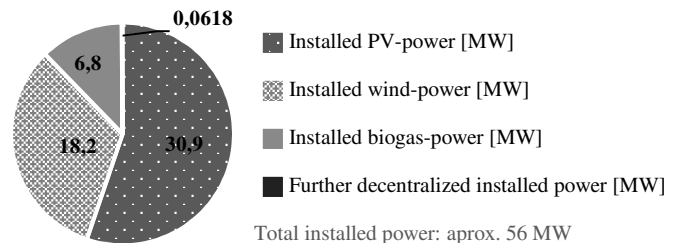


Figure 2: Composition of the installed producer power

For the correlation analysis, five big DEPs are considered. Their rated power may be obtained from the following table.

TABLE II. DESIGNATION AND RATED POWER OF THE DEPS

Designation of the DEP	Type	Rated Power
WEA 1	wind	10,0 MW
WEA 2	wind	6,15 MW
PV 1	PV	2,20 MW
PV 2	PV	2,07 MW
PV 3	PV	1,67 MW

In this paper, all statements refer to the calculation direction system for consumers. An inductive behavior leads to a voltage decrease, whereas a capacitive behavior leads to a voltage increase.

III. CORRELATION ANALYSIS BETWEEN LOCAL AVAILABLE MEASUREMENTS AT DEPS AND THE OVERALL Q-BEHAVIOR AT THE TRANSFORMER

This section deals about the analysis of the correlation behavior between potential local available measurements or information to the overall Q-behavior of the grid group. Scatter plots and correlation coefficients are used for the assessment.

A. Time of Day correlation

The correlation between the time of day and power quantities of the grid group is shown in the following Figure 3.

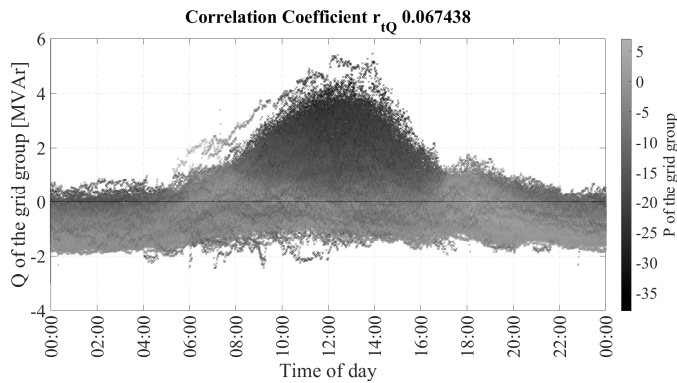


Figure 3: Correlation behavior between time of day to Q of the grid group at the transformer over the observation period from March 2016 to March 2017

There is a very low linear correlation between daytime and the reactive power at the substation transformer. The highest Q-values occur in the afternoon. The upper quantile of the Q-values occur at high return feed and follows the bell-shaped diurnal variation of photovoltaic plants. However, in the afternoon is also a wide scattering, thence a prognosis with only temporal values is insufficient. Further quantities are required, whose suitability will be analyzed in the following course of this work.

B. Effective power, solar irradiation and wind speed correlation

Figure 4 shows the correlation of the effective power of the biggest PV-plant PV 1 to the reactive power of the grid group at the transformer. The correlation behavior of the PV-plant is high. This effect can be observed at all PV plants. The dominance of the PV power in this grid group is the main reason for this behavior. A certain amount of PV-plants in the low voltage level have a $\cos \varphi(P)$ -control system, which causes a higher purchase of inductive reactive power at points with high feed-in power to keep the voltage in the grid stable.

The major reason is that all PV-plants feed in with high power at points in time with high solar irradiation and cause a high purchase of inductive reactive power in the grid operating resources, e.g. in transformers and power lines. This interaction-effect can be also seen in Figure 5, which shows a

particularly good correlation behavior of the solar irradiation to the reactive power of the grid group.

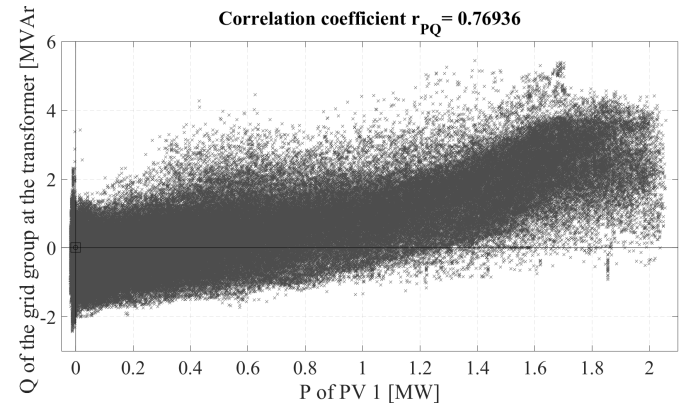


Figure 4: Correlation behavior between reactive power P at PV1 to Q of the grid group at the transformer over the observation period from March 2016 to March 2017

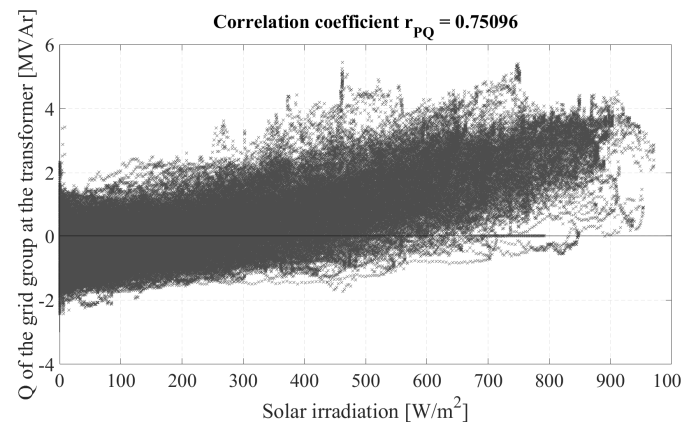


Figure 5: Correlation behavior between solar irradiation to Q of the grid group at the transformer over the observation period from March 2016 to March 2017

The correlation behavior of the effective power at the biggest wind-plant WEA1 to the overall Q of the grid is shown in Figure 6.

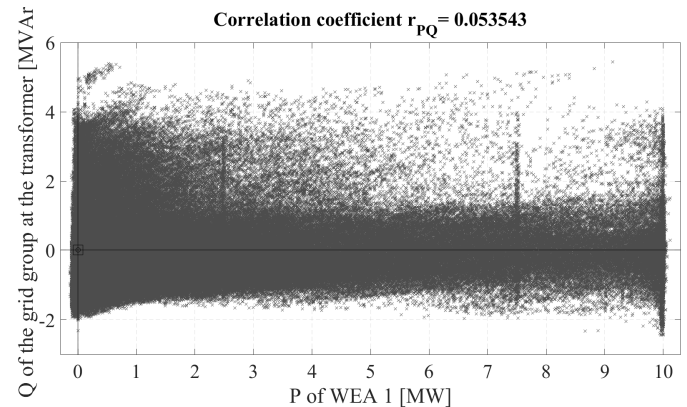


Figure 6: Correlation behavior between reactive power P at WEA1 to Q of the grid group at the transformer over the observation period from March 2016 to March 2017

There are two main reasons for this low correlation. There are only few points with a simultaneous high feeding-in effective power and a high purchase of inductive reactive power, but even points with a purchase of capacity reactive power. In the night there is no feed-in of PV-power. The installed wind-power is much less than the installed PV-power in this grid group. This leads to the conclusion that there exist no operating points with a high inductive power purchase at night (vgl. Figure 1), because of underutilization of grid operating resources. Another point is the combination of a $\cos\varphi(U)$ -control system of the wind-plants, fluctuations of the voltage from the high-voltage level and the deadband of the control system for the tap changer at the substation transformer. At operating points with a voltage-decrease of the high-voltage level and without a change of the tap at the transformer, the $\cos\phi(U)$ -control system at the wind plants reacts by purchasing capacitive reactive power. These operating points can be seen in the III. Quadrant of Figure 1 and are responsible for the scattering at points with a high feeding-in effective power.

The second reason is, that in this area in Bavaria are not that many points in time with a high wind speed, which can be seen in Figure 7. This causes a wide scattering at points with a low and middle feeding-in effective power and a low correlation of P or wind speed to the reactive power.

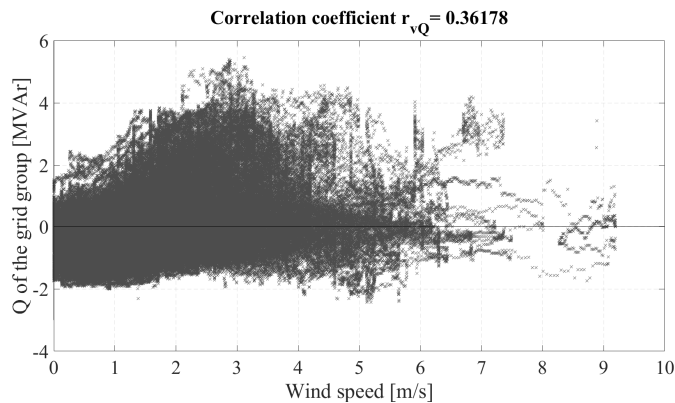


Figure 7: Correlation behavior between wind speed to Q of the grid group at the transformer over the observation period from March 2016 to March /2017

C. Voltage Correlation

In this subsection, the correlation behavior between voltages at DEPs and Q of the grid group is analyzed. Figure 8 shows this correlation of PV2 and PV3. These plants are controlled by a $\cos(\varphi) = 1$ control system. Due to this voltage independent control system, the correlation is in general not as high as the correlation behavior of the effective power.

The correlation coefficient of PV3 is more than twice as high as the coefficient of PV2. Both plants are in the same string, but PV3 has a higher electrical distance to the transformer. Therefore, the voltage uplift at high return feed is higher, causes a stretching of the point cloud and leads to a higher correlation coefficient.

The wide scattering in the marked area is caused by operating points at night, where almost no load flows occur. At

these points the operating resources are underutilized and purchase capacitive reactive power. The photovoltaic plants are not able to take influence at night, which leads to a worse correlation of the voltage. By suppressing these points and directing the view at time periods by day, values of correlation coefficients up to 0,6 can be reached.

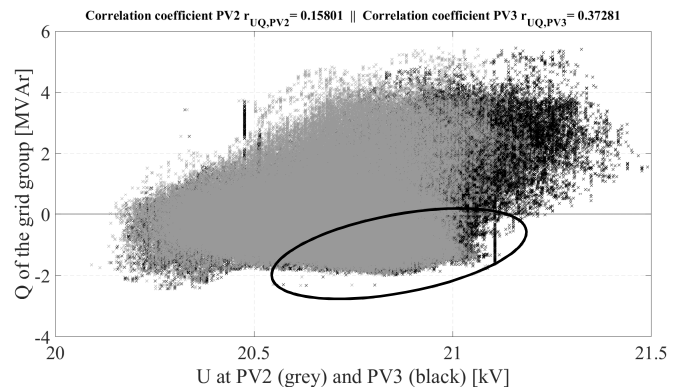


Figure 8: Correlation behavior between voltage at PV2 (grey) and at PV3 (black) to Q of the grid group at the transformer over the observation period from March 2016 to March /2017

Figure 9 shows the correlation behavior of voltage at the wind energy plant WEA2. This plant is at the very beginning of the string and has a short electrical distance to the substation. Its string doesn't contain many photovoltaic plants. This leads to lower voltage values as at PV2 and PV3. Even operating points with high return feed of the PV-plants can not cause a raise of the voltage at this plant. Higher voltage values appear at operating points with low load flows, while capacitive reactive power is purchased. The correlation coefficient gets inverted.

The wind energy plant takes a considerable influence on the correlation behavior within the marked area. In this sector are operating points with maximum feed in of the plant WEA2. The $\cos\varphi(U)$ – control system causes a voltage decrease at the plant and thus a deterioration of the correlation coefficient.

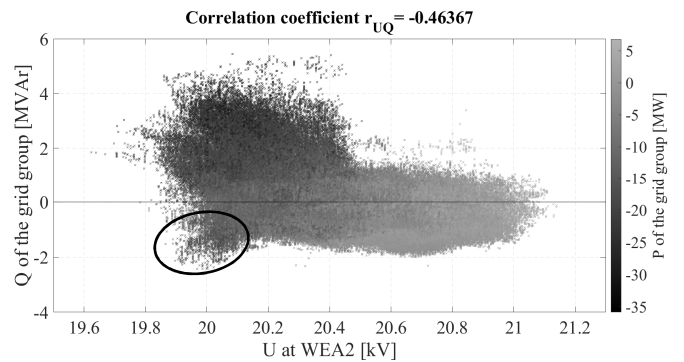


Figure 9: Correlation behavior between voltage U at WEA2 to Q of the grid group at the transformer over the observation period from March 2016 to March 2017

D. Temperature Correlation

Figure 11 shows the correlation behavior of the local ambient temperature and the reactive power. A slight trend is recognizable. Values with a high inductive reactive power purchase occur more intensely at points in time with an elevated temperature (especially in spring and in summer). However, the sole correlation of the temperature is not sufficient for the regression analysis.

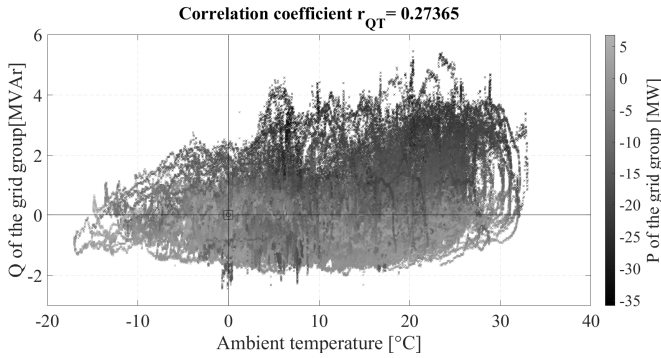


Figure 11: Correlation behavior between wind speed to Q of the grid group at the transformer over the observation period from March 2016 to March /2017

IV. TEMPORAL INFLUENCING QUANTITIES

Besides analyzing the correlation behavior in general, it is in addition useful to consider the influence of the regarded period of time. This chapter deals with the influence of temporal characteristics. The effective power P at photovoltaic plants has an overall high correlation behavior and is easy to measure on site. Therefore, the analysis of the temporal sensitivity of the correlation behavior is exemplary shown on P at PV1. For a better prognosis of Q by using more local available measurements, it is useful to analyze all quantities with regard to their sensitivity to other potential influencing quantities.

A. Influence of season for the correlation of P

The influence of the seasons can be seen in Figure 14 and Figure 10. In autumn and winter are less points with high return feed and high inductive reactive power purchase.

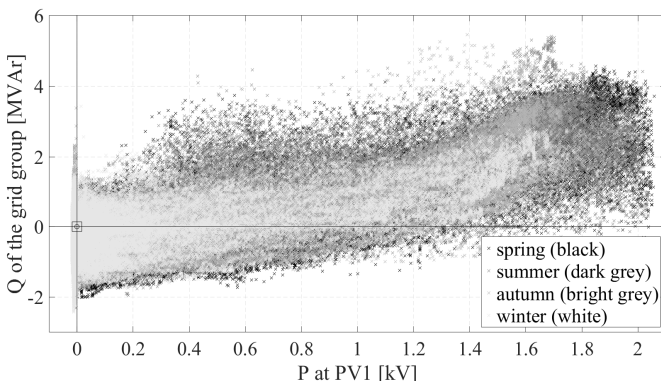


Figure 14: Influence of season for the correlation of P at PV1 to Q of the grid group at the transformer over the observation period from March 2016 to March 2017

The dominance of the photovoltaic plants is reduced. The correlation coefficient of PV1 falls from 0,82 in summer to 0,55 in winter, while the correlation coefficients of the wind energy plants gets slightly increased (cf. Figure 10).

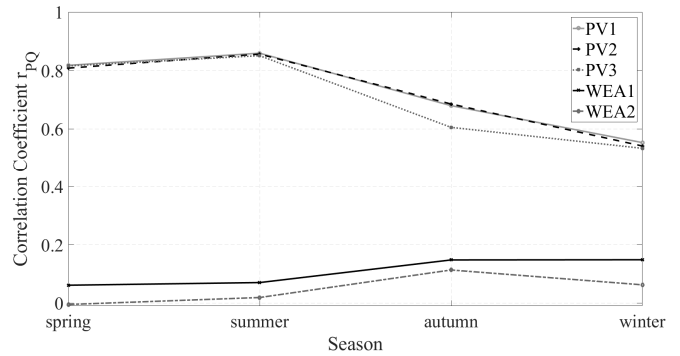


Figure 10: Influence of season for the correlation of P at the DEPs to Q of the grid group over the observation period from March 2016 to March 2017

B. Influence of type of day for the correlation of P

Figure 13 and Figure 12 show the influence of the type of day. One can see a vertical offset between the diverse types of days. The correlation coefficient changes only slightly over the type of days. At this point, attention should be drawn to the fact that the number of data is reduced at the classification 'holidays'.

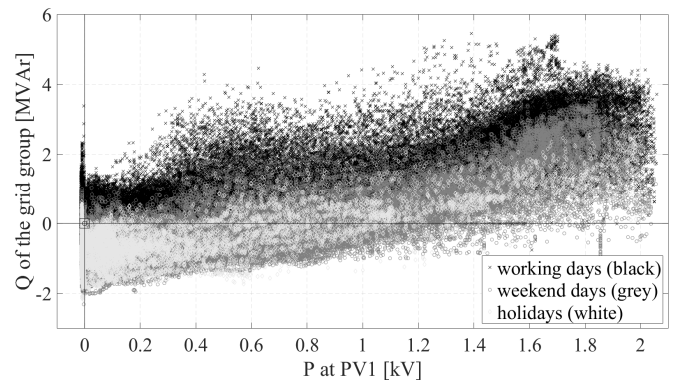


Figure 13: Influence of type of day for the correlation of P at PV1 to Q of the grid group at the transformer over the observation period from March 2016 to December 2016

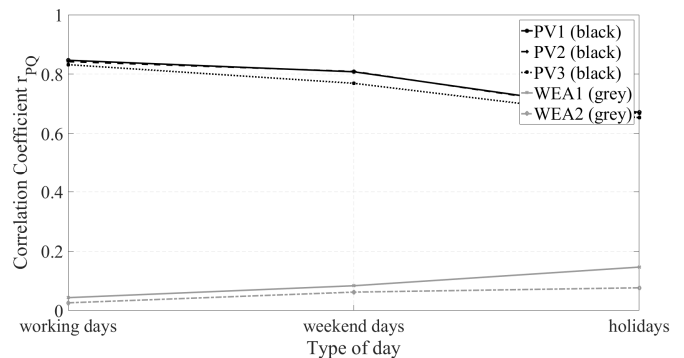


Figure 12: Influence of type of day for the correlation of P at the DEPs to Q of the grid group over the observation period from March 2016 to March 2017

C. Influence of time of day for the correlation of P

Another major influence factor is the time of day. Figure 15 shows this influence to the correlation behavior of P at PV1 to Q. As expected, values of P are very low at 04:00 to 05:59 in the morning. But in the course of the day, the correlation coefficient raises up to almost 0,8.

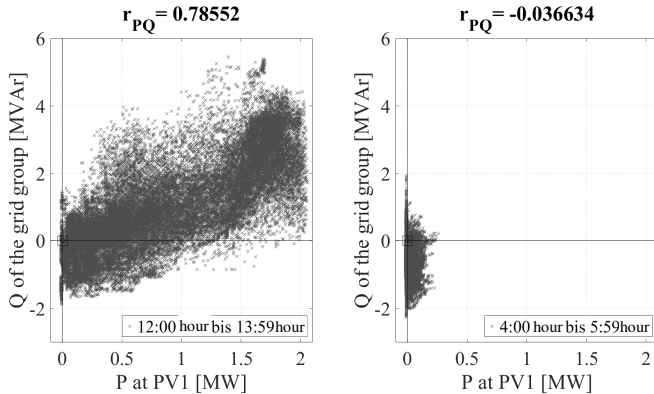


Figure 15: Influence of time of day for the correlation of P at PV1 to Q of the grid group at the transformer over the observation period from March 2016 to March 2017 at 12:00 am - 01:59 pm and 04:00-05:59 in the morning

Figure 16 shows the course of the correlation coefficients at the DEPs in the course of the day. The influence of the time of day is immense. Photovoltaic plants have a particularly good correlation behavior during the hours of sunshine, whereas wind energy plants have a good correlation behavior during the night hours even though they are not the dominant plant type in this grid group.

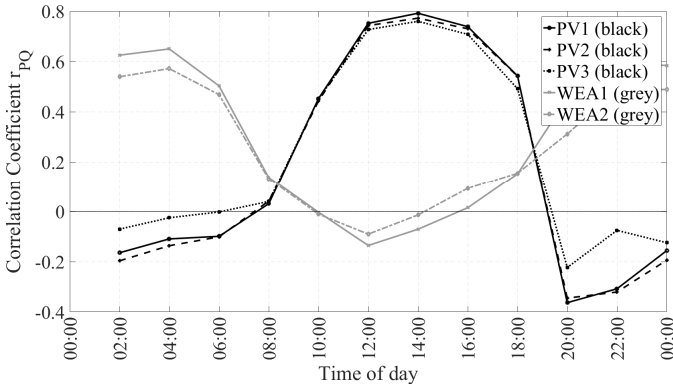


Figure 16: Influence of time of day for the correlation of P at the DEPs to Q of the grid group over the observation period from March 2016 to March 2017

V. SUMMARY AND CONCLUSION

An overview over correlation behaviors between all regarded local available measurements to the reactive power at the grid group is provided in TABLE III.

The major influence is the type of the dominant energy plant in the grid. The best correlations can be observed for photovoltaic plants and with solar irradiation. The worst correlations can be noticed for wind energy plants. The reason is the high proportion of installed PV power in this grid group.

Other grid groups with a higher proportion of wind energy plants might show an inverse behavior.

Time of day, temperature and wind speed are not sufficient as sole variables for the prognosis of Q. But they might be suitable as additional variables for the multiple regression analysis in order to increase the accuracy of the prognosis.

TABLE III OVERVIEW OF THE CORRELATION BEHAVIOR BETWEEN ALL REGARDED VARIABLES

	Time of day	Effective Power	Solar irradiation	Wind speed	Voltage	Temp
r	0,07	PV1	0,77	0,75	PV1	0,34
		PV2	0,76		PV2	0,16
		PV3	0,75		PV3	0,37
		WE A1	0,05		WE A1	-0,1
		WE A2	0,03		WE A2	-0,46
						0,27

The following TABLE IV shows the maximum range of the correlation coefficients by the variation of the temporal influencing quantities season, type of day and time of day on the correlation behavior of P at PV1 and WEA1 to Q. The range can assume values between 0 (no change in the correlation behavior during the variation) to 2 (correlation behavior changed from direct proportionality to inverse proportionality or vice versa). The higher the range the higher the influence of the temporal quantity.

TABLE IV: MAXIMUM RANGE OF CORRELATION COEFFICIENTS BETWEEN P AND Q AT PV1 AND WEA1 BY VARIATION OF TEMPORAL INFLUENCING QUANTITIES

	Season	Type of day	Time of day
Range of $r_{PQ,PV1}$	0,31	0,18	1,15
Range of $r_{PQ,WEA1}$	0,09	0,10	0,78

Time of day and season have a significant influence to the correlation behavior (especially to the PV correlation behavior). They should be considered in the prognosis model.

The next step is to create the prognosis model by regression analysis. All variables will be implemented in a multiple regression function according to their analyzed correlative relevance. Thereby it is important to observe the influencing quantities. The influence of a quantity can be implemented by creating regression parameter vectors \vec{b}_x in notation (2). Therefore, the influence of a variable for the prognosis can be reduced to zero at certain points in time (e.g. P-correlation of PV-plants at night). The optimal model will be found by adding and reducing the variables and influencing quantities according to their relevance by observing the coefficient of determination R^2 . The regression model with the best coefficient of determination (number from 0 to 1, which indicates the quality and accuracy of the prognosis) can be used for the creation of the characteristic curves for the Q-controllers at the DEPs.

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