UNIVERSITY OF TWENTE.

Faculty of Electrical Engineering,
Mathematics & Computer Science

A day ahead electricity storage flexibility prediction for peak shaving.

Kristian Keller

Thesis Master of Computer Science
September 2016

Supervisors:
Prof. dr. ir. G.J.M Smit
Prof. dr. J.L. Hurink
Dr. ir. M. E. T. Gerards
Dr. S. Nykamp M.Sc.

Computer Architecture for Embedded Systems Group
Faculty of Electrical Engineering,
Mathematics and Computer Science
University of Twente
P.O. Box 217
7500 AE Enschede
The Netherlands

Abstract

More and more renewable electricity sources have been integrated in the energy grid in recent years. This is a positive development from an ecological point of view but it also brings new challenges for the electricity grid. One of the problems is the peak load resulting from abundant photovoltaics (PV) or wind power generation. In these peak situations the energy grid is used near to its limits or even overloaded. However, although these bottleneck situations are only temporary (the sun only shines during the day and wind is also only blowing at certain times), a stable electricity grid needs to be dimensioned for such worst case scenarios. These scenarios are occurring in the distribution grid at times with almost no demand and a high renewable power sources. In order to overcome the need for reinforcement for these temporary situations, the distribution grid provider requires a smart way to reduce or shift the energy peaks over time. One of the possible options for this is an electricity storage. The electricity storage can buffer power peaks caused by the renewable power producer. In situations of increasing power flows through e.g. a transformer, the storage can start charging as soon as a certain threshold is reached. In this way the power peak at the transformer is limited to this threshold. The storage can be discharged when the power flow decreases below the threshold.

In this master thesis a method is presented that predicts when and to what extent such a storage is used within the distribution grid for peak shaving. Hereby we limit our focus to renewable generation from PVs. We develop a regression based forecast for the PV generation and the power flow in the grid at the grid transformer for the next day. The used regression forecast method is tailored to forecasts in non-stable weather regions like in Germany or the Netherlands. To increase the accuracy of the forecast a fitting method is added that calculates a separate regression function for specific time intervals in order to adjust to the present situation in the grid and the actual PV generation.

We show that it is possible to forecast the state of charge (SoC) in the storage a day ahead quite accurately. As the results show that the storage is not used all the time, an interesting follow up question is to investigate if at certain times a certain amount of storage capacity can be given for use to a third party. For this, it is necessary to know how much capacity has to be used to balance the grid and at which time the storage inverter can not be used to its full potential, because that would endanger the grid. These two constraints are called ”grid requirements”. The term ”grid requirements” represents the capacity constraints of the storage itself and the power constraints of the storage power inverter. Based on the known grid requirements, the unused capacity can be given to a third party. This unused resources are called flexibility.

In practice it is important that for the use of flexibility by a third party strict boundaries are predicted and imposed. They have to ensure that the use of the flexibility by a third party does not put the grid in danger. In order to make the communication about flexibilities between the Distribution System Operator (DSO) and third parties easier, a so-called traffic light concept was published by the Germany DSO union BDEW. In this concept a manner of prioritisation of grid situations is given. It introduced three phases and coordinated the use of the flexibility. We incorporate the specification of the boundaries on the flexibility of the use of a storage by a third party in this traffic light concept.

To test the developed methods, a specific case of the German DSO Westnetz GmbH is used. This specific situation occurred in the area of Wettringen, Germany, where a temporary reinforcement was necessary in order to reduce the power peaks of PV generators. A regular 10-kV cable could have been used as reinforcement to overcome the voltage problems, but due to other grid reinforcements this cable would have been needed only for five years and after that it would be obsolete. Furthermore, load issues on transformers (30/10 and 10/0.4kV) would not have been reduced by the cable. Westnetz decided to invest in storage for this situation instead and to evaluate the economic and technical benefits of a temporary energy storage instead of introducing an extra 10-kV cable.

Contents

Chapter 1

Introduction

In the last century the daily life has became more and more electrified. Nowadays the western world is a high-tech social environment, including comfortable homes, high level of medical care and working places with more and more IT, which all needs electricity. This increasing electricity demand, however, has to be satisfied without any black outs as our daily life completely depends on the availability of electricity.
The sources for the electricity production have changed. Until a few years ago the electric power was produced by large power plants that use fossil fuels to produce large amounts of power on central locations. This power was been transported over a large transmission and distribution grid through the country. But these power plants based on fossil fuels have two disadvantages. On one side the amount of these fossil fuels is limited and on the other hand the resulting electricity production has negative impact on our climate. This is the reason why a transition is taking place. More and more power generation based on renewable sources, like wind turbine and photovoltaic (PV), are being used. This change is supported by the governments of most of the western countries.
The mentioned changes lead to new challenges for the distribution grid. The power is no longer primarily produced in a few central places but rather in many distributed entities. This results in changes for the grid environment itself. It can now happen that there is more power production (due to wind turbines and PV) than demand in a local distribution grid so that there is a power flow from the distribution grid to the transmission grid. Furthermore, the voltage may exceed the given limits due to a local increase of the voltage cause by the power production in the distribution grids. This voltage increase depends on several parameters such as the distance of the generator to the next voltage influencing transformer, the impedance of the local grid, the voltage level or the size of the generator. Another challenge is that renewable production does not provide constant and easy to predict power. This makes it more troublesome to maintain a balanced distribution grid.
In order to overcome the challenges emerging from the renewable power producers,

the grid has to change to a grid that commonly is known under the phrase ”smart grid”. Within smart grids one of the possibilities is to flatten the power profile of PV by temporary storing a part of the produced power in a storage. These storages offer also some additional advantages. For example, electricity storage may help to maintain the voltage level and can react fast on fluctuating energy demands. Furthermore, a storage can be built for mobile use. That is a big advantage compared to installing more underground cables. But storage technologies are still in the developmental stages and in most cases more expensive than conventional grid reinforcement.

1.1 Motivation

The motivation of this thesis is to investigate the use an electricity storage in a distribution grid in an efficient way. Nowadays such storages are only in general used for one purpose. The storage is either used for grid purpose (e.g., peak shaving) or for market purpose (e.g., to exploit price spreads at an energy exchange). If both purposes would be combined, a win-win situation for the DSOs and the other parties may occur. The DSOs can use the storage in order to maintain the distribution grid, can save temporary investments and can save renewable energy for later use (which might be lost if there is no storage). On the other hand, the society also has an advantage because they pay (indirectly) for the grid maintenance of the DSO. If the DSO can save money for reinforcements and maintaining the grid, the society has to pay less money for investments in the energy grid. But to be able to combine market and grid purposes, it is necessary to predict the power production on beforehand in order to know how much of the capacity of the storage is needed to balance the grid. This is the starting point of this research.

1.2 Practical research issue

This work is conducted in cooperation with the company Westnetz GmbH. Westnetz GmbH is a DSO (Distribution Grid Operator) and a part of the RWE innogy, S.E. and has different research projects in the area of renewable energies and smart grids. One of the projects is realised in Wettringen. Here an electricity storage is used in the low voltage grid to maintain the voltage level in the grid and additionally to buffers the PV peaks that may occur during sunny days in the afternoon that would lead to a violation of the transformer capacity. In the following paragraphs the situation in Wettringen/Germany is described in more detail. Wettringen is a rural area with lots of PV installations. The PV installations in a certain part of Wettringen are all connected to one substation transformer that connects the distribution grid (0,4 kV) to the transmission grid (10 kV). The number of PV installations has been increased over the years. Today the panels that are installed in this part of Wettringen can produce a peak load of approximately 700 kW. The roll out of these PV generators in the distribution grid may introduce stress to the grid and introduce two problems. The first is that the voltage level at the end of a feeder may reach the upper limit of the voltage tolerance of the standard for electricity grids. The second problem is that the PV installations can produce power peak of approximately 700 kW, which can lead to an overload of the transformer because the transformer, used in this part of Wettringen, has only a capacity of 630kW. Hence, if there is low demand and high PV generation in the distribution grid of Wettringen the power peak can cause an overload at the transformer.

These are the reasons why Westnetz GmbH has chosen Wettringen as the location for the storage research project. The storage was installed in August 2015 in order to prevent the problems described above. The storage was dimensioned to be able to handle the worst case scenario, which means a situation with almost no demand and full PV production of all panels. However, it is not likely that the storage is fully used most of the time, because the PV production depends on the sun, which has certain fluctuations. On the other hand, grids have to be dimensioned for the worst-case scenario and the maximum load to avoid black-outs. Furthermore, as the weather conditions in the western part of Germany are unstable it is difficult to predict the usage of the storage. Simulations before starting the project and results from the testing phase show that between the end of October and April the storage is not used because the produced power can be fed into the grid without risks. Furthermore during the remaining time of the year the storage is rarely used entirely because of seasonal influences and the movement of the sun. It has been observed that the power production is heavy fluctuating during the day and the storage can only reach its full potential on some days in the year.

That is why Westnetz GmbH now is looking for a method that is able to forecast the storage usage for the next day in order to use the full potential of the storage. In the end a forecast method is required considering the following three aspects :

- The power flow over the transformer. This allows to calculate how much power is in the distribution grid and how much power needs to be fed in the storage.
- The needed capacity of the storage to balance the grid and its state of charge during the day.
- Using the two aspects above it is possible to determine the possibilities for the market use of the storage. In this context, these possibilities are denoted as ”free flexibilities”. These flexibilities, which are offered to the market, are not allowed to endanger the grid stability. The grid balance always has priority in order to prevent black outs.

1.3 Goal of this thesis and research questions

The goal of this thesis is to investigate the possibilities to forecast the flexibility of a storage used to avoid overloading of the transformer in a distribution grid. In order to achieve this goal, several research questions from different areas are considered.

- How much renewable energy is installed in the distribution grid behind the transformer?
- Which factors have the greatest impact to the power flow at the transformer?
- How can such factors be forecast?

These questions have to be answered in order to be able to forecast the power flow over the transformer one day in advance. Together with Westnetz it was decided to use a the already mentioned part of the distribution grid of Wettringen as test grid. If the word ”grid” is used in the remaining of this thesis, it refers to the grid part of Wettringen. This grid was chosen for two main reasons. First, it is a test project of Westnetz, which implies that much sensor data is available and all details of the grid assets are documented. The second is that the storage was integrated in order to balance the PV production of this area.
The research analysis in hand the power flow between the three most important grid assets (transformer of the grid, the inverter of the storage, the demand of the household and the PV generation) of Wettringen and aims to find an appropriate method to forecasting the power flow at the transformer and the storage flexibilities one day

ahead. The goals can be summarised in the following research questions.

Main research question

- How can the flexibility of an electricity storage used primarily for peak shaving be predicted a day ahead?

Sub research question

- What grid assets (e.g generators,consumers, technical limits ...) are most important for the forecast and how is the power flow between them (in the considered part of the distribution grid of Wettringen)?
- Which method can be used to forecast tomorrows PV production (in the area of Wettringen / Germany)?
- What forecast accuracy can be achieved and what can influence the forecast accuracy?
- How can the important information mentioned in Section 1.2 be calculated and visualised?

1.4 Structure of the thesis

The thesis is structured in the following way. Section 2 provides some background knowledge and important information that is needed to understand the decisions made in this thesis. The calculations of the free flexibility are divided in two parts. In Section 3, the given theoretical base of this thesis is presented. Furthermore, a discussion is given that presents an approach of handling the use of flexibilities with more parties. Section 4 shows the practical application of the method presented in Section 3 to an flexibility prediction in a electricity grid with storage asset and heavy impact of PV generation. In Section 5, the results of the previously developed calculation methods with considering the measurement data of Westnetz GmbH are given. The thesis concludes with Section 6, which contains the primary conclusions and further work.

Chapter 2

Background and Related Work

This chapter provides background knowledge needed to understand the decisions made in the remainder of the thesis. It seems that this research is one of the first that studies the forecast of free flexibilities in electricity storage in smart grids. Therefore, we start with a short analysis of the research question and explain why information on the power flow in the considered grid is the starting point for this research. Based on this, in Section 2.2 a description of the grid and the assets in Wettringen are given. Furthermore, an overview of the geographical area is shown, and the electricity grid and the grid properties are presented. The next section deals with the so called ”traffic light” concept, which was introduced by ”Bundesverband der Energie- und Wasserwirtschaft e.V.” (BDEW, in english: federal association of energy and water economics). This organisation is a union of more than 1800 German companies that are working in the areas of energy and water management. In March 2015 they provided this traffic light concept for new smart grid technologies. It contains best practise and ideas, which ensure that the taken steps and investments are compatible with each other. The last section provides an explanation of the PV forecast method that is used in this thesis.
Summarising, this chapter is structured as follows:

- Analysis of the research question and the starting point (Section 2.1).

- Analysis of the test grid area (Section 2.2).

- Introduction of the ”traffic light” concept of BDEW (Section 2.3).

- Decision and adjustments of the PV forecast method used in this thesis (Section 2.4).

2.1 Analysis of the research question and the starting point.

The main aim of this thesis is "to calculate the free flexibilities of a storage asset one day ahead". Within a literature research (Appendix A) it was investigated which knowledge on free flexibilities in distribution grids was available. The outcome was that there is hardly any research in the area of grid related electricity storage and calculation of free flexibilities. Therefore a step back was made to get a better insight in the research questions. It can be noted that most of the questions of Section 1.3 are related to the calculation of the power flow at the transformer in the grid. More precise, if the power generation of the renewable energy production and the demand could be forecast a day ahead, it is possible to calculate the usage of the storage. Based on this, we can determine the capacity used for buffering the renewable energy peak during the next day and calculate the free capacity of the electricity storage (of Wettringen). This free capacity determines the flexibility of the storage. But if a third party wants to use this free flexibility, there must be rules for the usage in order to prevent dangerous situations in the grid. As a consequence, there should be constraints in the usage of the flexibilities.
Based on the above, the thesis was started with the idea to analyse the grid situation and then try to forecast the information, which are needed to calculate the flexibility of the next day.

2.2 Analysis of the sub grid in Wettringen

The Wettringen distribution grid is located in Muensterland, Germany, which is a rural area with a lot of farms and PV installations. Due to the massive PV power generation it occurs in peak hours that the power generation is 20 times higher than the demand in the area. In the considered part of distribution grid eight houses (farms) are present. This distribution grid is connected together with similar low voltage areas to several medium voltage lines (10-kV) which are connected to the upstream grid (30-kV). This upstream substation is located in the centre of Wettringen. The considered houses (farms) have large PV installations on the rooftops of their buildings. Summarising, the area has a small electricity demand and on sunny days a much higher power generation. For more details, we refer to [1]. As already mentioned, it is important to know exactly what assets are installed in the grid of Wettringen and how the assets are connected with each other. In Figure 2.1 an insight into the infrastructure of the Wettringen area is given.

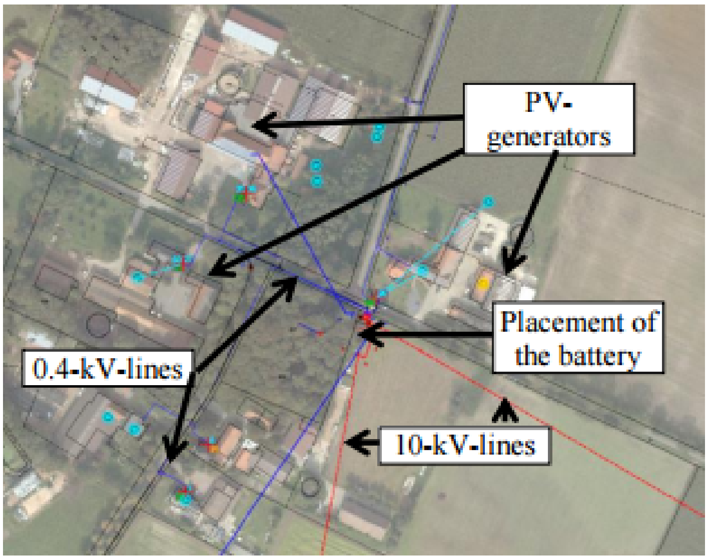


Figure 2.1: ”Location in Wettringen with grid assets, farms and PV-generators” [1]

In the area there are twelve different PV installations at the four farms with a total generation capacity of 687 kW (individual installations ranging from 10 kW up to 155kW power generation), whereby all installations are built on the rooftops of different buildings. This means that all PV installations have different vertical and horizontal orientation. The different orientations influence the PV generation, especially since the two largest installations do not face south directly. This means that a small shift between the irradiation peak and the power peak is expected. To verify this, a 24h observation was made. In Figure 2.2 the observation of the solar irradiation and the power level at the transformer is visualised, in order to prove two facts. The first fact is the impact of the PV generation on the grid and the second is the relation between solar irradiation and power generation.

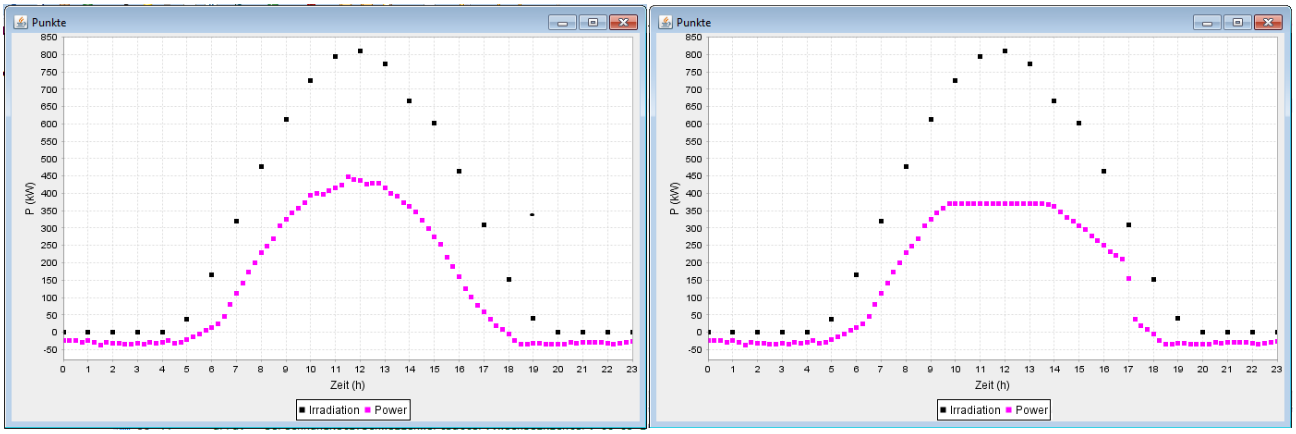


Figure 2.2: Power flow at the transformer with and without storage on in 08-05-2016

Note, that in Figure 2.2, a negative power value means that there is more electricity demand than production and electricity has to be imported from the transmission grid. A positive power value indicates that the production in the grid is high enough to satisfy the electricity demand and moreover electrical energy can be exported to the transmission grid. In the figure it can be seen clearly that on sunny days the impact on the grid resulting from the PV generators is massive. Furthermore it can be seen that on these days there is several times more electricity production than consumption in the grid. That is one reason why the storage was installed at the grid of Wettringen. The figure also shows a clear relationship between the irradiation and the power generation. In addition, the expected shift is also present. The measured irradiation peak is at 12:00 whereas the power generation peak is at 11:30.
To get an overview of the grid assets, a second analysis using the grid monitoring tool of Westnetz "ZLT" was made. In ZLT, selected grid assets and technical specifications are documented. Furthermore, the measured values of the power flows passing the grid assets can be found there. As in this 10-/0.4-kV substation measurements devices have been installed, the "net power flow" of the low voltage grid can also be achieved. The corresponding measurements show, that the installed PV panels have a production capacity of exactly 687kW and in the night the demand in the grid is almost 25 - 35 kW. The storage asset is directly connected to the transformer and has a small demand itself. A scheme for the connection of the main assets in the grid and some technical data are summarised in Figure 2.3.

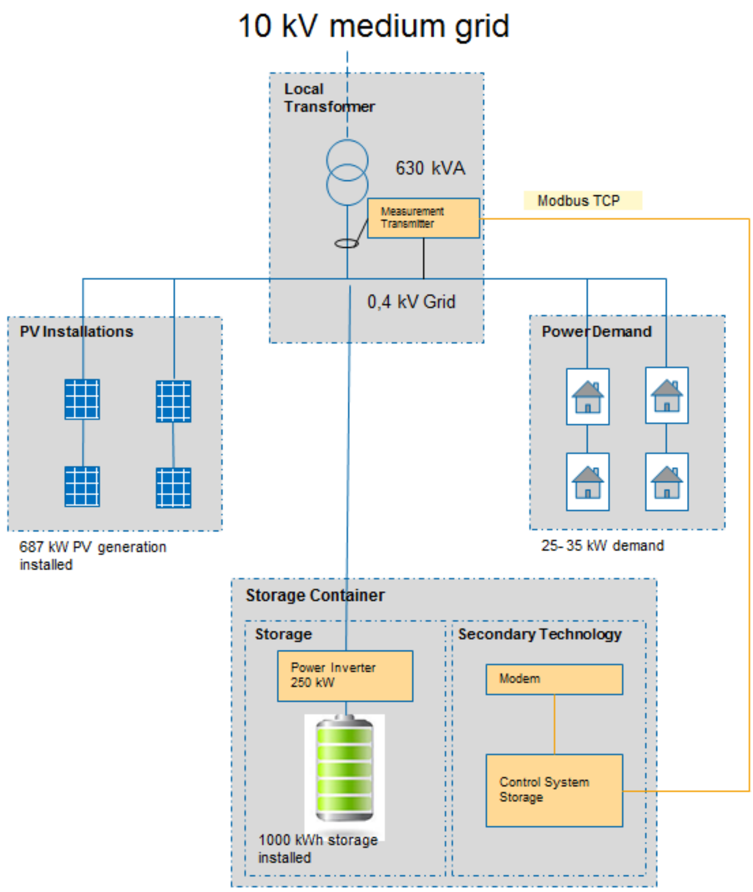


Figure 2.3: All assets of the grid in Wettringen

2.3 Smart Grids "traffic light" concept of BDEW

The "BDEW Bundesverband der Energie- und Wasserwirtschaft e.V." [2] is a union of more than 1800 German companies that are working in the areas of energy and water management. They published a discussion paper with a "traffic light" concept for smart grids in March 2015, which indicates the handling and the definition of free flexibility. In this paper an approach is described for communication between the market participants and the DSOs. This concept was needed because the previously known two phases (the green and red phases from the "traffic light" concept) did not suffice any more. The first phase was the phase when no problems are indicated in the grid. This phase is called the "green phase" in the "traffic light" concept. The second phase is when there are problems, e.g. a PV power peak, which may endanger the grid. This phase is known as "red phase" in the "traffic light" concept. These two phases could follow up each other immediately from the "no problem" phase to the "problem" phase (from green to red phase later on) in a worst case scenarios. That is why the new traffic light concept was extended. The new phase ("yellow phase") is inserted between the other two phases ("green" and "red") and exploits the two old phases to prevent the dangerous situation. This makes it easier to control the flexibility by a decentralised energy providers, smart grids and market participants. On the basis of the BDEW paper, new processes and protocols have to be developed.

2.3.1 Definition of flexibilities according to BDEW

Flexibilities can be used for different purposes. The BDEW discussion paper divides the use of flexibilities in three different categories:

- system purposes
- market purposes
- grid purposes

The first category is "system purposes" and means that the transmission grid operator uses the flexibility in order to maintain overall system stability. More precisely the transmission grid operator uses the flexibility to balance the electricity grid from the high voltage grid up to the transmission grid (220 kV, 380 kV) focusing on frequency stability. The second category is the "market purposes" category, where market players use the flexibilities to trade energy on the markets. These markets are centralised institutions (such as EPEX in Leipzig or APX in Amsterdam) and their main focus is on arbitrage to exploit price spreads. The third category is "grid purposes". Here the local grid operator use the flexibilities to prevent critical situations in the distribution grid and, hence, the focus is on local voltage or load problems. In this case, flexibilities can be used, e.g., to shift power peaks in time. In this way some of the traditional grid reinforcements may be avoided, reduced or temporarily shifted. This means that the use of flexibilities instead of traditional grid reinforcements can be directly or indirectly beneficial for many parties (grid owner, energy provider or/and energy customer). The BDEW "traffic light" concept prioritises the use of flexibilities in the grid area higher than in the market area. In this thesis the power flow behind the transformer in a distribution grid is used to consider the phase of the "traffic light", because the balance in the distribution grid always has the highest priority to avoid critical situations in it.

2.3.2 Definition of the three different traffic light phases

The main idea behind the ”traffic light” concept is that the state of a certain part of the grid during a time period is indicated using three colours: green, yellow and red. Dependent on the current traffic phase, different rules are applied for the usage of the flexibilities. These symbolised grid states makes the communication between the different market participants easier. In the context of this thesis the important participants are the local grid operator and the market player. In the BDEW concept the local grid operator determines the flexibility demand of the actual grid and assigns one of the three states. This process can be seen in Figure 2.4. The three phases are:

- **green phase**: In this phase (market phase) the trades between the market players and consumers/producers are not limited because there is no critical grid situation. The local grid operator maintains and monitors the grid, but there is no need to intervene and hence he has no need for any flexibility.

- **yellow phase**: In this phase (interaction phase) a possible critical situation or a bottleneck may occurs in the local grid. In this phase the local grid operator uses flexibilities in order to prevent the critical situation. The used flexibilities are no longer at the disposal of the market players, which means the market players are limited in their trades. This results in a need for communication between the local grid operator and the market players. Who actually contracts the flexibility (market or grid) is a question of negotiation and, thus, willingness to pay for it. This ensures an efficient usage of the flexibility. The used flexibilities can come from two different sides: user behaviour (adaption of generation/consumption) or energy storage.

- **red phase**: In this phase (grid phase) a critical situation or a bottleneck occurs in the local grid. Independently of the phase in which the grid was before, if a critical situation occurs the phases changes immediately to the red phase. In the red phase the local grid operator has all possibilities from the yellow phase and receives in addition the control over all assets (grid assests and all flexibility) in the grid. Now the local grid operator is allowed to regulate the assets directly or shut them down in order to prevent a black out.

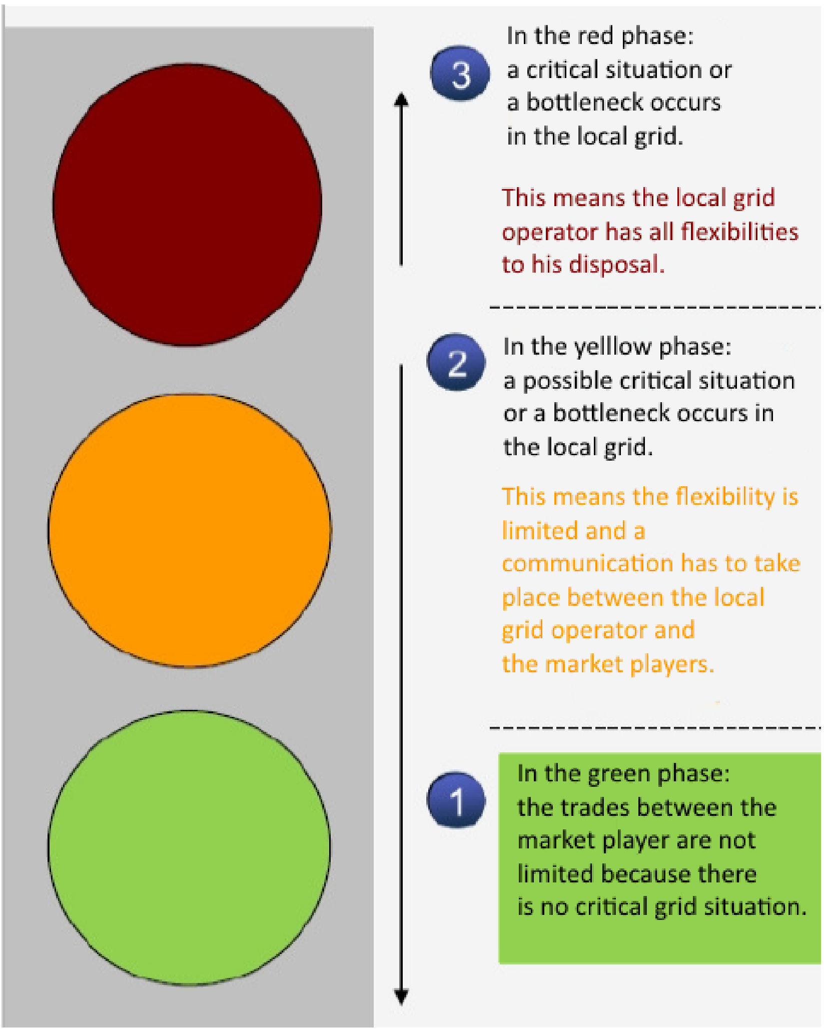


Figure 2.4: The rules in the three ”traffic light” phases

2.4 PV forecast method

As mentioned and shown in Section 2.2, PV generation has a heavy impact on the grid. Information on the power flow over the transformer is needed in order to determine possible ways of usage of the storage. As PV generation is the most important factor for this, a PV forecast method is needed. In a literature research on available forecast methods (see appendix A), it was found that there exist many different forecast methods and that all of them have their (dis)advantages. Furthermore it is very difficult to compare the methods because they are all customised to a specific situation and sometimes to geographical specialities. Additionally no long term data is available from the papers in the literature research.

Based on the results of the literature study it can be concluded that none of the presented methods is suitable for the project of Westnetz GmbH and a new method inspired by known methods has to be developed. The decision was made to use

a regression analysis as base method, because previous application of regression methods have shown that they have an advantage in forecasting weather related values in areas with unstable weather conditions and the given area of Wettringen has such unstable weather conditions. A regression method also has one additional advantage. As there is no data available on the precise demand of the houses in the area (there are only measurements at the transformer, the big PV generators and the storage itself), a regression method may consider the demand as a part of the forecast value. This can be done because it can be assumed that demand does not fluctuate a lot in the considered area. More precisely, a forecast method is used that calculates a regression function from the historical data (irradiation and power flow over the transformer consisting of PV generation and demand) and then forecast the power flow over the transformer with the help of the predicted irradiation value from the weather forecast. This weather forecast comes from Westnetz GmbH and is not discussed in more detail in this thesis.
In order to obtain an accurate power flow prediction at the transformer, our method does not use a single generated regression function for the hole day, it rather will calculate the regression function for a number of different time intervals during the day. The number of used time intervals is researched in this thesis. In addition, the period of historical data that is used to generate the regression function has to be analysed. All these parts are integrated in a fitting method that runs before the PV forecast method is used. This fitting method has been chosen to "learn" the changes in the surrounding, the change of season and the properties of the PV installations itself. The fitting part should guarantee that the forecast method is accurate in time.

2.5 Conclusion

To conclude this chapter, the distribution grid in Wettringen is suitable for this research. There is only a small amount of demand and a heavy PV generation in the distribution grid. The PV installations are located on different rooftops of farm buildings, that means the PV installations are facing in different directions, so that there will be a smoothing effect, because is may be possible that the PV installations compensate each others peaks and local minima. Furthermore, we introduce the BDEW "traffic light" concept, which defines free flexibilities and a communication concept with three phases in order to prevent miscommunication between the distribution grid provider and a third party. In the last section we present the results of our literature study and chose a regression method for forecasting purposes. The regression method is most suitable because it seems to deliver more accurate forecasts in unstable weather regions than the other forecast methods.

Chapter 3

Theoretical PV forecast and flexibility methods

This chapter describes the development of the regression method and the way how its output is translated to a flexibility forecast for an electricity storage asset. As there are no previous approaches to calculate flexibilities in grids with a PV impact and a storage facility, the method to calculate flexibilities has to be developed from scratch. The calculations or rather the forecast can be divided into two main steps. The first step is to forecast the power flow over the transformer in the distribution grid. For this purpose a PV forecast is needed, because the given grid is heavy dominated by PV generation. Additionally the demand has to be considered. The PV generation together with the demand reveal the power flow through the transformer. The second main step is the calculation of the flexibility of using the battery by third parties. The forecast power flow is the basis for these flexibility calculations.
Summarising, in this chapter, the theoretical background and the conditions of the following two main parts are explained:

- PV and power flow forecast
- Flexibility calculation according to BDEW

3.1 PV and power flow forecast method

As explained in Section 2.4, regression analysis is chosen as the base method to forecast the PV generation. In this chapter the theory behind regression analysis is briefly explained and the application to PV forecast is shown. In [3] it is written that regression analysis is a simple statistical tool to establish a connection between variables. It is widely used in many different areas, a.o. to forecast variables with the help of historical observations. For the problem considered in this thesis, the value to be forecast is the power flow at the transformer. It is assumed that this power flow is mainly depending on the irradiation. Formally, to express these relations, a regression uses variables. The variable which is the result or rather the forecasted variable is called the ***response*** variable (in our case it is the power flow). Furthermore the regression analysis needs one or more variables, which determine the response variable (in our case the irradiation). They are called ***predictor(s)***. In the following we use the terminology of [3]. Here Y denotes the response variable and $X_1, X_2...X_n$ denote the predictors. This implies that the regression is a function of the form:

$$Y = F(X_1, X_2...X_n) + \varepsilon, \tag{3.1}$$

where ε is a certain error, which represents an inaccuracy of the connection between the predictions and the response variables, in our case between the irradiation and the power flow.
According to [3] a regression analysis consist of the following steps:

- **Statement of the problem**: Regression analysis normally starts with a problem statement. The statement includes the questions, which should be answered with the regression, and the problem statement should have at least two variables with a connection included. This step is perhaps the most important, because wrong definitions or a misformulated question can result in wasted time and work.

- **Selection of potentially relevant variables**: In the second step the set of variables has to be chosen. The variables in the set should have a certain connection or influence on each other. First a response variable has to be chosen. This variable is (part of) the answer of the problem statement. Furthermore, there has to be chosen one or more variables, which describe or influence the response variable. These variables are the set of predictor variables.

- **Data collection**: Once the relevant variables have been selected, historical data of the environment under study has to be collected. Here the difference between controlled and uncontrolled environments have to be distinguished. In test environments it is possible to keep factors, which are not of interest, constant. But often the environment is not experimental, which means that it is not controllable. In both situations the data consists of observations. Each observation consists of a certain number of measurements. The results can normally be presented in a table of data where each column represents a variable and the rows represent observations. Each variable can be classified as quantitative or qualitative. For example in the case of determining the price for a house, the age or the number of bedrooms behave quantitative and variables like neighbourhood or house style would be qualitative. In the present of one or more qualitative variables there must be a method to convert them to calculable indicator variables in order to be able to work with them.

- **Model specification**: Under the phrase "Model specification" a concretisation of equation (3.1) is understood. The first element, which has to be concretise, is the connection between the response variable(s) and the predictor variable(s). Here, in general, linear or non linear connections are considered. This decision can be made either based on a literature study, an objective or a subjective assumption. Another element for the connections is the number of predictor variables. If there is only one predictor variable the regression analyses is called simple regression and with more than one it is called multiple regression. A further element is the number of response variable(s). The regression can have one response variable or a set of response variables. In the first case the regression is called univariate and in the second case the regression is called multivariate. The distinction between univariate and multivariate should not to be confused with the distinction of simple regression and multiple regression, the first distinguishes on the "input" of the regression, whereas the second distinguishes on the "output".

- **Method of fitting**: In this step the choice on the method to estimate the parameters for the model has to be made. This process is often refereed to as parameter estimation model fitting. The mostly used method of estimation is called the "least square" method. The least square method allows to calculate a regression line, which runs through the coordinate system in a way that it has the least squared distance to all data points. The least square method results in a set of parameters with desirable properties. In the cases that the least square method is not suitable there are other estimation methods, which can deliver better results.

- **Model fitting**: In the previous step the decision was made which error model is used for the evaluation. In this step the way how the parameters of the model should be fitted is described. The goal of the fitting is to reduce the error parameter from the previous step to a minimum when using the resulting model. The difference between ”fitting” and using the regression and thereby the vales of the response value is that the fitting method is running before the forecast is used and uses historical data to find the best parameters, which ”fit” the historical data. These best parameters are then used to forecast the response value with actual or future values (predicted values e.g. weather forecasts).

- **Model validation and criticism**: In this step the evaluation part is described. If it is not possible to validate the model in ”reality” (which is very often the case), a given data set is divided in two parts. The first part of the data set is used to run the model fitting. The second part of the data set is used to validate the achieved model parameters of the fitted model, e.g. the first part is used as input to the regression, which forecast the values for the second part of the data set. It is not possible to compare the result of the regression with the actual value (from the second part of the data set). Using these tests a validations of the assumptions made in ”Model specification” has to be made. This should be done before the response value(s) is used in further in practice.

- **Using the chosen model for the solution of the posed problem**: The last step is to evaluate if the result of the regression is really the ”solution” of the problem, which was the starting point of this development process. Furthermore, it may be that the new regression equation has some by-product. E.g. the developed regression analyses can give insights to other problems. For example it can analyse the effects of the surrounding environment by changing the predictor variable(s) or a forecast can be made with the help of the equation result (response variable). So in our case the influence of new PV installations can be simulated with the help of our regression analyses by changing the predictor variable. With this method changes can be calculated and possible problems like imbalances of the grid could be detected beforehand.

3.1.1 Statement of the problem

The problem to be solved using the regression analysis is defined in this subsection. In this thesis, the power flow at the transformer per time interval is needed as base for further calculations. Thus the problem statement is: ”How high is the power flow over the transformer at a certain time interval?”. Since it is known that the distribution grid, where this method should be applied, is heavenly influenced by PV generation, it is assumed that there is a strong connection between the a,ount of solar irradiation and the power flow at the transformer. Thus, to predict the power flow at the transformer, we first focus on predicting the PV generation, hereby assuming that the PV generation in the distribution grid is so heavy that it could be the main influencing factor on the power flow.

3.1.2 Selection of potentially relevant variables

In the second step of the regression analysis the relevant variables are chosen. Hereby variables, which have a connection to the problem statement of the previous subsection have to be identified. Obviously, the value to be predicted is clearly the power flow at the transformer and this flow is to a large extend depending on the power generated by the PV panels. Furthermore, we note that there is a strong connection between the sunshine and the produced power of the PV panels. The sunshine in this case is measured as irradiation value, because the irradiation is the medium that is converted to electricity in the PV panels. Thus there is a physical relation between the irradiation value and the produced power by the PV panels. This produced power by the PV panels determines - as mentioned - to a large extend the power flow which itself is measured by Westnetz directly at the transformer. One other aspect that determines the power flow at the transformer is resulting from the power consumption of the few farms. However, there is no data available for these flows and therefore in a first step we ignore the influence of these flows and evaluate later on if this is a feasible assumption. Summarising, the variables used in this regression analysis are the irradiation and the power flow at the transformer.

Based on the above, the terms response variable, which should be predicted, and the predictor variable, which is used as input for the prediction, can be defined. Following the problem statement, the power flow has to be forecast, ergo the power flow is the response variable, and the irradiation is the predictor variable.

3.1.3 Data collection

In this step the data collection is considered. The data sets used in this thesis are coming from the mentioned distribution grid of Westnetz. As this grid is used in practice, it is an uncontrolled environment. There are two points in the grid equipped with measurement instruments. First measurement is conducted at the storage itself. There is a variety of measurement values available concerning the storage status. The second measurement point is the transformer or rather the transfer point from the transmission grid to the distribution grid. The value of the power flow at the transformer, which is been used for the regression analyses, is measured here, and the values are fifteen minutes interval average values. The irradiation measurement and the irradiation forecast for tomorrow are provided by Westnetz GmbH. This data is for a near village named Ahaus, which is approximately 30 km (beeline) away from the storage in Wettringen. The irradiation data is available in average values per hour. As mentioned, power flow values, have an interval length of fifteen minutes. In order to get the same interval length for the weather forecast and the power flow data an average is calculated of the four power flow values within one hour, so that both values are considered at a hourly basis.

3.1.4 Model specification

In this step the model specifications are determined, meaning that the connection between the two variables is defined more precisely. Based on the "Smart Operator" project [4], we have chosen to use a linear regression and as acquired in (3.1.2) we use only one predictor variable. This implies that a simple regression analysis is used, meaning that 3.1 reduces to $y = f(x_1) + \varepsilon$, whereby $f(x) = ax + b$, with some parameters a and b that have to be determined. As the regression uses only one response value, the power flow, we have a univariate regression analysis. So the used regression is an univariate simple linear regression analysis.

3.1.5 Method of fitting

In this step, the best method to fit the regression function to a given data set is chosen. In the case of our research the regression analysis predicts the power flow at the transformer based on the irradiation. Thus a fitting method is needed that brings the predicted power flow as close as possible to the data of a given data set. The method we use is called the least square method. This method considers the data points of a given data set and calculates for a given function (3.1) the difference between the response value of a data point and the value which (3.1) calculated for the predictor value of this data point. These distance values are squared and integrated over all data points. The goal is now to find a regression function (3.1), which minimises this sum.

3.1.6 Model fitting

In this step data set used is fit to a linear regression function. In this thesis we assume that the power flow at the transformer is connected to the irradiation in a linear way. However, this assumption can only be used under some conditions, because in general the dominant PV generation in the distribution grid is normally not completely linear. It is known that the PV generation is also influenced by two other

aspects. The first aspect is the irradiation angle of the sunshine changes throughout the day and during the year (seasonal changes). The second aspect is that the PV generation is also depending on the temperature. That means there is also a seasonal component in the PV generation. Hence the model fitting has to be realised in such a way that these aspects are also considered.
In order to encounter the first aspect the regression is not made over the complete day, but the day will be divided in shorter time intervals. This is because we assume that the shorter the time intervals the smaller the influence of the irradiation angle. Hence the first fitting step is a trade off between number of data points and linearity within the time interval. In order to take into account the seasonal component (second aspect) the data set will be restricted. The regression analysis uses only a certain number of previous days as input. This is, because we assume that the seasonal changes are slow so that they do not change much in a period of 5 to 30 days.

3.1.7 Model validation and criticism

In this step the evaluation of the regression analysis and the assumptions are considered. Hence a value or method is needed to verify if the intended functionality is achieved. This means also that with this value or method the assumptions, which led to the regression analysis, can be verified. We use the difference between the forecasted power flow and the measured (real) power flow per time interval (d_t) as accuracy measure. With the help of these values the accuracy of the forecast in comparison to the real power flow can be determined. If the accuracy is not sufficient, changes may be needed in the time period or time interval of the two linearised assumptions (daily time interval, length of the time period).

As have been already mentioned we encountered a practical problem in the evaluation as we have no measurements of only the PV generation. In the used distribution grid of Wettringen only a composite of the PV generation and the demand can be measured at the transformer and we do not only get the pure PV generation but also the demand, used in the houses. As we may expect that this consumption is not dependent on the irradiation but other factors, the setup of our regression might be questionable. But there are two reasons why that may not be the case. First there are only eight houses in this part of the distribution grid and the data shows that the PV generation is much higher than the demand. So the demand in relation to the PV generation can only cause smaller fluctuations. The second reason is that the eight houses are farms. It is assumed that the daily demand of a farm is not fluctuating a lot, because the daily structure does not change that much from day to day (compared to other private houses where e.g. a difference between weekdays and weekenddays may be expected). Furthermore, as we have decided in the subsection "Model fitting", the regression will be carried out for hourly time intervals of the day separately and also only using data of a shorter period (how long the period should be will be part of this thesis). Based on these arguments, the demand of the houses in such a period may be assumed to be almost the same every day. As such the demand in the data of a regression can be assumed to be (almost) constant and thereby it can be integrated in the regression as base load. Thus, the regression should be able to forecast the composite of PV generation and the demand.

3.1.8 Using the chosen model for the solution of the posed problem

In this step the purposes and possible by-products are evaluated. The regression analysis, designed in this thesis, is to forecast the power flow at the transformer. It has the limitation to only works when it has at least two data set pairs with different predictor variables (irradiation values), because otherwise it is not possible to calculate a regression function. That means the designed regression forecast can only forecast values if the sun is up. However, in case for a given regression, whereby all irradiation values are zero, we may chose a constant regression function $f_x = b$.
Furthermore there are some by-products. One is that with the help of the introduced regression analyses the base load (demand) can be determined. This base load is the offset of the regression function. The offset can be calculated by determining the zero passage of the regression line.
An additional by-product is that the developed method can be used to simulate the changes of the power flow if more PV generation would be installed. With the help of these simulations the need of future grid enforcements can be determined.

3.2 Sample Power flow regression forecast

In this section a sample regression analysis is given. This sample demonstrates the idea behind a forecast with the help of a regression analysis in order to forecast the power flow for the next day. For the sample regression the definitions of the last section are used. Note, that the respond variable was defined as the power flow and the predictor variable as the irradiation. These two variables are visualised in a coordinate system whereby the respond variable is the y-axis and the predictor variable is the x-axis. The resulting coordinate system is given in Figure 3.1.

As described in the previous section the regression is used to forecast the power flow with the help of the relation between the irradiation and the power flow. Thus

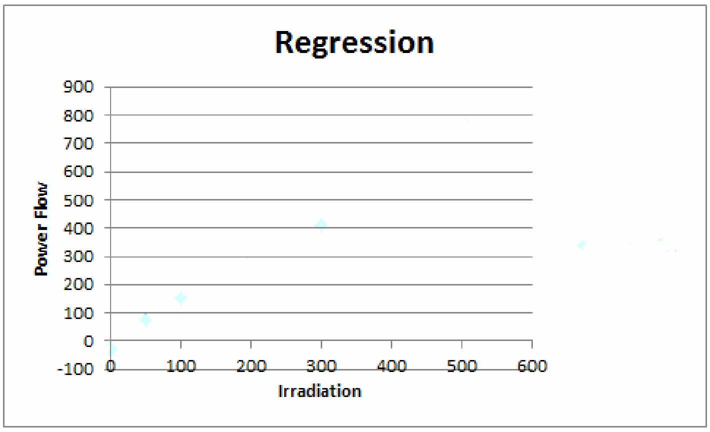


Figure 3.1: Sample of a regression coordinate system.

to calculate a suitable regression function as input, historical data tuples [irradiation/power flow] are needed. For the considered example the historical data tuples are given in Table 3.1:

Irradiation	Power flow
0	-35
100	150
200	280
500	780
300	410
50	75
0	-25

Table 3.1: irradiation/power flow tuples

These data tuples now can be plotted in the coordinate system and the result can be seen in Figure 3.2

Looking at the figure a linearity of the data in the coordinate system seems to be present. But for the further regression process the corresponding regression function is needed. This function is calculated with the least square method. That means the function is calculated in such a way that this function is as close as possible to all data tuples whereby the closeness is determined by squared distance. The equation for a linear function is:

$$f(x) = ax + b, \tag{3.2}$$

where "a" denotes the slope and the "b" denotes the offset (the y-axis zero crossing). In literature, there are equations given how to calculate these parameters a and b for

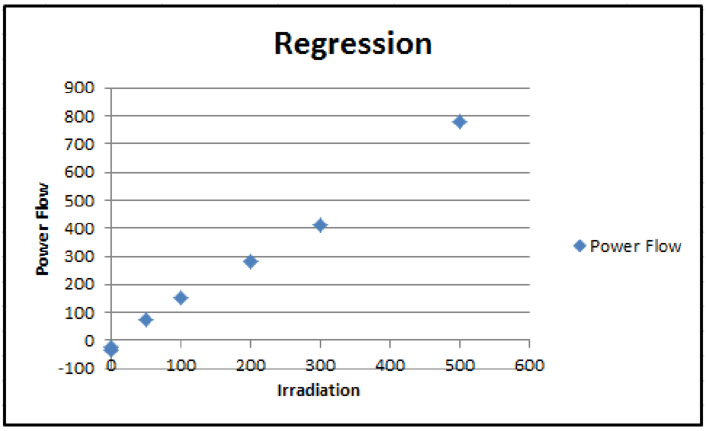


Figure 3.2: Sample data inserted in the coordinate system.

a least sqaure regression (see [3]). For a given set of data points $(x_1, y_1)...(x_n, y_n)$ the values of a and b are calculated by:

$$a = \frac{\sum xy \frac{\sum x * \sum y}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}}, \tag{3.3}$$

and

$$b = \frac{\sum y - (b_1 * \sum x)}{n}. \tag{3.4}$$

For the data points given in Table 3.1 this leads to:

$$a = \frac{587750 \frac{1150 * 1635}{7}}{392500 - \frac{1150^2}{7}} = 1,5,$$

and

$$b = \frac{1635 - (1,5 * 1150)}{7} = -13.$$

These constants now define the linear function:

$$f(x) = 1.5x - 13.$$

This function $f(x)$ can be inserted in the coordinate system. The result can be seen in Figure 3.3,

$$f(x) = 1.5x - 13.$$

With the help of the linear function, which was calculated here, the resulting power flow, for e.g. a irradiation value of 400, can be forecast by

$$f(400) = 1.5 * 400 - 13 = 587.$$

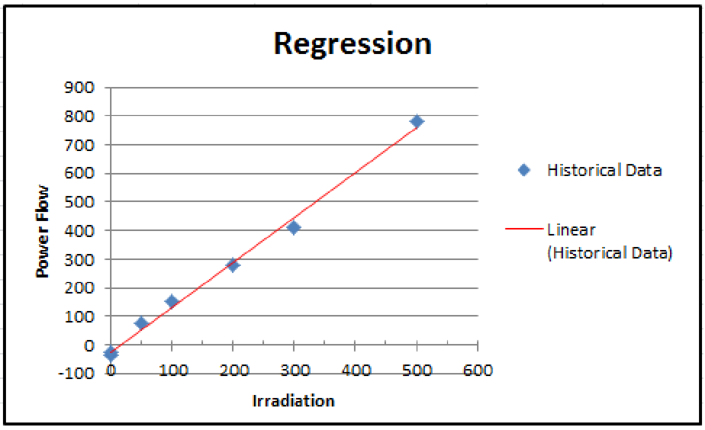


Figure 3.3: Regression coordinate system with added regression line

With this type of calculations the forecast for the whole day can be made. As described before, the regression is made with the historical data points of a certain number of last days. For each time interval of the day the calculation will be made separately. The results of the calculation is the power flow at the transformer for the next day.

3.3 Flexibilities according to the BDEW concept

This section makes the connection between the "traffic light" concept and the power flow in a grid. The "traffic light" concept helps dividing the power flow in three phases (see Section 2.3). The connection between the theory from the "traffic light" concept and a power flow over the transformer (the measured power flow from 07.05.2016) is illustrated in Figure 3.4. The power flow at the transformer from Figure 3.4, at the beginning of the day is flowing from the medium voltage grid to the low voltage grid, which is indicated by the negative power value. The sunrise on this day was at 5:50 and at that time the PV generation is steeply rising. At approximately 6:00, the grid is balanced, which means that the production and the demand are equal. From 6:15 on the PV generation is higher than the demand and has its peak value at 11:30. After the peak, the production is decreasing until 18:15. After 18:15 there is no PV production anymore.

For the "traffic light" concept, also the characteristics of the equipment in the grid are important to determine the DSO constraints. In our case the transformer threshold is 370 kW (indicated as red line $g_{(x)}$ in Figure 3.4). Hereby, the transformer is able to transport a higher value of power, but this value has been chosen due to a limited amount of power passing upstream to the medium voltage level and leading to a voltage increase in the complete area. This threshold gives the upper bound on the maximum load of the transformer. In addition a second threshold is defined from the transformer threshold. This is given by the threshold of the transformer minus the maximum load for the storage inverter (250 kW). The second threshold is needed because from this threshold on the storage inverter can not be used to its full potential for other than grid purposes given otherwise the transformer threshold might be violated. This second threshold is given as 120 kW (indicated as yellow line $g_{(x)} - h_{(x)}$ in the Figure 3.4).

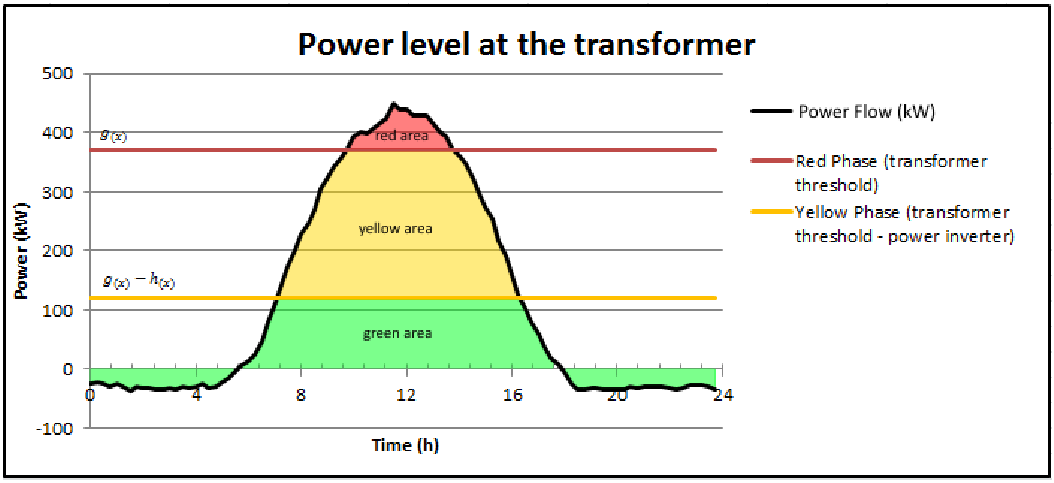


Figure 3.4: Power flow at the transformer with the constraints

The first and obvious observation of Figure 3.4 is that the two thresholds divide the power flow in three areas:

- **The green area:** Here the storage inverter can be used without constraints, since it can not endanger the grid.
- **The yellow area:** Here the use of the storage inverter is limited, since if the storage inverter is used in the wrong way it can violate the transformer threshold.
- **The red area:** Here the storage inverter has to be used in a certain manner in order to respect the transformer threshold.

In the "traffic light" concept also three phases are mentioned that can be related to the power flow. The grid limitations match exactly the "traffic light" constraints. So the grid limitations can be used to formulate "traffic light" constraints for the flexibility handling. These constraints can be formulated as follows:

- **The green phase:** In this phase the storage flexibility may be used without constraints, because it is not possible to endanger the grid with the use of the flexibility. Therefore, it is possible to permit a third party to use all flexibility. This phase is called **market phase** in the "traffic light" concept.
- **The yellow phase:** In this phase the use of the flexibility is limited, because if the flexibility is used in the wrong way it can violate the transformer threshold. Therefore communication is needed. However, if a clear schedule is given and certain constraints are fullfilled, using the remaining flexibility can be permitted. This phase is called **interaction phase** in the "traffic light" concept.

- **The red phase:** In this phase there is no flexibility left, because it is reserved for the local grid operator to balance the grid. This phase is called **grid phase** in the "traffic light" concept.

The mentioned grid limitations from above lead also to the transition rules between the phases. Figure 3.5 gives a summary of the phases and the transition rules in the form of a state diagram.

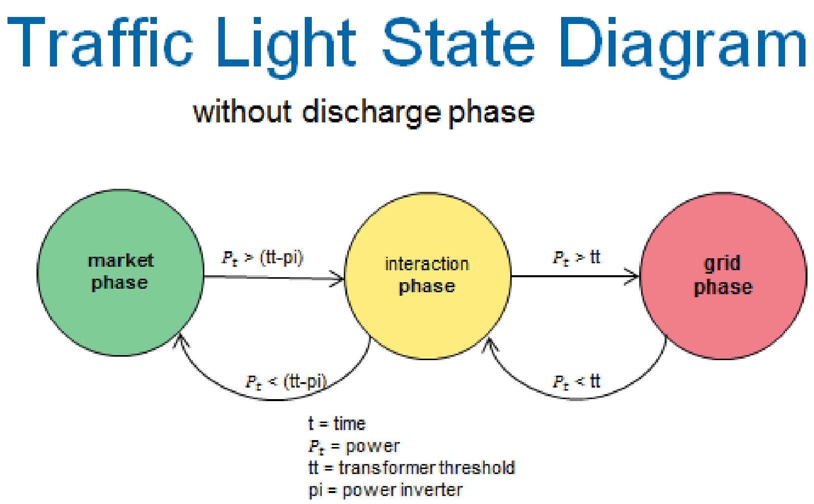


Figure 3.5: Traffic light model constraints applied to a grid with storage asset.

To be able to use the flexibility of the storage safely, a third party needs additional information. This information can be described as time schedules, which specify how the flexibility with regard to the "traffic light" constraints and the transition rules are used. For this purpose two schedules are needed. The first provides the capacity constraints, since the storage is finite. The second gives the power constraints to ensure the grid stability.

3.3.1 Capacity constraints

The most obvious constraint is the capacity constraint. This constraint has to ensure that at the beginning of the red phase there is enough free capacity to buffer the PV peak. The grid always has the highest priority in the project in Wettringen, which means that a third party, who uses the flexibility of the storage, has to guarantee that the storage has a certain amount of free capacity at the begin of the red phase. Otherwise this could be dangerous for the grid and violate one of the traffic light concept rules. To guarantee that there is enough free capacity, two approaches are possible. The first is to make a schedule with the information when and how much capacity is needed to guarantee that buffering the PV peak is possible. This implies a schedule with forbidden areas in which the third party is not allowed to operate. This schedule can be given to the third party and this party has to guarantee that they will not violate this schedule (see an example schedule in Figure 3.6).

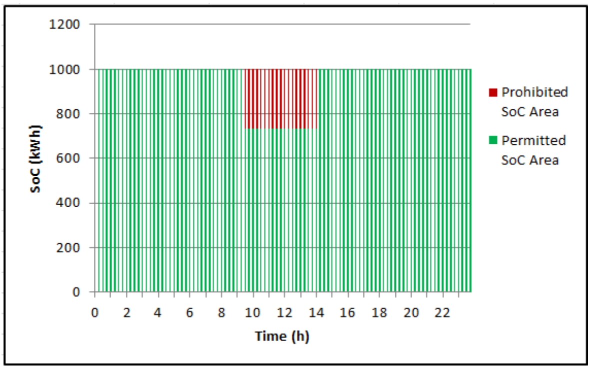


Figure 3.6: Capacity constraints without discharge Phase

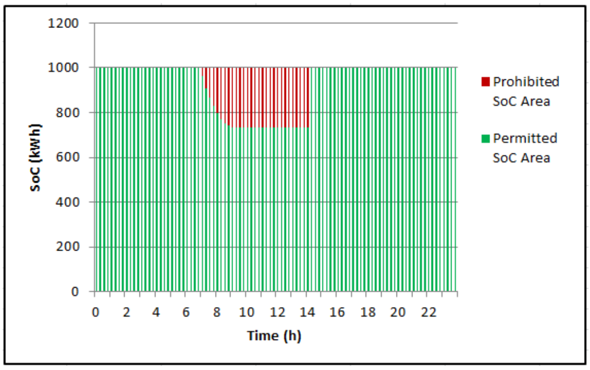


Figure 3.7: Capacity constraints with discharge Phase

The second approach is to plan a discharge phase. That means the state diagram of the ”traffic light” model has to be extended with a new state. The new state (orange phase) is inserted between the second state (yellow phase) and the third state (red phase). The new state (discharge phase) is a phase that is used to block a certain number of time intervals to free enough capacity to buffer a power peak. This new state would be controlled by the local grid operator and it is used to ensure that there is enough free capacity at the beginning of the red phase. Note, that this approach reduces the flexibilities for the third party. An example of the schedule with a mandatory discharge phase is given in Figure 3.7. The resulting state diagram of the new ”traffic light” is shown in Figure 3.8.

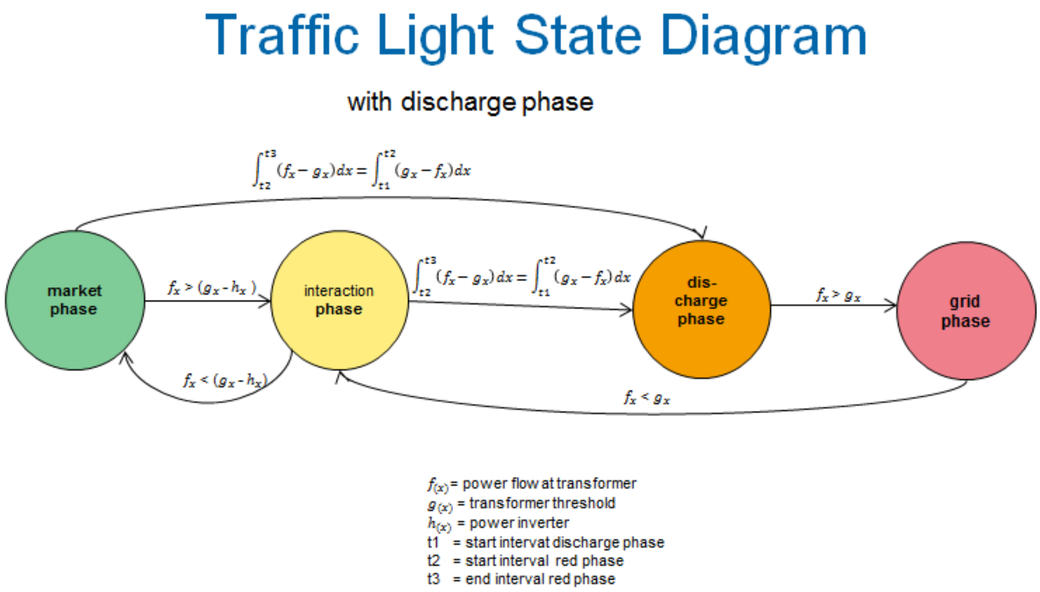


Figure 3.8: Discharge phase added to "traffic light" state diagram

3.3.2 Power constraints

The second (and less obvious) constraint is the load at the transformer. Here the communication (of the power constraint) is very important because otherwise the grid can be in danger again. If the power flow in the grid increases, above a certain threshold, the storage inverter can no longer be used to its full potential, because otherwise the power at the transformer might get above the transformer threshold (the yellow threshold in Figure 3.4). More precisely, as the power flow in the grid plus the energy discharged from the electricity storage is also not allowed to get above the red line. That is why the discharge possibilities are restricted if the power flow in the grid is in the yellow area in Figure 3.4). Thus in such periods communication and coordination between the local grid operator and the third party is needed. For this purpose, a schedule of power constraints is communicated in order to specify the forbidden area and how much capacity has to be free at the beginning of the red phase. Here, the discharge phase from the capacity constraints has certain influence, because if there is a certain amount of free capacity, until the beginning of the red phase, the flexibility for freeing it are no longer for disposal for the third party. Thus there are also two possibilities for power constraint schedules. One, which can be seen in Figure 3.9 without a discharge phase and the second, which can be seen in Figure 3.10 , with a discharge phase, .

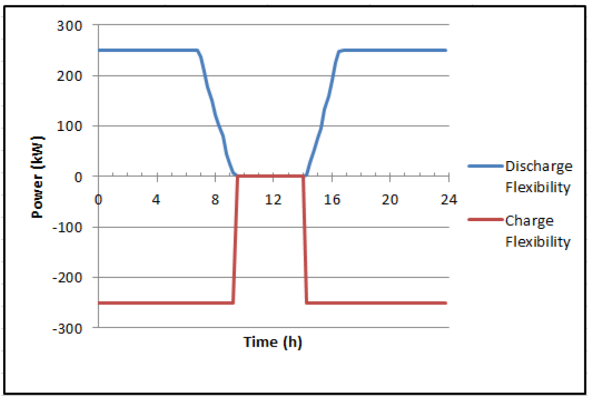


Figure 3.9: Power constraints without discharge Phase

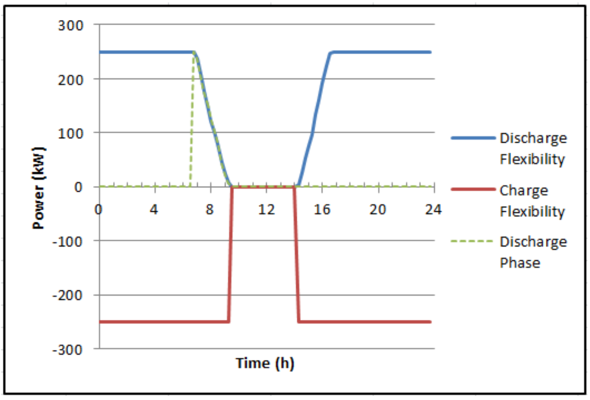


Figure 3.10: Power constraints with discharge Phase

3.4 Conclusion

To conclude, the third party can use the free flexibilities of the storage, which is specified with the help of the two previously described schedules. The two schedules describe all dependencies and constraints that are important. The difference between the two versions is the discharge phase (orange phase). The advantage of the version without discharge phase is that the flexibilities can be used more freely. The local grid operator has to rely on the third party that they do not violate the rules shown in Figure 3.6 and Figure 3.9. The version with the discharge phase is safer for the local grid operator, since the grid operator withholds a small amount of the flexibilities for discharging the storage in a way that ensures that the PV peak can be buffered in all circumstances.
Further important points in this section are the dependencies discovered during the process of the ”traffic light” state diagram. The first dependence is that the yellow phase depends only on the power flow. If the power flow does not exceed the $g_{(x)} - h_{(x)}$ threshold, there will be no yellow phase, because the grid can handle the power flow even if a third party is discharging the electricity storage at full power. The second dependence is that the possible orange phase depends on the red phase, because the storage is only charged during the red phase. This means if there is no red phase scheduled, there is no need to discharge the storage (orange phase).

Chapter 4

Practical power flow forecast and flexibility methods

In the previous chapter, the theoretical issues and constraints of flexibilities and power flow forecast were discussed. In this chapter these theoretical aspects are used to develop methods that forecast the free flexibility. These methods are applied to measurement data from the grid in Wettringen.
Furthermore, the process of forecasting the storage flexibility of a distribution grid with electricity storage in practise is explained. This process is divided in two main steps. The first step is to forecast a daily schedule of the power flow at the transformer. By using the theories of the previous section, we develop a regression method that can forecast the composite of PV generation and the demand at the transformer. Subsequently, the way of customisation and the fitting method is described.
In Section 4.2, a practical method of calculating the flexibility is shown. The power flow schedule from step one is the basis for this calculation. For this flexibility schedule the auxiliary variables (e.g. SoC and power at the storage inverter) are needed to calculate the capacity and power constraints. These constraints define the boundaries for the third party, as discussed in Section 3.3.1 and Section 3.3.2.

4.1 Power flow calculation in a day ahead application

In this section the theories of the previous section are realised in practice. We assumed that the power flow has a linear connection to the irradiation. In order to verify this assumption we pictured a point cloud of all data points (irradiation / power flow tuples) for one day. The result can be seen in Figure 4.1.

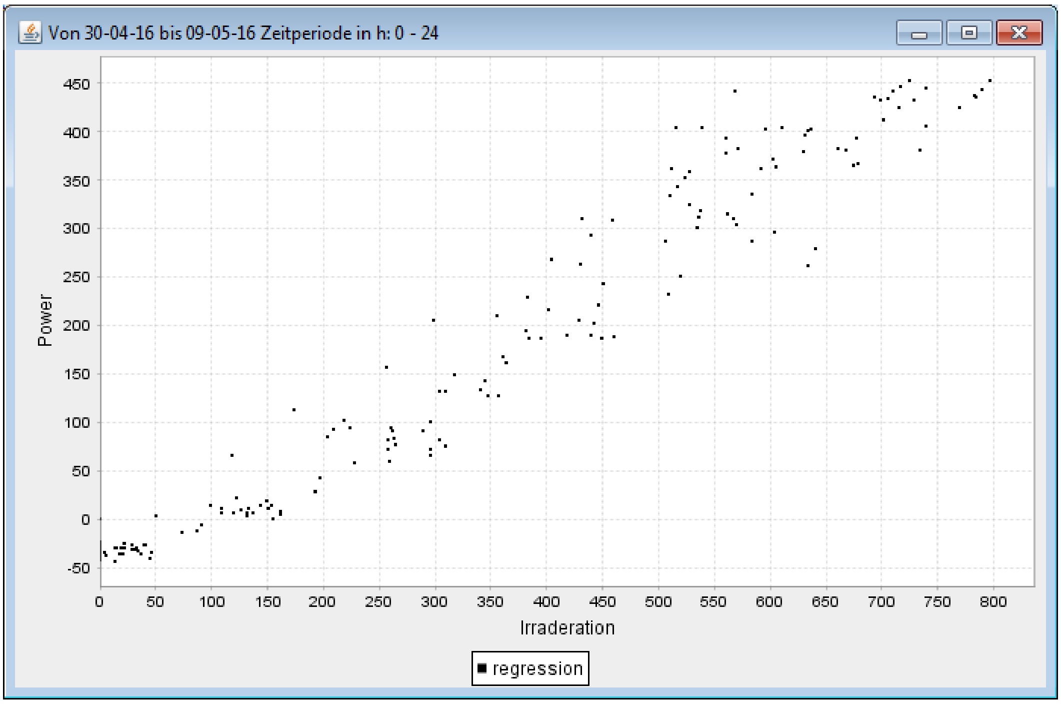


Figure 4.1: Point cloud of irradiation / power flow tuples for 24 hours.

The figure shows that there is an approximately linear relation. Especially when you look at the low and high values (start and end) of the cloud. That means that a regression should be more accurate in predicting the low and high irradiation values and less accurate in between. The shape of the cloud can be explained with the weather condition. The wider spreading of the points in the middle of the cloud are the situations with unstable weather. Thus if there is almost no sun. That also means there is not much fluctuation in the value over time and the points of the cloud are close to each other. But if there is unstable weather also the sun light is unstable and the irradiation value is only a n average value. The result of middle irradiation values are more widely spread points in the cloud.
As second issue is the choice of the data points used for determine the regression function. We have to define the time intervals per day and the time period per year in such a way that the data points are as near as possible to a line.
These issues have heavy impact on the accuracy of the power flow forecast. For the choice of these aspects are trade offs. The trade off is between accuracy and

the number of data points. In general it can be said that the shorter the period the less changes of the environment (like irradiation angle or weather changes). That means the forecast has a higher accuracy if the periods are short. But the shorter the periods the less data points are in the period and a regression analysis requires a certain number of data points as input. For the regression method it can be said that fewer data points leads to less accuracy. So we need to find a certain period length that is short enough to minimise the environment changes but is long enough to have the required number of data points for the regression analysis.

4.1.1 Defining time interval per day for linearization purposes

In this section the best choice for the length of the time intervals per day is defined. For this purpose the time interval was set to different values. In Figure 4.1, which was made with data tuples of 24 hours, it can be seen that the cloud shows in general a linear behaviour but for some shorter intervals the deviation from a linear behaviour is given. That is the reason why we divided the 24 hours in shorter time intervals. More precisely the 24 hours were divided in intervals of length 4 hours, 2 hours and 1 hours intervals and for all intervals point clouds were made. The most interesting intervals are the ones of the midday hours because there is the most sunshine and due to the sunshine the most power generation. That is why the midday hours are also for the flexibility calculations the most interesting ones. In the midday hours the weather is mostly relatively stable. For forecasting reasons, the morning hours with unstable weather conditions are more interesting. That is the reason why always two point clouds are shown here, one from the morning and one from the midday.

Point clouds with the time interval of 4 hours:

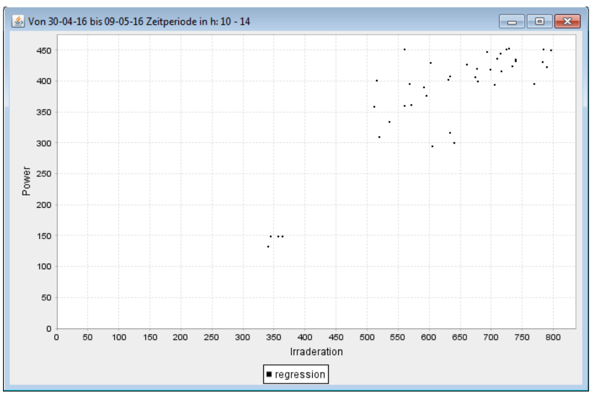


Figure 4.2: Time Interval from 10:00 to 14:00 (RMS: 14.6)

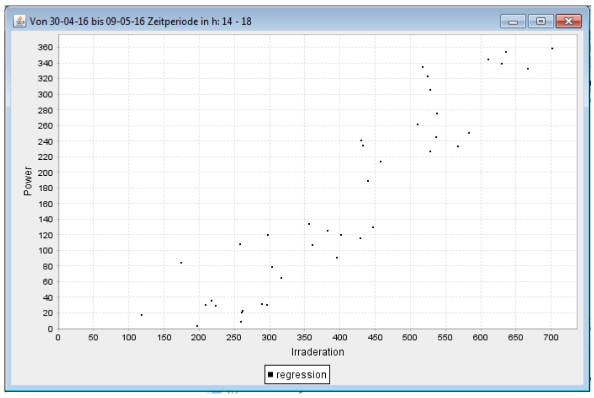


Figure 4.3: Time Interval from 14:00 to 18:00 (RMS: 21.64)

Point clouds with the time interval of 2 hours:

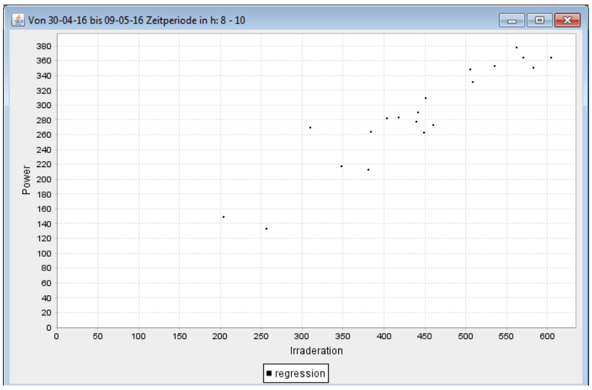


Figure 4.4: Time Interval from 08:00 to 10:00 (RMS: 8.57)

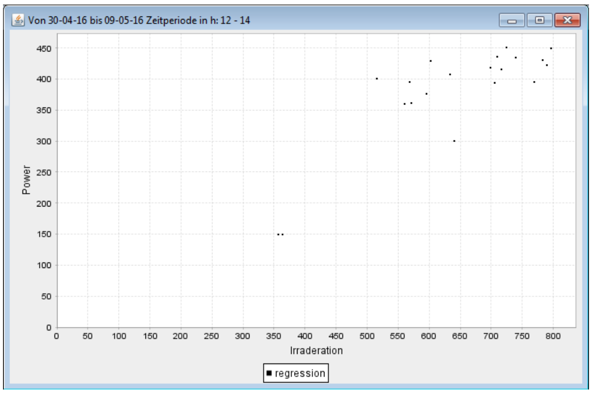


Figure 4.5: Time Interval from 12:00 to 14:00 (RMS: 10.41)

Point clouds with the time interval of 1 hours:

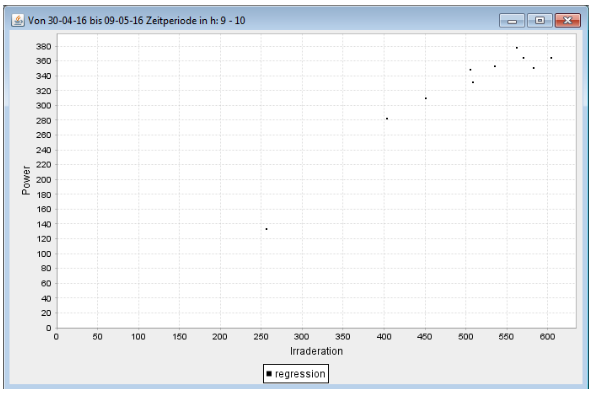


Figure 4.6: Time Interval from 09:00 to 10:00 (RMS: 6.1)

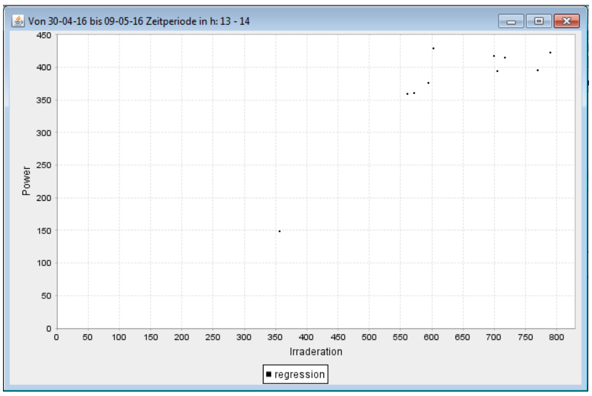


Figure 4.7: Time Interval from 13:00 to 14:00 (RMS: 7.37)

All these point clouds are made from the same 10 day data set (from 30-04-2016 till 09-05-2016). As earlier explained the shorter the time intervals the fewer data points appear in the figures. Furthermore it can be seen that the point cloud of Figure 4.2 and Figure 4.3 with a four hour time interval is a widely spread cloud which is neither linear in the begin, nor in the end part. So this interval length is not suitable for our purpose. Next the one hour interval clouds of Figure 4.6 and Figure 4.7 are compared. In the figures it can be seen that there are only ten data points per cloud. That can have a negative influence on the regression function, because with less data points outliers may have a higher influence on the regression function. Furthermore it is obtainable that the points of Figure 4.6 show a nice linearity. The second cloud in Figure 4.7 however the cloud falls apart in two parts with different shapes. That is why also this time interval is not suitable for our purpose. So the best shaped

cloud can be seen in Figure 4.4 and Figure 4.5. It can be seen that Figure 4.4 has also a certain linearity (almost the same as in Figure 4.6). Additionally also Figure 4.5, which illustrates the midday values has a linear shape if the three data points, which are below the power of 300 kW, are neglected.
Because of this analysis results, the length of the time interval per day was defined to be two hours. This interval length is used for all further calculations and observations.

4.1.2 Defining time period of days per year for linearization purposes

In this section, the best (in terms of linearity) historic time period to be used for the regression is investigated. In Section 3.1.6 it was described that the smaller number of historical data is used to calculate the regression function the smaller the seasonal changes are (e.g. the temperature changes). In this section we are looking for a time historic period of days that shows a linearity. In contrast to the previous section, when we considered intervals per day, we now differentiate the number of previous days, which are used as input data for the regression analysis. For this purpose we used the result of the last section (2 hours as time interval) and we chose two time intervals (from 8:00 to 10:00 and from 14:00 to 16:00) during the day. The first time interval (from 8:00 to 10:00) is a more unstable time interval, because the sun starts to shine and rises during this time interval. The period (from 14:00 to 16:00) is a more stable time interval, because the sun stands high and there is a lot of power generation. Point clouds are calculated for four different length of time periods: five days, ten days, twenty days and thirty days as historical input data. The point clouds are shown in Figure 4.8 - 4.15

Point clouds with a time period of five days:

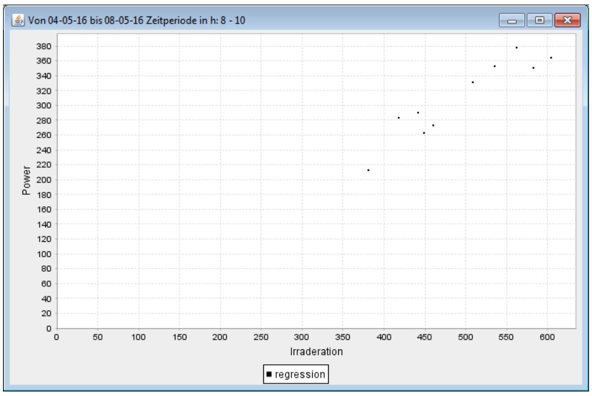


Figure 4.8: Time interval from 08:00 to 10:00, 5 days historical input data (RMS: 6.9)

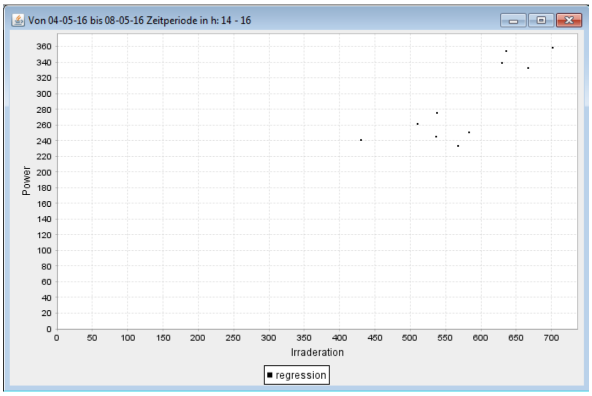


Figure 4.9: Time interval from 14:00 to 16:00, 5 days historical input data (RMS: 7.92)

In the figures with only five days historical data input, the points are not spread over the complete spectrum of possible irradiation values and this may lead to bad predictions outside this spectrum. Rather there are separated points, which give an idea of a linearity. In our opinion there are not enough points to calculate a regression function with a certain accuracy.

Point clouds with a time period of ten days:

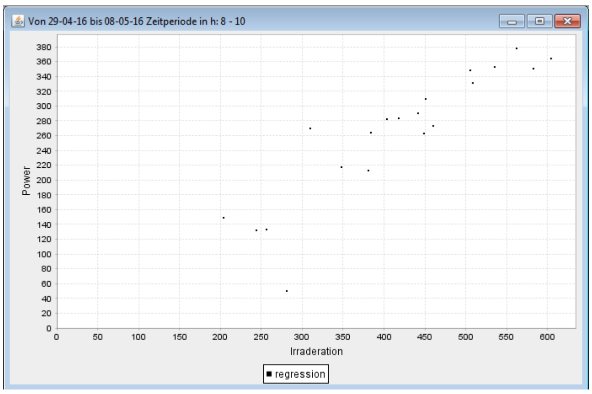


Figure 4.10: Time interval from 08:00 to 10:00, 10 days historical input data (RMS: 9.23)

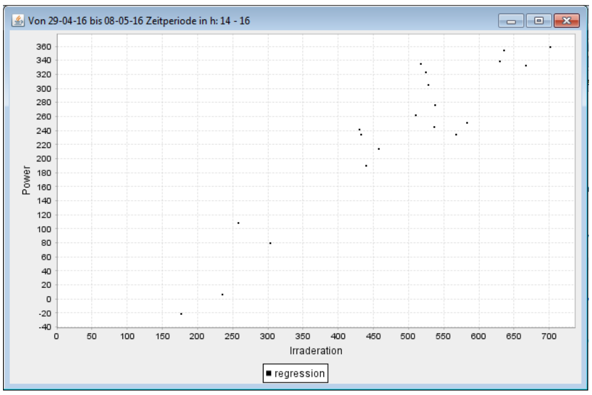


Figure 4.11: Time interval from 14:00 to 16:00, 10 days historical input data (RMS: 12.11)

In the figures with ten days historical data input, the point are spread over the complete spectrum. Furthermore, the data points are located in a sort of line and in Figure 4.10 a clear linearity can be obtained. In Figure 4.11 also a linearity is present, but in the end (high irradiation values) there are some outliers.

Point clouds with a time period of twenty days:

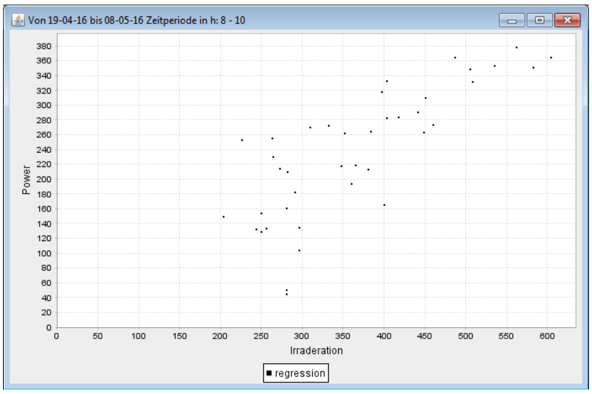


Figure 4.12: Timeinterval from 08:00 to 10:00, 20 days historical input data (RMS: 15.5)

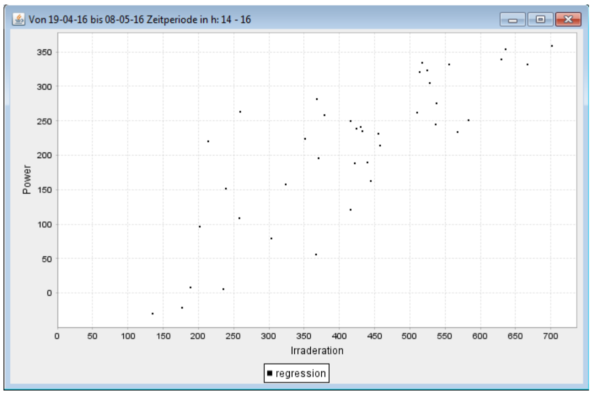


Figure 4.13: Time interval from 14:00 to 16:00, 20 days historical input data (RMS: 22.6)

In the figures with twenty days historical data input, a sort of point cloud occurs. However, the point cloud does not show the same linearity as the one with ten days input. The data points of this point cloud are more spread and a small influence of the seasonal changes may already be present.

Point clouds with a time period of thirty days:

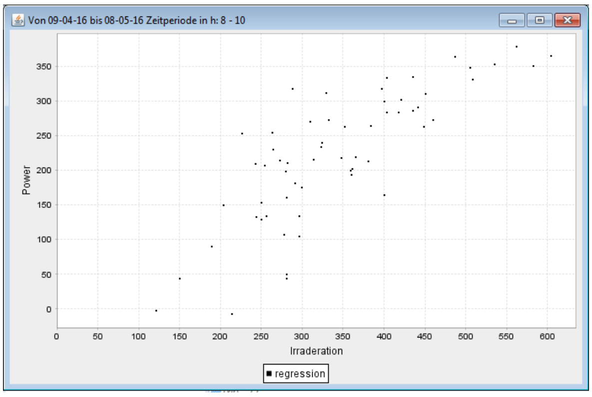


Figure 4.14: Time Interval from 08:00 to 10:00, 30 days historical input data (RMS: 19.52)

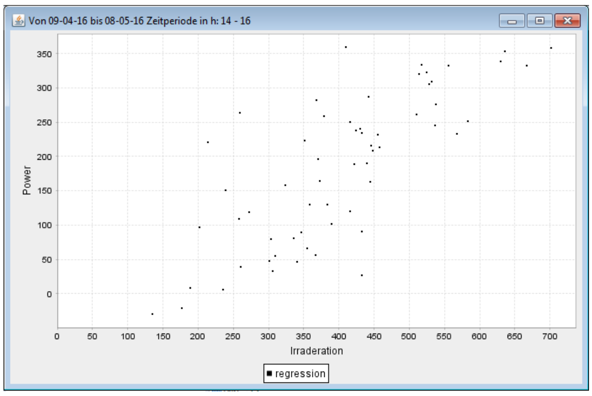


Figure 4.15: Time Interval from 14:00 to 16:00, 30 days historical input data (RMS: 29.77)

In the figures with thirty days historical data input, a point cloud does not occurs. The data points of the point cloud are widely spread over the coordinate system and the influence on seasonal changes can be seen.

To summarise this section, it can be said that the point clouds, which are made with 10 days of historical data input, seem to show the best trade off between linearity and number of data points. That is why we chose to use a 10 day input as time period for all further calculations.

4.2 Calculation of flexibility according to BDEW concept

In this subsection it is explained how the flexibility is calculated. The actual calculation method is based on the theoretical "traffic light" concept explained in Section 3.5. The method implements the theoretical rules of the "traffic light" concept with some extension in order to make it work in practice. In general, for each time interval the current phase and the flexibility value have to be calculated. To achieve this, the main step is divided in three substeps. The first step is to calculate the grid states. It i.e. per time interval the phase is determined based on the power flow, which is measured at the transformer. Additionally the auxiliary variables (e.g. SoC and power at the storage inverter) have to be calculated per interval because they are needed to calculate the flexibility rules in the second substep. In the second step, the power and capacity constraints are calculated. The results depend on the phase, in combination with the auxiliary variables. With the help of the power and capacity constraints, the flexibility rules can be calculated and as a result the flexibility schedule for the next day can be derived by calculating two diagrams, which visualise the flexibility rules. In the third step the discharge phase is calculated. As described in Section 3.3.1, there are two approaches possible, one with and one without discharge phase. This means that the third step depends on the contract with the third party. This step calculates the last possible time interval when the storage has to start discharging to be able to buffer the power peak of the red phase.
The phases that the method distinguishes are:

- green phase
- yellow phase
- red phase
- orange phase - discharge (optional)

With these four phases, all relevant states of the grid can be distinguished. In the next three subsections, the three steps are explained in more details.

4.2.1 Grid state calculation

As mentioned above in in the first step, the phases and the auxiliary variables have to be calculated. The phases have to be determined in the first step, because the flexibility calculations depend on the phases. Furthermore the power flows at the transformer and at the storage inverter have to be calculated because they are needed for the SoC calculations. We use the phrase SoC as a term for the storage capacity that is used to buffer the PV peak. Furthermore, we use the phrase "maximum SoC" as a term for the maximum storage capacity that is used to buffer the complete PV peak of tomorrow. Thus the The SoC is also needed for the capacity constraint calculation. So the first step is the determination of the phase, based on the power flow at the transformer ($P_{(t)transformer}$), which is forecast as described in Section 4.1. To determine the phase, $P_{(t)transformer}$ is compared to the two thresholds ($P_{(t)threshold}$ and $P_{(t)threshold} - P_{(t)inverter}$). The next step is to calculate the maximum allowed power at the storage inverter. This maximum value can be calculated using the power flow at the transformer and the transformer threshold ($P_{(t)threshold}$). The resulting maximum power flow $P_{(t)storage}$ is given by:

$$P_{(t)storage} = P_{(t)transformer} - P_{(t)threshold} \tag{4.1}$$

The energy stored in the electricity storage is measured in kWh. The derived power $P_{storage}$ determines the required charging power for the storage. As in the given data, the length of the data interval is only 15 minutes (a quarter of an hour), the value $P_{(t)storage}$ has to be divided by four because the energy flows only a fourth of an hour. In the calculation of the SoC, '$P_{storage}$ is divided by four.

$$SoC_{(t)} = SoC_{(t-1)} + \frac{P_{(t)storage}}{4} \tag{4.2}$$

With this equation the $SoC_{(t)}$ can be determined for each time interval. Further the maximum SoC per day ($SoC_{(maximum)}$) can be determined as well. In a next step the $SoC_{(t)}$ values of each time interval are integrated and the result is the forecasted $SoC_{(maximum)}$ of the next day. This is also the capacity, which has to be free at the start of the red phase in order to buffer the next days PV peak. This capacity has to be free at the start of the red phase because then no more discharge is possible any more and the PV peak has to be buffered. Otherwise the capacity rules will be violated in the red phase.

Note, that the values used above are forecast and the weather conditions in Wettringen are rather unstable. Therefore a security threshold may be needed in order to guarantee that the flexibility rules are not violated. For this purpose a worst case scenario of every month is calculated from the historical data. Worst cast scenario means the highest PV generation and hence the highest power flow at the transformer measured in the corresponding month. So it is searched for every time interval in the historical data for the highest power flow at the transformer. With this method a worst case power flow at the transformer is generated and with this power flow the SoC is calculated again and the difference between the forecasted discharge phase and the worst case is added to Figure 3.7 and results in Figure 4.17, which can be seen below.

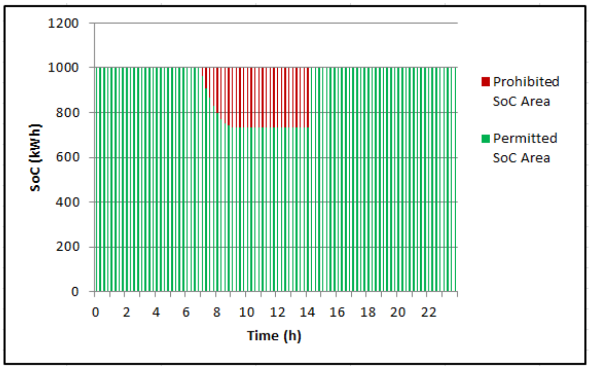


Figure 4.16: Capacity constraints with discharge phase

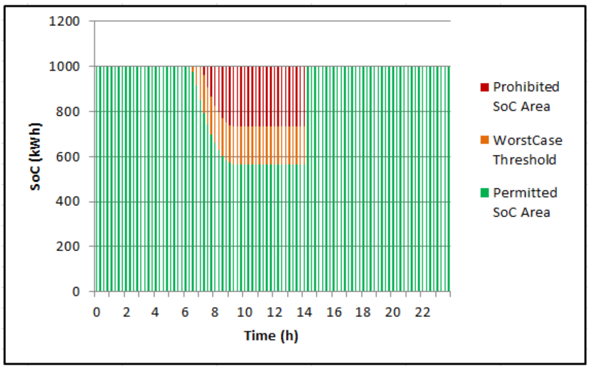


Figure 4.17: Capacity constraints with added worst case threshold

4.2.2 Calculation of free flexibilities

In the second step the free flexibilities are calculated using the method introduced to calculate the charge and discharge capacity, which can be given to a third party. Thus two values and a corresponding schedule over time have to be calculated. One is the charge flexibility ($f_{(t)charge}$) and the other is the discharge flexibility ($f_{(t)discharge}$). Both values give the maximal possible value for charging respectively discharging that do not violate the "traffic light" rules. Hence the calculation includes the full potential of the storage inverter minus the power, which is used for grid purposes. Also the "traffic light" concept has to be respected. That means this method is divided in the four phases. The calculation of the different phases is as follows:

- **green phase:** In the green phase, the storage is not used for grid purposes. Therefore the full potential of the storage inverter can be used for other purposes.

$$f_{(t)charge} = -max.P_{inverter} \tag{4.3}$$

$$f_{(t)discharge} = max.P_{inverter} \tag{4.4}$$

- **yellow phase:** In the yellow phase, a certain part of the capacity of the inverter is used for grid purposes. Thus only the remaining part can be used for other purposes, but it has to be ensured that the $P_{(t)threshold}$ can not be violated. The yellow phase is defined in such a way that the power flow is between $P_{(t)threshold}$ and $P_{(t)threshold} - P_{(t)inverter}$). With this knowledge it can be derived that the remaining flexibility is the value of subtracting the power flow from the threshold.

$$f_{(t)charge} = -(P_{(t)threshold} + P_{(t)powerflow}) \tag{4.5}$$

$$f_{(t)discharge} = P_{(t)threshold} - P_{(t)powerflow} \tag{4.6}$$

- **red phase:** In the red phase, the inverter is completely used for grid purposes and no flexibility is given to a third party.

$$f_{(t)charge} = 0 \tag{4.7}$$

$$f_{(t)discharge} = 0 \tag{4.8}$$

- **discharge phase (optional):** Here, the storage is discharged with the free flexibility, which would normally be given to a third party. That means the electricity storage is discharges with the maximum of the storage inverter capacity without violating the $P_{(t)threshold}$. The maximum of the storage inverter capacity was already defined as $P_{(t)threshold} - P_{(t)powerflow}$. Furthermore, in this phase no charging is possible.

$$f_{(t)charge} = 0 \tag{4.9}$$

$$f_{(t)discharge} = max.f_{(t)discharge} \tag{4.10}$$

The structure of the method, which is calculated for every time interval in the schedule, is shown in Figure 4.18.

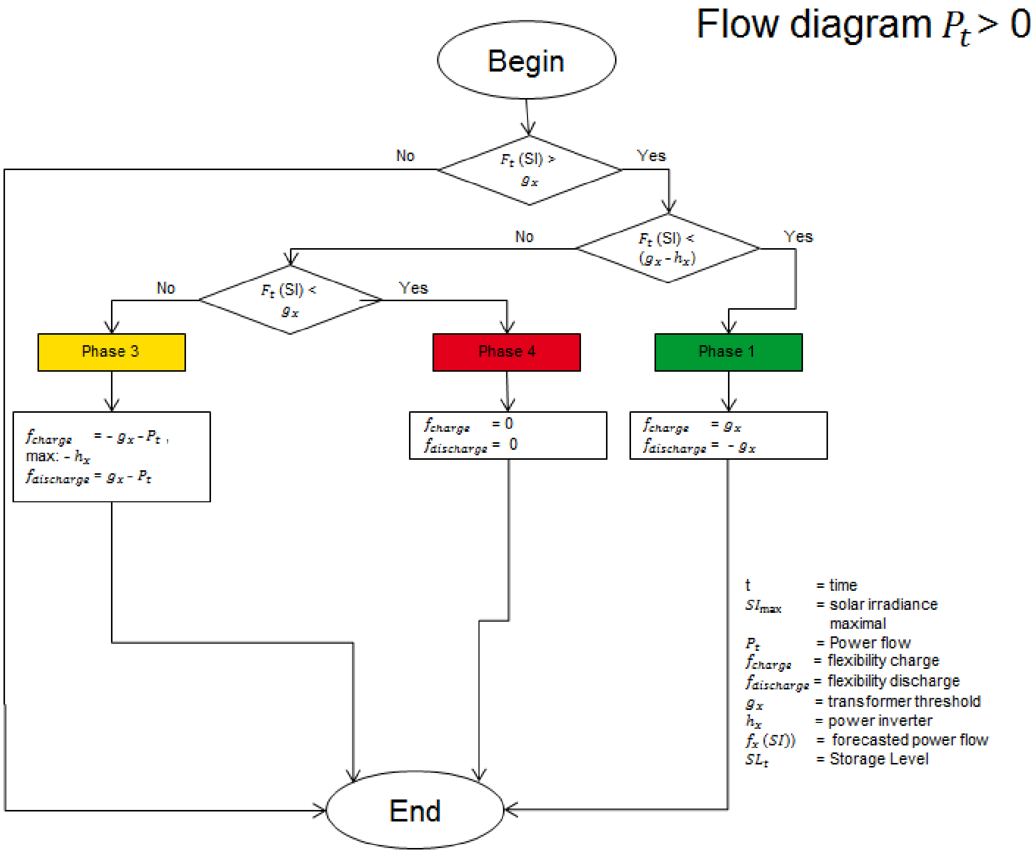


Figure 4.18: Calculate the charge and discharge flexibilities.

4.2.3 Discharge phase calculation

In the third step the discharge phase is calculated. This phase is inserted between the yellow phase and the red phase of the ”traffic light” concept in order to ensure that there is enough free capacity in the storage to buffer the PV peak. Thus the method calculates the start time interval of the discharge phase. This time interval is located before the red phase, so that in the time intervals between the red phase and the start interval of the discharge phase is enough free flexibility to discharge the storage in order to produce enough free capacity to buffer the PV peak. For this calculations of the start time interval, the red phase and the maximal SoC of the day must be known. Then it is a simple matter of calculating the area between two graphs. This can be seen in Figure 4.19.

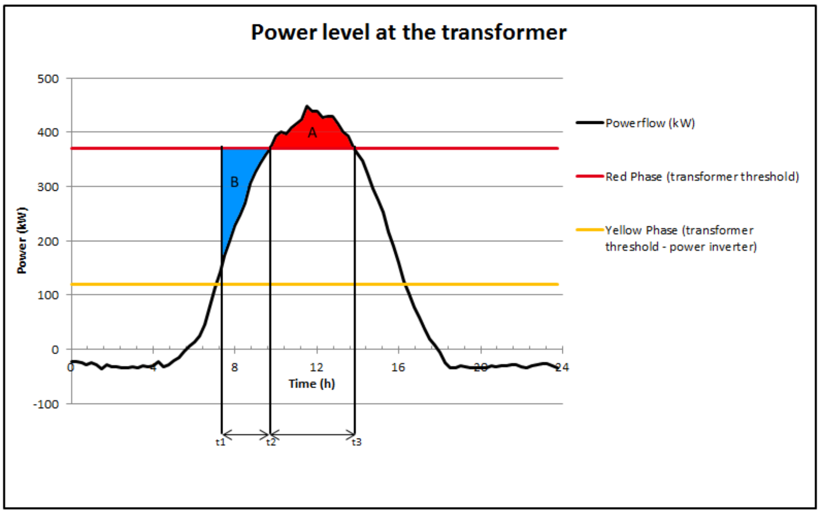


Figure 4.19: Calculating the start time spot for discharging.

As it can bee seen in Figure 4.19 the red area A, from t_2 to t_3, is the PV peak that has to be stored. The value of maximum SoC of this day (which has to be discharges until t_2) is given by the area of A (red marked in the figure). In order to calculate the blue area B, an iterative procedure begins at the first time interval of the red phase t_2. For this purpose the discharge flexibility of the time intervals are added. The procedure is started at t_2 and goes backwards (t_{-1}). In each iteration, the discharge flexibility is added and compared to the Value A. If the Value of B is equal or the first time greater that the value of A, the start time interval of the discharge phase is found (this point is marked with t_1 in the figure). This means if the local grid operator wants to be sure that there is enough capacity free in the storage and chose to control the discharge itself, t_1 is the time spot when he has to control all of the free flexibilities. So the third party would lose the possibility to operate in the time spot between t_1 and t_2.

4.3 Conclusion

To conclude this chapter, the theoretical regression method was defined for the practical use. That means we determined the time interval during the day to two hours, because the point cloud of this time interval shows the best trade off between linearity and number of data points. In addition the historical time period as input data for the regression function was set to ten days, because this time period seems to have enough data points to calculate a regression function and has the lowest seasonal influences. So the regression function is calculated from the last ten days. Furthermore, we presented the practical connection between the BDEW concept and the real distribution grid. In this process the three phases of BDEW (green, yellow and red) were defined. We show how to calculate the free flexibilities, which are narrowed by the power and capacity constraints. In addition we developed a fourth phase (orange), the discharge phase, which should help the distribution grid provider to monitor the third party. In the discharge phase, also the last possible time interval to start discharging the electricity storage to buffer the PV peak at the start of the red phase is calculated.

Chapter 5

Results

5.1 Abstract

In this chapter, the results of the regression analysis are shown. As described in the previous chapters, the power flow at the transformer is forecast by the regression analysis. The forecasts are based on measurement data from Westnetz. Important measurements in the data set of Westnetz are: weather forecasts (we only use the forecast of the irradiation (FI)), measured weather data (the measured irradiation (MI)) and the measured power flow at the transformer. Two different time series that need to be predicted are considered. For the first series we forecast the power flow at the transformer for all days of a specific week and for the second series we forecast a specific day of the month (the 8th) from April until August. The complete results of these series can be found in Appendix B. In this chapter only excerpts of these measurement series are used.

5.2 Introduction

The results of the forecasts are compared and validated with the help of root mean square (RMS). The RMS is a method used a.o. in statistics and indicates an average error between two data sets. In our case, we compare the forecast power flows to the real power flow at the transformer. The error represents the deviation of the forecast value from the real value, which means the best error would be zero, but mostly it is near zero. Furthermore, we calculate the average deviations between the forecast and the real power flow (this can be positive or negative), because if the forecast is in one time interval predicted too high and in an other too low, these two predictions faults might compensate each other when this prediction is used to

derive the storage capacity. The forecast may have a sufficient accuracy, even when it deviates in some intervals from the real power flow.
In Section 5.4, an example of a result table (Table 5.1) and the values shown in the table are described and shown. For the remainder of the chapter, only figures or parts of the tables are shown. As mentioned before, the complete result set and tables can be found in the Appendix B.

5.3 Simulation setup

To evaluate the ideas and as a production prototype, a Java program was written. The program is designed to run continuously on Westnetz servers and forecast the flexibility of the electricity storage in Wettringen. This means a certain quality and stability is required because the program will be used for further research and perhaps commercially. The program carries out several tasks. The first task is to import weather forecast and storage data. The weather forecast is provided as an XML file and the storage data is delivered as a CSV file. Both files are imported and stored in an Oracle database. In this process both data are synchronised by the UTC date. Also a selection has to take place during the import because only the weather forecast from Ahaus is needed. The next task is the selection of the input data for the regression algorithm. This is done by a SQL command from the Java program via a JDBC7 interface. This way the program communicates directly with the database and conversion problems are prevented. The next task is to calculate the regression and the forecasts of the power flow for the next day. Based on of these power flows the storage flexibility can be calculated as well. The final task is to store the results in a database table.

5.4 Introduction to the simulation results

This section provides an introduction to the simulation results. These results are the basis for the remainder of the chapter and serve the purpose of validating the developed forecast method. For each simulation the following results are documented:

1. **Time**: The values given in this column indicate the start time of the given interval. For example 01:00 indicates that the time interval starts at 01:00. The end-time of the interval follows either from the given length of each time interval, it is also the value of 'time' given in the next row. Note that some of the values given in the following columns are not values of single measurements but average values over the given time interval.

2. **Real Power Flow**: In this column, the average measured power flow at the transformer are given.

3. **Forecast Power Flow (FI as input)**: This column shows the values of our forecast method with the forecast irradiation as input.

4. **Forecast Power Flow (MI as input)**: This column shows the values of our forecast method with the real measured irradiation (measured in Ahaus/Germany) as input.

5. **Slope**: This column shows the slope of the calculated regression function for the power forecast.

6. **Intercept**: This column shows the interception of the calculated regression function with the y axis, which indicates also the demand in the distribution grid.

7. **Error (FI as input)**:This column shows the deviation between the real measured power flow and the forecast power flow of column FI.

8. **Error (MI as input)**:This column shows the deviation between the real measured power flow and the forecast power flow of column MI.

In order to clarify the above, the values for 08-05-2016 are given in Table 5.1. As numbers are not always that intuitively understandable, we visualise the results also in different diagrams. In the following we show only diagrams, the complete result tables can be found in Appendix B.

Time (hours)	Real Power Flow [kW]	Forecast Power Flow (FI) [kW]	Forecast Power Flow (MI) [kW]	Slope	Intercept	Error (FI) [kW]	Error (MI) [kW]
00:00	-30.81	-32.04	-32.04	0.00	0.00	1.22	1.22
01:00	-27.44	-31.20	-31.20	0.00	0.00	3.76	3.76
02:00	-26.06	-31.24	-31.23	0.00	0.00	5.18	5.17
03:00	-36.47	-34.36	-34.35	0.00	0.00	-2.11	-2.11
04:00	-43.30	-28.70	-28.69	0.73	-28.70	-14.60	-14.60
05:00	-4.59	5.41	4.48	0.46	-15.43	-9.99	-9.06
06:00	51.37	81.13	85.78	0.52	-2.65	-29.76	-34.41
07:00	159.47	177.93	186.28	0.49	25.49	-18.46	-26.81
08:00	272.78	265.26	278.26	0.59	-6.73	7.52	-5.49
09:00	364.33	335.74	344.96	0.58	-12.49	28.60	19.37
10:00	424.20	411.32	406.68	0.66	-75.40	12.87	17.51
11:00	451.23	441.78	450.03	0.69	-98.03	9.45	1.18
12:00	449.80	432.64	448.36	0.63	-68.11	17.17	1.43
13:00	422.74	408.96	412.16	0.64	-96.44	13.78	10.57
14:00	358.98	320.05	336.98	0.60	-103.85	38.93	21.99
15:00	250.99	211.87	227.53	0.47	-64.73	39.12	23.46
16:00	129.23	106.68	116.00	0.35	-47.75	22.56	13.22
17:00	30.32	28.55	34.12	0.27	-50.05	1.78	-3.80
18:00	-25.18	-22.64	-21.56	0.10	-37.42	-2.54	-3.61
19:00	-39.60	-34.98	-35.48	-0.06	-33.06	-4.63	-4.11
20:00	-36.97	-36.86	-36.86	0.00	0.00	-0.11	-0.10
21:00	-32.62	-37.13	-37.12	0.00	0.00	4.51	4.50
22:00	-26.83	-34.26	-34.26	0.00	0.00	7.43	7.42
23:00	-22.65	-15.73	-15.73	0.00	0.00	-6.92	-6.92

Table 5.1: Results of 08-05-2016

5.5 Validation of our power flow forecast

In this section we show several simulations of the power flow forecast with different data sets as input values in order to validate our power flow forecast method. In the first step simulations were made with measured irradiation values as input to our forecast. The measured irradiation was used in these simulations to negate the influence of the weather forecast inaccuracy. Then the resulting inaccuracy is only the inaccuracy of our method. For the simulation two days were chosen. The first day was in a relatively stable weather period (08-05-2016) and the second in a relatively unstable weather condition (08-07-2016).

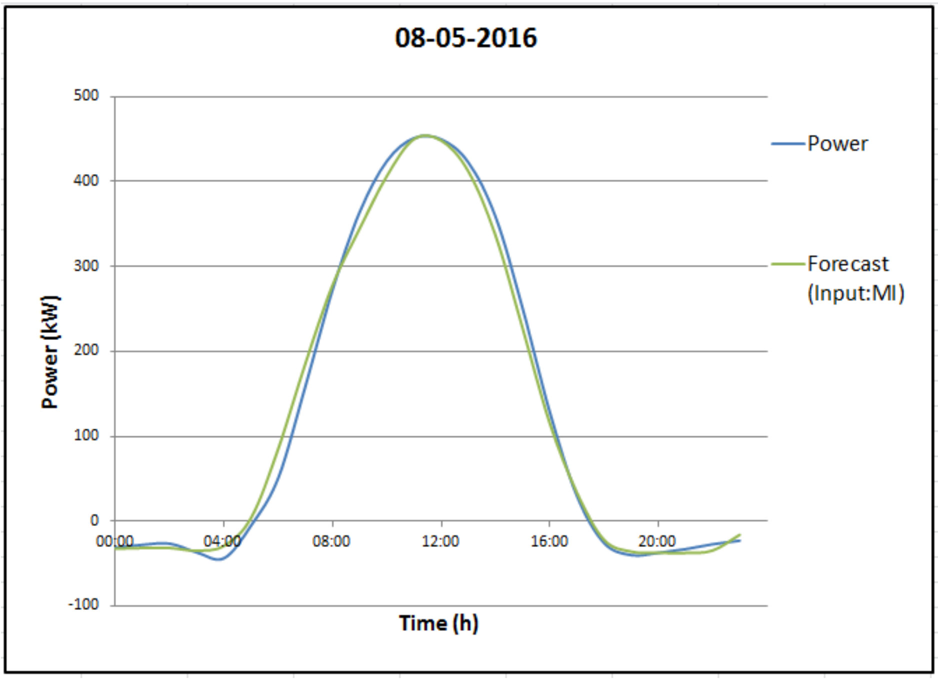


Figure 5.1: Forecast results of 08-05-2016.

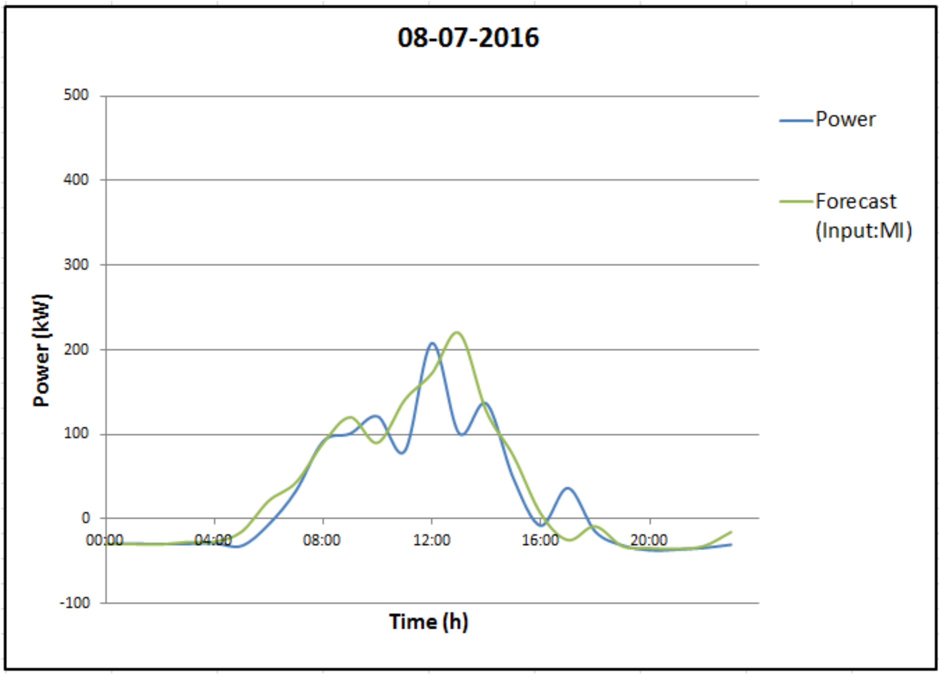


Figure 5.2: Forecast results of 08-07-2016.

The relevant part of the forecast results is the part when the sun is up and the PV installations generate power. For the considered day this is the time between 05:00 until 17:00. In Figure 5.1 the forecast of the sunny day 08-05-2016 can be seen. The real power flow has a nice parabola form, which means there were no clouds in the sky and the PV installations are continuously producing power. Furthermore it can be seen that the results of our forecast method are almost the same as the real power flow. We calculated the deviation per time interval between the real power flow and the forecasted power flow and the average deviation was 0.82kW (the largest deviation during this day was at 06:00 with -34.42 kW).

Figure 5.2 shows the forecast for an unstable weather period. The real power flow has a certain number of peaks and local minimums. This indicates that the sky was cloudy and so the PV installations produced fluctuating power. The shape of the real power flow and the forecast power flow are almost the same, except at sometimes there is a time shift. This can be explained due to the input values. These input values are measured in Ahaus, while the PV installations are located in Wettringen. That is a distance of approximately 30km. Thus the clouds are earlier (or later, depending on the wind direction) in Wettringen than in Ahaus. But this shift has negligible impact on the forecast, because the average deviation is only -7.58 kW per time interval (the largest deviation during this day was at 13:00 with -118.65 kW).

To summarise the results, our power flow forecast has a quite good accuracy if we use the measured irradiation as input. We expect that the accuracy can be further increased if there would be a weather measurement and forecast directly in Wettringen.

5.6 Forecasting power flow with forecast irradiation

This section presented the results of our power flow forecast with the forecast irradiation from the weather prediction as input. Furthermore the difference in power flow forecast accuracy between our method with the forecast irradiation and measured irradiation as input are shown. For this purpose we simulate the same days as in the previous section, but now with the irradiation values of the weather prediction instead of the measured irradiation as input. Note, that the weather prediction is for the same weather station (Ahaus) as the measured weather values.
As described in the literature research (Appendix A), it is in general easier to forecast stable weather periods than unstable weather periods. However, in the area of Wettringen, there is quite often an unstable weather situation with a lot of fluctuation. This means it is more difficult to have precise weather predictions since it is among others difficult to forecast the movement of the clouds. Due to these considerations the irradiation input of our method will include a certain inaccuracy already from the beginning on.
In the following two figures (5.3 and 5.4), three lines are shown. The blue line is the real measured power flow at the transformer. The green line is the forecasted power flow with measured irradiation as input to our forecast method. The red line is the forecasted power flow with forecasted irradiation from the weather prediction as input to our forecast method.

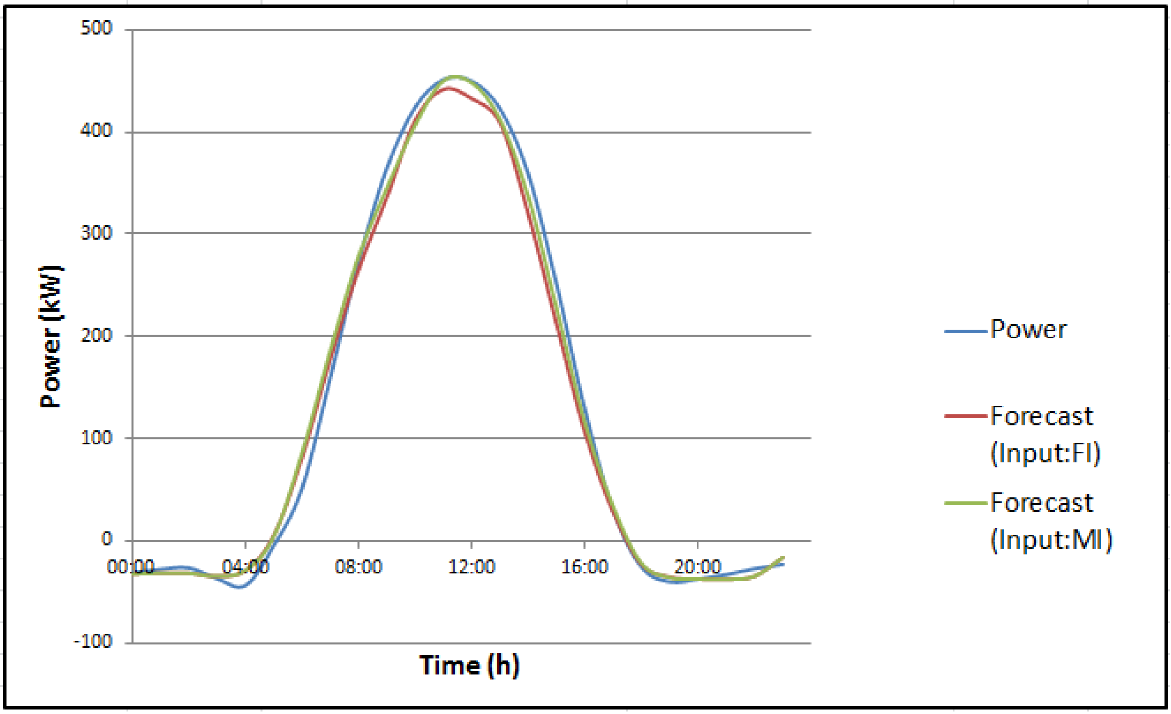


Figure 5.3: Forecast results of 08-05-2016.

Figure 5.3 shows the forecast from 08-05-2016 is shown. It was a warm and sunny day without many clouds. Further the shape of the power forecast with forecast irradiation differs only slightly from the real measured power flow and the forecast power flow with measured irradiation. The power flow forecast with measured irradiation has an average deviation of 0.82 kW whereas the power flow forecast with forecast irradiation has an average deviation of 5.20 kW. So if the weather period is good only a very small inaccuracy is introduced due to the forecast irradiation.
On the other hand, in Figure 5.4, the forecast of 08-07-2016 is given, which was a day in a more unstable weather period. This can also be observed from the accuracy of the two forecasts. The power flow forecast with measured irradiation has an average deviation of -7.58 kW whereas the power flow forecast with forecast irradiation has an average deviation of -20.74 kW. Thus, in this case most of the inaccuracy comes from the inaccuracy of the predicted irradiation.
The above considered factors must be kept in mind when considering the flexibilities. The presence of prediction errors implies that there must be a certain safety threshold if this method is used in practical cases.

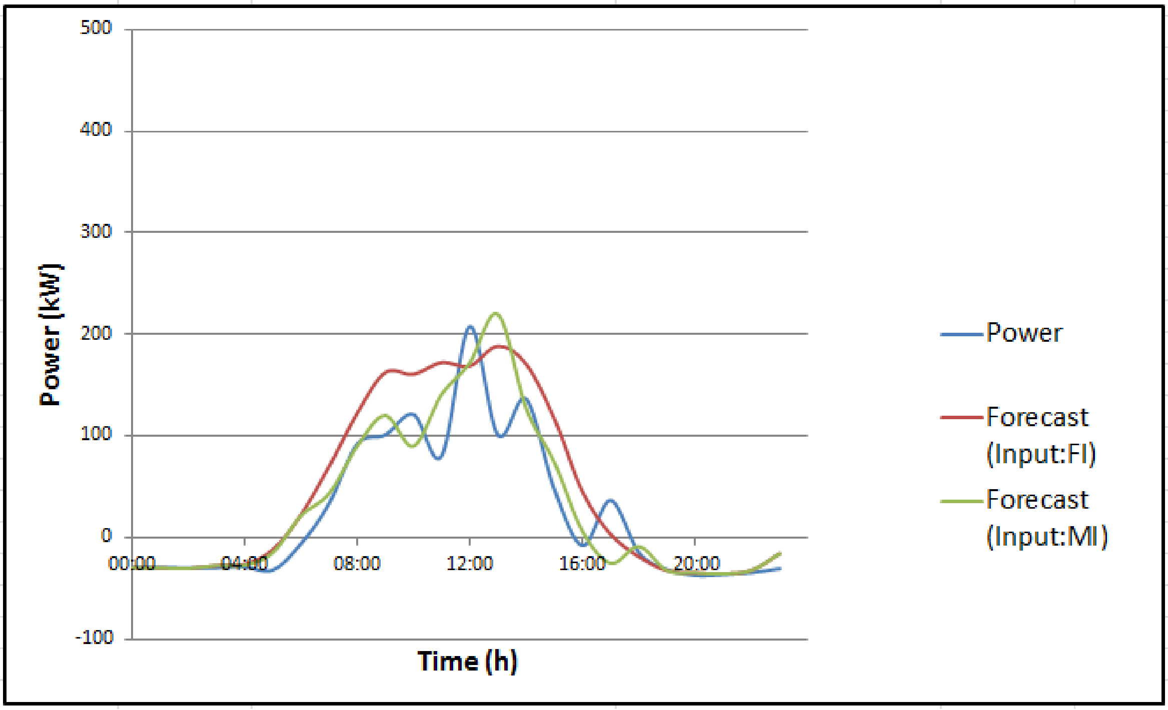


Figure 5.4: Forecast results of 08-07-2016.

5.6.1 Daily pattern

In this section we investigate the slope of the regression function in more detail. For this purpose we calculate the regression function for each hour over the period of a month. Note, that the slope of the regression function indicates the efficiency of the conversion of irradiation in power for the PV installations of Wettringen.
The slope for the month April is shown in Figure 5.5. The exact numbers and the visualisations of April until August can be found in Appendix B.

The figure shows the changes of the slope within the day and through the days of the month. However, for a better analysis, more details are necessary. For this we plot in Figure 5.6 the slope of the regression function for a single day (20-04-2016). Note, that there are time intervals where power is consumed (power is flows from the medium voltage to the low voltage grid) and time intervals when power is produced (power flows from the the low voltage to the medium voltage grid). In the first set of time intervals (from 03:00 until 06:00 and from 17:00 until 19:00) the assumption that the grid is heavily dominated by PV generation is not valid, because there is almost no PV generation.
This means the power flow values are mainly determined by the demand in these intervals, only very small irradiation values occur and that for these irradiation values similar power flow values occur for these irradiation values. For small positive values of irradiation the slope of the regression function is steeper than normal.

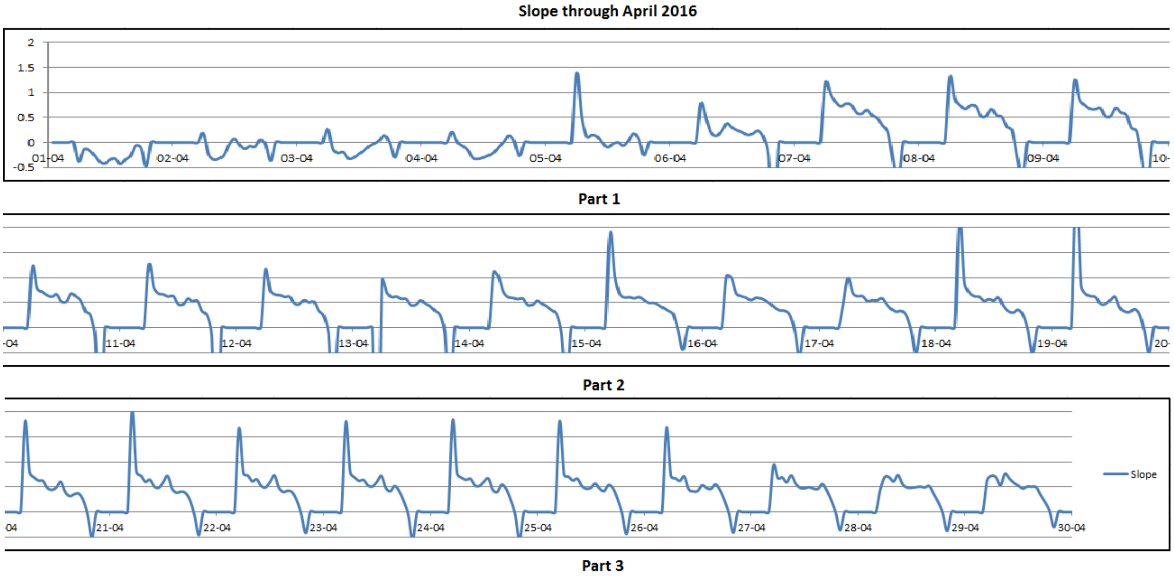


Figure 5.5: Slope through April 2016

This behaviour produces the two big peaks (one positive at 05:00 and one negative at 20:00). But times with almost no irradiation are less interesting, because the electricity storage will not be used for peak shaving purposes in these time intervals. The general shapes of the slope for the days are quite similar. A daily pattern however, changes slowly over time. It can be seen that the PV installations are most efficient between 10:00 and 14:00, because in this time period the slope is high and the slope is an indication of the efficiency. Furthermore the pattern shows a quite stable slope, which fluctuates around 0.5.

Because the PV panels are all installed on the roof tops of the farm buildings, they face in many different directions and have different angles to the sun. So there should not be a large peak at midday when the sun is highest, but rather we may expect some smaller peaks during the day. There are two bigger peaks (next to the ones with almost no PV generation) over the day. The first occurs around 09:00 and the second around 13:00 (see Figure 5.6). We assume that these peaks may come from the larger PV installations in the distribution grid of Wettringen. Two of the PV installations in Wettringen (126.9 kW and 154.8 kW) have their own smart meter built in, which sends the measurement data of the generated power to the control centre. These two PV installations are from the same farmer, and therefore we assume they stand close to each other. However, the PV installations are installed on two different rooftops. With the data from these PV installations we are able to compare the power generation of the two PV installations with the slope values of the regression function, which indicates the efficiency of the PV installations. We expect that the power generation shows power peaks at the same times where the slope is highest. To investigate this, we again considered the data from 20-04-2016. Figure 5.7 shows the power generation profile of two PV installations in the distribution grid of Wettringen. This profile shows the power generation from 20-04-2016.The peak at 09:00 is exact at the same time in both figures (5.6 and 5.7). The slope peak at 13:00 is not exact matching with the power peak, but the power generation at 13:00 is already quite high. We assume that one of the other PV installations that has a peak at 13:00 and in sum with the other PV installation the peak is hence shifted to 13:00.

From the above it can be concluded that not all PV installations face the same direction. However, because also the production of both PV installations in Figure 5.7 has two peaks, we assume that also the individual PV panels on both rooftops face two different directions. Based on the shape of the production curve, we may assume that a small number of panels face east; at 09:00 the sun shined from east (more precise from $100.66°$, retrieved from [5]). The majority of panels face southwest, because at 13:00 the sun shined from southwest (more precise from $191.01°$, retrieved from [5]).

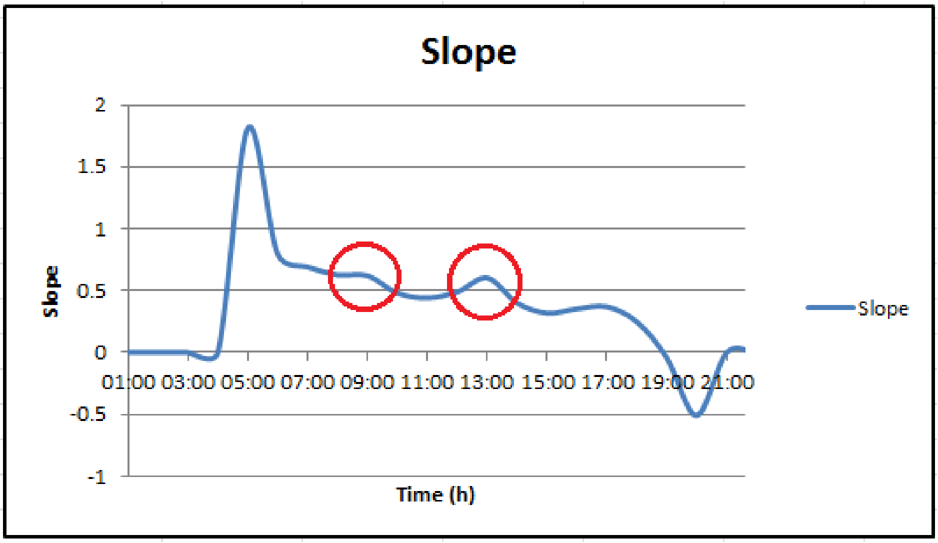


Figure 5.6: Slope 20-04-2016

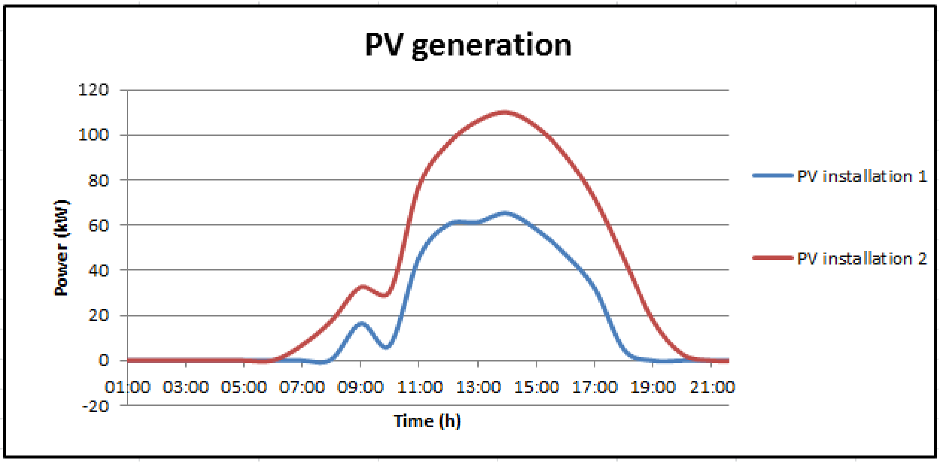


Figure 5.7: Power generation 20-04-2016

5.7 Regression analysis of the slope changes over the month

The last section shows that there is a daily pattern in the slope, which only slowly changes over time. This section studies in which way the slope changes during a month. This may aid at determining the slope for future days. Hence, we simulated a time period from April until July. In Figure 5.8 we present the achieved slope for the time interval between 12:00 and 13:00.

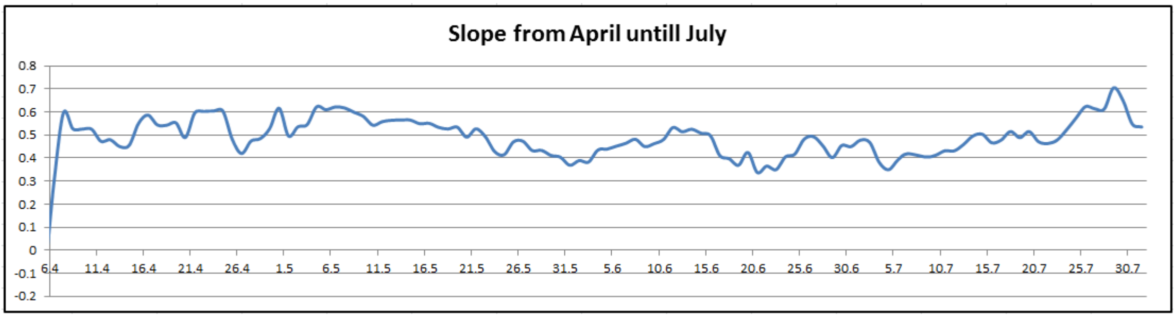


Figure 5.8: Slope changing within the month (from April until July)

The figure shows that the slope roughly deviates between 0.4 and 0.6 and no trend can be seen.

The next step is to calculate a regression analysis for the slope over the month. To study the changes in the regression slope, we take a second regression of this slope. Since the further explanation may become confusing because we now discuss the second calculated regression slope, which is calculated from the slope values (presented in Figure 5.8), we will refer to the old slope (Figure 5.8) as 'efficiency'. To study now the efficiency changes over time, we calculate the (efficiency) slope. This means that we take tuples [date,efficiency] of a specific time interval per day as input for the regression. The regression was made for the hourly intervals between 06:00 until 17:00, because the rest of the day no or only very limited amount of power is generated and thus these intervals are not interesting for this thesis. In the following we present the achieved results for the time interval between 12:00 and 13:00.

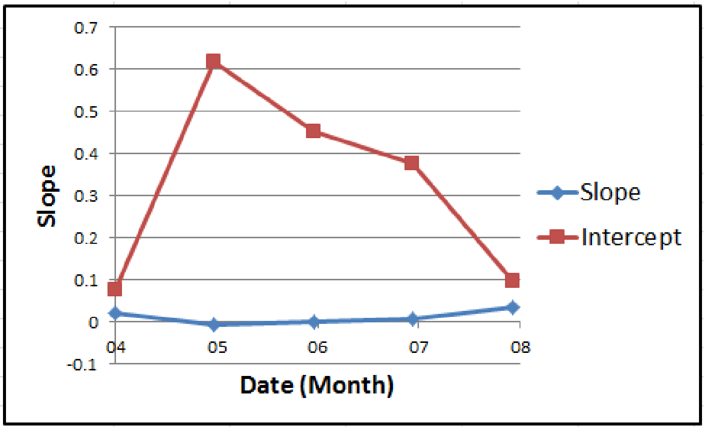


Figure 5.9: Regression analysis of the slope changes over the month

Figure 5.9 shows the slope (of the efficiency) and intercept changes over multiple months, starting in April and ending in the begin August. This period the efficiency did almost not change in the month itself or the regression function (i.e., change of efficiency) changes only slightly within one month. However, the intercept, which represents an indication of the efficiency per month, changes per month. The efficiency during May is maximum and decreases slowly in the following months. We assume that the temperature has also a larger influence on the efficiency and may explain this observation.

5.8 Accuracy of the power flow forecast

In this section the importance of the accuracy of the forecasted power flow at the transformer, and the connection between irradiation and accuracy of the power flow forecast is discussed. We study the accuracy and mainly investigate when forecast has a negative impact. For this, we first consider how we use the forecast results. The important fact here is that the forecasted power flows are not the goal itself, but they are used to calculate the usage of the electricity storage. As such a negative impact of inaccurate power flow forecast only occurs when we come to a situation where the storage usage is based on an inaccurate forecast there is not enough free capacity in the storage to buffer a large PV peak. Conversely, this means that the accuracy is needed at times when the storage has to be used. In the case of

Wettringen this is the case when the power flow at the transformer is over 370 kW. As shown in the literature research it is easier to forecast the power flow for stable weather conditions than for unstable weather conditions (i.e., many clouds in the sky).

Furthermore, the power production increases over 370 kW only when the sun shines a lot, meaning that we should have a (relatively) clear sky and stable weather conditions. But these prerequisites are also the best conditions for our forecast method. This connection is illustrated in Figure 5.10. The figure shows the power flow in blue,

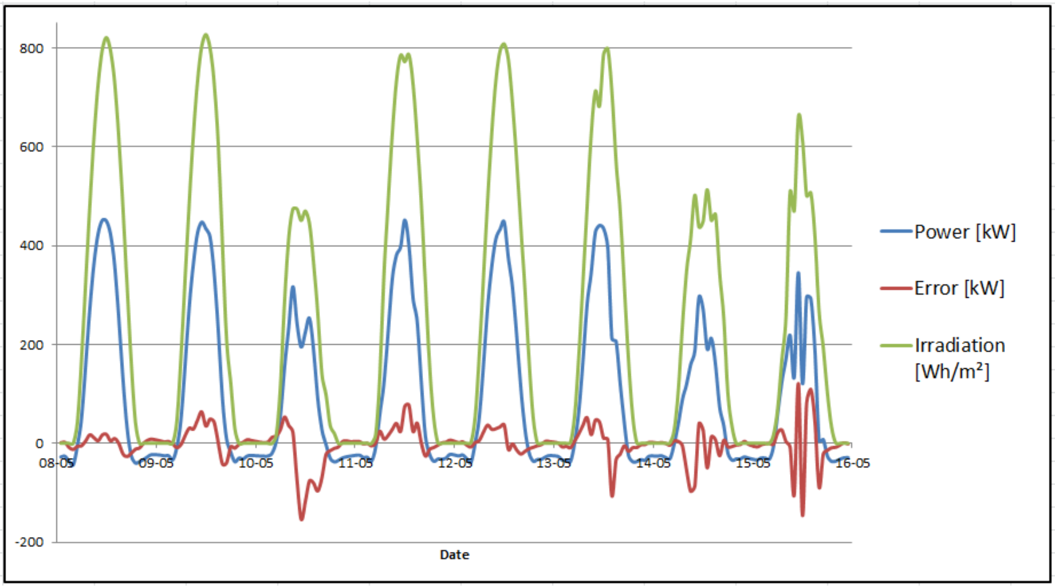


Figure 5.10: Comparison power power flow and error rate.

the irradiation value in green and the deviation error in red. The figure shows that in the first two days (08-05 and 09-05) there was stable weather. The power exceeds over 370 kW and on both days the deviation error does never increases over 30 kW. This means that the forecast accuracy is sufficient. On the other hand, on days with unstable weather conditions (e.g. 15-05.), the accuracy is lower. However, this does not have a large impact because the power flow does not exceed over 370 kW, which means the storage is not needed on this day for grid purposes.

To summarise this section, the relation between the irradiation and deviation prediction error (and indirectly between power and deviation prediction error) is an advantage of this method, because when a high accuracy is needed, the weather conditions are stable, which means the forecast accuracy is likely quite good.

5.9 Points of improvement for the regression method

In this section we discuss points of improvement for the regression method, which were noticed in the process. One such point is the weather forecast itself. The used weather forecast was provided by Westnetz and originates from Ahaus. The distance between Ahaus and Wettringen is approximately 30 km. So the forecasted and measured weather values may deviate from the real weather in Wettringen due to this distance of 30 km. This can be seen, e.g. in the forecast results of 08-08-2016. In Figure 5.11 the real power flow (blue line), the forecasted power flow with **f**orecast **i**rradiation (FI, red line) and the forecast power flow with **m**easured **i**rradiation (MI, green line) can be seen. The real power flow has a peak at 08:00, which is not seen in the forecast power flow with FI (red lines) and only slightly in the forecasted power flow with MI (green line). However the weather forecast and measured weather data do not indicate such a peak. The missing peak in the weather data can be explained due to the distance between Ahaus and Wettringen. A cloud was perhaps present in Ahaus and not in Wettringen. This unstable weather can also be observed in the PV generation. The PV generation only slightly exceeds 300 kW, which is approximately 50% of the generation capacity.

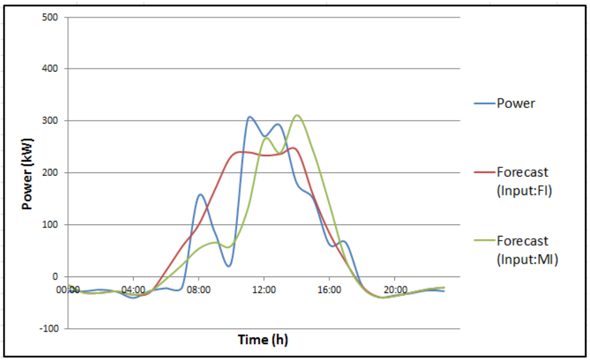


Figure 5.11: Forecast results of 08-08-2016

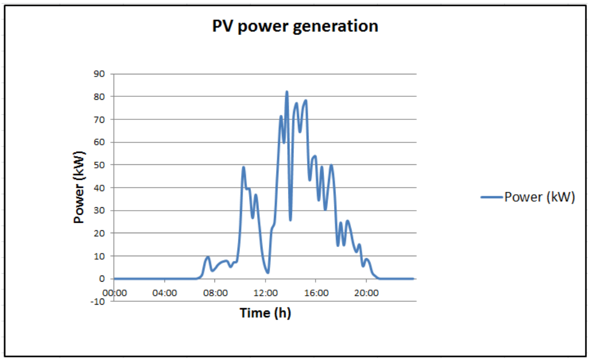


Figure 5.12: PV generation of one of the installions of Wettringen

A second observation is that during the simulations we noticed that there is sometimes a time shift between the forecast and the realisation. However, this time shift is not constant. Sometimes the forecast is shifted to the left (the forecast peak is earlier than the real power flow) or to the right (the forecast peak is later than the real power flow). In order to eliminate the possibility that the time shift is a result of errors in the forecast irradiation, we simulate with both the forecasted irradiation and the measured irradiation. The results for two specific days can be seen in Figure 5.13 and 5.14.

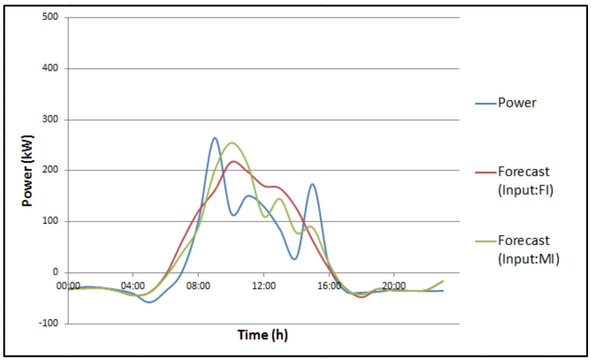


Figure 5.13: Power flows of 08-04-2016

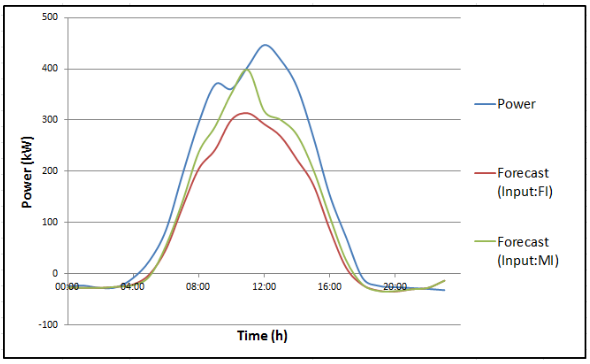


Figure 5.14: Power flows of 08-06-2016

In these figures it can be seen that both graphs (red line is with forecast irradiation and the green line is with measured irradiation as input to our forecast method) shows the time shift. Thus the time shift is not a result from errors in the input data. Looking further at the data, the conjecture came up that the time shift could have been introduced due to geographical distance between Ahaus and Wettringen, meaning that the wind speed and direction could be an explanation for the time shift. Based on the direction of the cloud movements it may occur that the clouds are on some days earlier in Ahaus than in Wettringen and if the wind comes from the opposite direction the clouds would be later in Ahaus than in Wettringen.

In order to verify this assumption we looked for the wind direction at 08-04-2016 and 08-06-2016 and visualised the result on a map (see Figure 5.15). In this figure

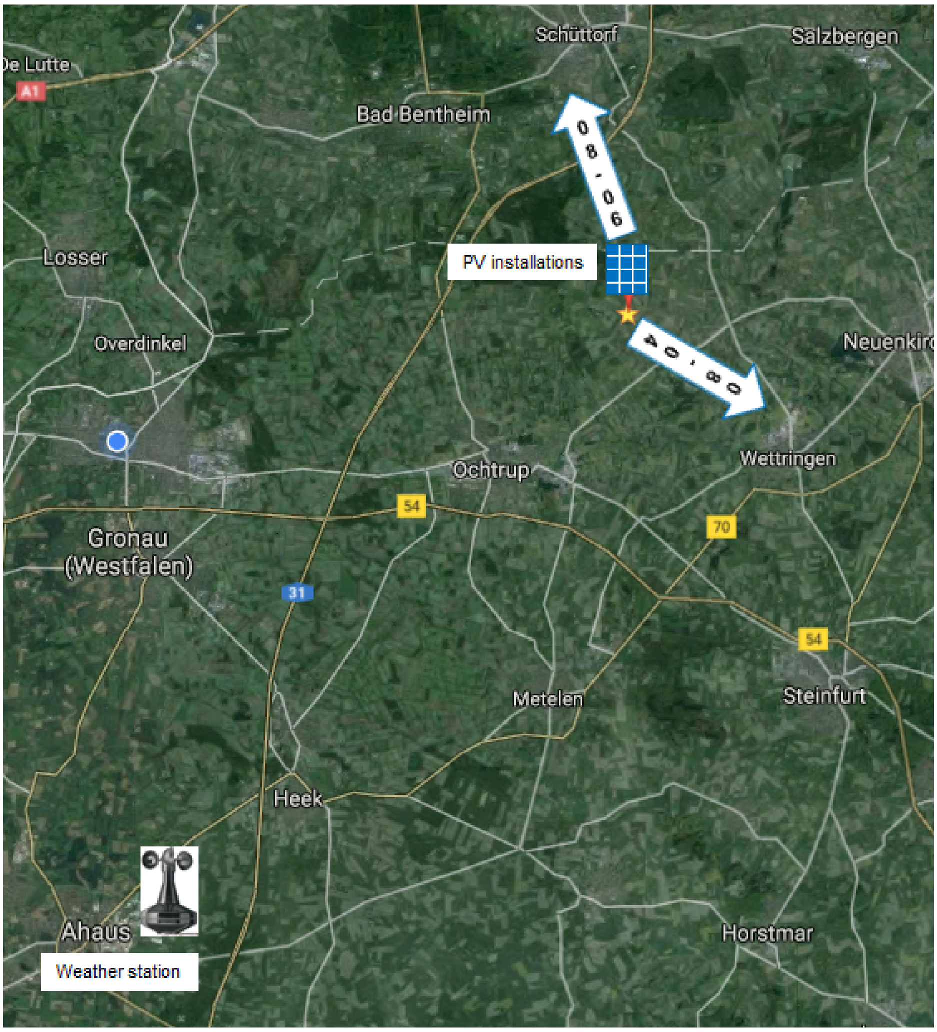


Figure 5.15: The figure shows the location and wind direction.

the two important places (weather station and PV installations) are shown and the wind direction on the two days are illustrated with arrows. The arrows point in the direction the wind was blowing on the specific day. The result confirms our assumption. The wind comes from south (between $230°$ and $250°$) at the 08-04-2016 and at the 08-06-2016 the wind comes from north ($360°$ and $40°$). Thus the wind direction was almost opposite on these two days and the cloud movement may explain the time shift.

5.10 Conclusion

To conclude this chapter, we show the results of different power flow forecasts and analyse it. On days with stable weather periods, the forecast power flow is almost the same as the measured power flow. In these situations the average deviation (e.g., 08-05-2016) between the forecast power flow and the measured power flow was 0.82 kW. On the other hand, in more unstable weather periods (e.g. 08-07-2016), the average deviation is only -7.58 kW per time interval. In this situation, the shape of the forecast is mostly shifted in time, so the shapes did not match. Hence, even if the forecast shape and the measured shape did not match, the results did not deviate much due to the time shift. Furthermore, we present a number of causes for the time shift, e.g., the distance between the weather station (Ahaus) and the electricity storage (Wettringen). In addition we look further in the slope and found out that there are daily patterns, which only change slowly during time. In the end we investigate the question whether we need a certain accuracy for our forecast of the electricity storage flexibility. It was found that the accuracy is needed when the storage is used for grid purposes (buffering the PV peak in order to prevent danger for the distribution grid) and is on days with good weather conditions, which implies a high value of irradiation and high PV generation. Thus the interaction between the irradiation and deviation error(and indirectly between power and deviation error) is an advantage of this method, because when a high accuracy is needed, the weather conditions are stable, which means the forecast accuracy will be quite high.

Chapter 6

Conclusions and recommendations

This chapter contains the conclusions and recommendations for further work. In the first section the conclusions of this thesis are drawn and the research questions are answered (Section 6.1). In the second part recommendations for further work are mentioned, which are important for the improvement of the forecast method developed in this thesis (Section 6.2). Both parts contain a certain part of own opinion and are not of a neutral point of view.

6.1 Conclusions

Based on the previous chapters and the results, the research questions of Section 1.3 can be answered. The main research question is:

How can electricity storage flexibility used primarily for peak shaving be predicted a day ahead?

In Chapter 3 we presented a forecast method and applied this to measurement data in Chapter 4 to forecast the electricity storage flexibility. The most important step in the process of forecasting the storage flexibility is the forecast of the power flow at the transformer. Thus our method is divided in two main parts:

1. **Forecast of the power flow at the transformer:** We showed that it is possible to forecast the power flow at the transformer with a regression analysis. This regression analysis works with input tuples [irradiation/power flow]. Furthermore, we researched the best parameters for the regression analysis and made simulations with (real) measured data of Westnetz GmbH, in order to validate our regression analysis. The results indicate that a forecast of good enough quality is possible.
   The forecast is most relevant at times when the electricity storage has to buffer

a PV peak. Furthermore, PV generation is highest when the weather is stable and the sunny. In such weather scenarios the forecast accuracy of the presented regression is the best. So in the scenarios when the accuracy is important, our presented results show that our regression method can be used to forecast the power flow at the transformer with sufficient accuracy.

2. **Calculation of the electricity storage flexibility:** For the second part, we showed that the electricity storage flexibility can be calculated. For this, it is important to know the power flow in the distribution grid. These flows are used to calculate when and how much electricity storage is needed for balancing the grid. Based on this the unused part of the storage can be calculated, taking into account a certain safety threshold. This part can be used by a third party as flexibility for market purposes. Furthermore, we presented a way to communicate and visualise the free flexibility so that no miscommunication between the distribution grid provider and the third party can happen.

Sub research questions

- **Which method can be used to forecast tomorrows PV production (in the area of Wettringen / Germany)?** In the literature research presented in Appendix A, we analysed different forecast methods and concluded that a regression analysis is most suited for the area of Wettringen, because regression analysis provides a certain forecast accuracy, even with unstable (hard to predict) weather conditions (for more information see Appendix A).

- **What grid assets (e.g., generators,consumers, technical limits, ...) are most important for the forecast and how is the power flow between them (in this part of the distribution grid of Wettringen)?** In Chapter 2 we analysed the important grid assets and showed that the power flow at the transformer is the basis for all storage flexibility calculations, i.e, it is important to forecast the power flow at the transformer as accurate as possible. Furthermore, we have shown that the base load (the demand in the distribution grid) can be neglected in the power flow forecast if it is stable in the forecast time interval, since in this case it only shifts the regression function. This means that only the coefficient for the constant part of the function is changing (the b part of $f(x) = ax + b$).

- **What forecast accuracy can be achieved and what can influence the forecast accuracy?** As mentioned before, the power flow at the transformer is the basis for all calculations and we showed in the results that the power flow forecast depends on the forecast irradiation values. Additionally we showed that several other effects have an impact on the forecast, e.g., if the weather station is not located at the point of interest (in our case in Wettringen). Already a small distance between the weather station and the forecast area (in our case 30 km) can have an impact on the forecast accuracy. For example, it may happen that the forecast is shifted in time or the forecast power flow has small differences to the real power flow, because due to the cloud movements the irradiation values are different at both locations. So in case of stable weather conditions our method achieves an excellent forecast accuracy, e.g., the forecast at 08-05-2016 has only a average deviation of 5.2 kW per time interval. This is less than 1% (0.756) of the maximal installed power generation (687 kW installed PV generation). In times with more unstable weather conditions, our method provides a sufficient accuracy, e.g., at 08-07-2016, the average deviation is -20.79 kW per time interval. This is a deviation of 3.03% deviation of the maximum generation capacity. Furthermore, we observed that at times the electricity storage is needed (i.e., when there is a a lot of power generation), the weather conditions are mostly stable.

- **How can the important information mentioned in Section 1.2 be calculated and visualised?** In the process of this thesis, we noticed that the information mentioned in Section 1.2 are only intermediate variables in the forecast method. The information that a third party needs to know to use the free flexibility are the power and capacity constraints. These constraints are the limitations that should not be violated, because otherwise the distribution grid would be in danger. Therefore, we present a way to forecast and visualise these constraints for the next day. With the help of the results of our flexibility forecast method (including a certain safety threshold), a third party is able to use the free flexibility of the electricity storage.
  For this, a platform might be programed to visualise the flexibility on beforehand to the market providing a non-discriminatory way of exploiting the potential of the storage system.

6.2 Recommendations for further work

In this section we recommend important further work. These are issues that received our attention during the development of a basis method that calculates the flexibility of an electricity storage in a distribution grid with heavy PV generation. The method gives accurate and promising flexibility forecasts. Nevertheless, there are recommendations for improvement for further work:

1. **Improve the weather forecast:** The results of this thesis show that a great part of the inaccuracy depends on the quality of the prediction of the irradiation value of the weather forecast. This means that the weather forecast is the most important point to improve. One point of attention is the location of the weather forecast. In this thesis we worked with weather forecasts for Ahaus, which is approximately 30 km away from the PV installations. A more accurate and local weather prediction would improve the power forecast. Westnetz gets weather forecasts for different weather stations, of which three are located in a 50 km radius. One possibility would be to aggregate the forecasts of these three stations, perhaps a with a distance dependent weight. Then the nearest (Ahaus) has the most impact, but also the other stations, can influence the weather forecast for Wettringen itself.

2. **The irradiation values itself:** The measured irradiation values are point values (i.e., instantaneous measurement); while the power values are the average of the complete time interval. Thus for the regression tuples point measurement are matched with an average value. We assume that this has an impact on the accuracy, especially in unstable weather periods. It is better to also have an average of the irradiation value over the time interval.
   Furthermore, the accuracy would improve when the average irradiation values are in 15 minutes time intervals. Westnetz GmbH already measures the power values in a 15 minutes time interval, but the irradiation values are only available on an hourly basis. Thus, we calculated average power flow values of hourly basis in this thesis for the regression input tuples. We assume that the accuracy may increase if we have regression input tuples with 15 minutes average values for power flow and irradiation.

3. **Weighting of the power flow:** The importance of the accuracy of the resulting power flow is not the same at all times . A small inaccuracy during the green phase has a small impact because the difference does not endanger the grid stability. In the yellow phase, the calculated schedules could change slightly due to inaccuracy. However, this has only little influence and also does not endanger the grid stability. However, in the red phase, the accuracy is really

important, because the smallest fluctuation can endanger the distribution grid stability. So we suggest to weight the data points in the regression analysis, so that the points with high irradiation (most likely in the red phase) will get more influence than the data points of the other two phases.

4. **Error detection in the regression analysis:** We suggest to build in an outlier detection analysis because outliers have, due to the use of the least square method for making a regression, large influence on the linear regression function, which subsequently has influence on the power flow forecast.

5. **Demand forecast:** The combination of PV generation and demand can be forecast with in a linear regression analysis when the demand is very small in comparison to the PV power generation, or when the demand is relatively stable per time interval of the regression analysis. But for other demand / generation ratios, or large fluctuations on the demand side, it may be better to divide the power flow in a demand and a generation flow.

Bibliography

[1] S. Nykamp, T. Rott, N. Dettke, and S. Kueppers, "The project" ElChe" Wettringen: storage as an alternative to grid reinforcements-experiences, benefits and challenges from a DSO point of view," in *ETG-Fachbericht-International ETG Congress 2015*. VDE VERLAG GmbH, 2015.

[2] B. B. der Energie-und Wasserwirtschaft e.V., "Smart Grids Ampelkonzept," March 2015. [Online]. Available: https://www.bdew.de/internet.nsf/id/20150310-diskussionspapier-smart-grids-ampelkonzept-de/$file/150310%20Smart%20Grids%20Ampelkonzept_final.pdf

[3] S. Chatterjee and A. S. Hadi, *Regression analysis by example*. John Wiley & Sons, ISBN, 978-0-470-90584-5, Edition, 5th, 2015.

[4] R. Deutschland, "Der Smart Operator in der Pilotgemeinde Kisselbach," September-2014 Retrieved, 16-04-2016. [Online]. Available: http://www.rwe.com/web/cms/de/2467062/rwe-deutschland/energiewende/intelligente-netze/smart-operator/modellregionen/kisselbach/

[5] H. S. . T. Hoffmann, "Sonnen Verlauf," Retrieved, 12-09-2016. [Online]. Available: http://www.suncalc.org/

Appendix A

Literature Research

August 22, 2016

WHICH METHODS CAN BE USED TO FORECAST TOMORROWS PV PRODUCTION IN ORDER TO ESTIMATE FREE STORAGE FLEXIBILITIES.

LITERATURE STUDY

Kristian Keller

Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS)
Computer Architecture for Embedded Systems

Supervision:

Prof. dr. ir. G.J.M Smit	University of Twente
Prof. dr. J.L. Hurink	University of Twente
Dr. ir. M.E.T. Gerards	University of Twente
Dr. M.Sc. S. Nykamp	WESTNETZ

ABSTRACT

The German DSO Westnetz required a temporary 10-kV-reinforcement in the area of Wettringen / Germany.This reinforcement was temporary necessary in order to reduce the power peaks of PV-generators. A normal 10-kV cable could have been used as reinforcement. But a cable do not reduce the peaks, rather it make it possible to shift the problem to a higher grid layer. In the higher grid layer the problem itself decrease because the higher grid is designed for greater power. However, the special situation in this area implies that the cable is only needed for 5 years and after that it is obsolete. Thus the cable investment would be lost after 5 years and the problem with the power peaks is not solved. That is why Westnetz decided to invest in storage capacity for this situation instead and now they want to evaluate the potential economic and technical benefits of the temporary storage. One observation is that the storage is only used in the middle of the year; approximately from April to October. Moreover, in this time period the storage is most of the time not entirely used.

In this study a method is developed, that predicts, when and to which extend the storage is used. Furthermore, the method forecasts the state of charge and the time periods when the transformer is able to do additional charging or discharging. Based on this the storage flexibilities can be predicted. To make a prediction of the usage of the storage, the power provided to the storage has to be estimated. Therefore, the amount of power, which is consumed and produced in this area, has to be known.

The research focused on forecast methods of PV production and their difference. This includes relevant input variables and facts that affect the accuracy of PV forecast methods. As a result the research gives an advise and shows the advantages for a certain PV forecast method that can be used to forecast the Westnetz storage.

CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The company WESTNETZ tries to overcome these challenges with the help of a storage that maintains the balance in a part of the distribution grid. Moreover the storage is able to buffer a certain amount of generated power to prevent the grid from overloading. As a storage for such a scenario is expensive and WESTNETZ wants to use it in an economic way. However, this is not a trivial task, due to that is difficult because of the unstable weather conditions in the western part of Germany. a first analysis shows that from the end of October to April the storage is not in use for grid flattening reasons because the produced PV power is much lower than production from April to October. Furthermore during the rest of the year the storage is almost never entirely used because the power production only achieves the maximum power production in the middle of the day. If Westnetz wants to use the free capacities of the battery for other purposes, the power production has to be predicted beforehand in order to know how much of the capacity of the storage is needed to balance the grid. From this, an estimation can be made how much capacity is left for other services.

1.1 Research description

This literature study forms the base for the master thesis, which includes the implementation of a method to forecast tomorrows free flexibilities of a storage device in a distribution grid.

WESTNETZ initiated in the last year different project, in order to push their grid storage research to the next level. In the last year a storage was build in Wettringen, a rural area of Germany. It is one of the first research project where a storage is added to the distribution grid. The storage aims to maintain the balance in the grid. Furthermore, the storage can flatten the power peaks that are a consequence of the fluctuating power generation of the renewable energy sources in the local distribution grid. The storage was dimensioned in a way that it can buffer the difference between the highest power peak and the transformer capacity. As a consequence the full capacity of the storage is only used in rare cases during the year. This means that the storage has free flexibilities most of the time. This is the starting point for this research.

This literate research shows ways to predict tomorrows free flexibilities of a storage device in a distribution grid. In the first step, the search for research papers with the purpose to predict free flexibilities in a storage. However, as no papers of this specific subject could be found (in Google scholar) and also no articles in relevant conference journals, the second step was to look for alternative solution. For this we had to analysed the situation in Wettringen in order to find the influences which have the most impact on the flexibilities. The storage was build in a rural area with some farms, which are equipped with PV. The installed PV-panels can produce power of approximately 700 kW. On the opposite in this area the power demand is low and approximate 50-70 kW. Further more, the capacity of the transformer for this area is limited to 630 kW. Hence the most important factor in the beginning is to know how much PV production is fed in the grid and how much of it has to be buffered by the storage. Thus, in this study we focus on PV forecast algorithms, relevant input variables for these algorithms, and factors that affect the accuracy of PV forecast. More specific we need to find a method to predict al the influences in order to forecast the free flexibilities for tomorrow. In the master thesis it is also investigated, if one should take into account also the local demand to forecast the usage of the storage.

CHAPTER 2

THEORETICAL BACKGROUND

This chapter gives an overview of important background knowledge. The intention is to provide the reader with knowledge to understand the decisions within the research. This chapter is structured in three sections:

- Important forecast variables:
  In this section it is explained which variables are often used to forecast PV production and which purpose they have in corresponding method. Furthermore their affect on the method is shown.

- Different PV forecasting periods:
  The forecast algorithms can be divided in three different time periods: STLF (short term load forecast), MTLF (medium term load forecast) and LTLF (long term load forecast). In this section the corresponding time periods are defined. Additionally, the purpose for the use of different time period and imput variables are explained.

- Factors that influence forecast accuracy:
  Many factors play a roll in PV forecasting, which makes it difficult to forecast the power generation of a PV with a high accuracy. In this section it is shown which factors mainly influence the power production and the problems that come with these factors.

2.1 Important Input Variables

In this section the effect of the two most important input variables, weather data and historical load data, are shown. Everybody can understand that weather data is one of the most important input variables for PV load forecast. As reported in [15] frequently used variables are temperature, humidity, wind speed and irradiation (cloud cover). Among all this variables the temperature is the one which is used the most in forecast methods and seem to have a great effect on the PV production. In literature, many different ways are documented in which the relationship is described between temperature and PV load. In the year 2001 a research has ascertained that 13 out of 22 load forecast methods use the temperature as thier main factor [10]. Next to the temperature the irradiation is an important factor in PV forecast [19]. The sunrays are the energy provider which the PV can convert to electrical energy. Therefore, the rays and irradiation angle are very important for the pv's production. This combination is often used in methods of regression analyses, for instance in [16, 11]. The biggest disadvantage of weather data as input value is the weather itself. The weather is unstable so that even the weather forecast for the short future (one till seven days) has already a certain inaccuracy. If the result of a weather forecast is used to forecast the PV production the result is at least as inaccurate as the weather forecast itself. The second important input variable is historical load data. The previous load data provides a relationship between certain input data and PV production as well. It is mostly used in Neural network to forecast the PV production. As input data either one day per year in a certain time period (for example the 21.01. of the last twenty year) or all days in a certain time period (for example every day of the last two weeks) is used. The difficult in forecast methods with only historical data as input data is that weather changes are not recognised by the system.

2.2 Different PV forecasting periods

Today there are many different forecasting methods in the literature available, which are used for different purposes. As mentioned in the previos section, forecasting algorithms are not only divided by the used input variables but also by the time horizon of the forecast [12, 2, 15]. Based on this, they can be divided in three categories:

The first and shortest time horizon is the short term load forecast (STLF). The methods of this category provide a forecast time horizon from one hours up to one week. For control techniques, like power balancing, this time period is too long. That is why sometimes this period is once more divided in a very short term load forecast (VSTLF) which is only from 1 hour to 6 hours and the rest of the normal STFL period. For both time intervals the main input variables are weather data, seasonal data and historical load data. The STLF usually aims for a daily load curve and the peak load per day. Corresponding methods are normally used for operation and maintenance like power balancing. In this context there is a need for a certain planning to be able to satisfy the fast changing and unpredictable demand of the service district, such that the energy provider can guarantee a reliable energy supply.

The second time horizon is the medium term load forecast (MTLF). Methods for this period, forecast the load from one week up to one year ahead. They aims mostly for a curve over the time period with the accuracy of one day. Furthermore the peak load and the average load is provided per day. The input values incorporate mostly additional influences like demographic and economic factors. The energy provider uses these methods to perform long term schedules to predict and order a certain basis amount of energy based on his prediction of the end user needs.

The last time horizon is the long term load forecast (LTLF). It last from one year till twenty five or thirty years. For these methods the population growth and gross domestic products have to be considered. The scale of the result is either daily or weekly. Method for such time periods usually use to plan extensions of assets. They are needed to calculate the economic position of new projects.

The information of the section is summarised in the Figure 2.1.

	Temperature	Economics	Land Use	Updating Cycle	Horizon
VSTLF	Optional	Optional	Optional	<= 1 Hour	1 day
STLF	Required	Optional	Optional	1 Day	2 weeks
MTLF	Simulated	Required	Optional	1 month	3 years
LTLF	Simulated	Simulated	Required	1 year	30 years

Figure 2.1: Classification of load forecasts [15]

2.3 Factors that influence forecast accuracy

The PV forecast mostly uses values as input that on their own already been forecasted, or they have inaccuracies themself, like the weather indicators. So the forecasting of PV suffers from forecasting uncertainties occurring before the PV forecast takes place. This implies that all steps of the PV forecast have to be as accurate as possible in order to get a satisfying accuracy . In [19] four key factors are identified that mainly influence the accuracy:

- Surrounding area and weather conditions
- Forecast area
- Forecast horizon
- Accuracy metric used

2.3.1 Surrounding area and weather conditions

As stated in [19, 10], the accuracy of the different forecast methods are mostly depending on accurate climate and weather forecasts. The following examples show that studies all over the world have shown that forecast errors are lower in areas with a more stable climate. [6] found out that it is easier to achieve a low forecast error in the south or the central part of Spain as compared to the north. Also [17] studied the forecast error in Europe. If one compares the forecast errors from this two researches, the error from Spain is much lower (approximately 20% lower) than the error from the other parts of Europe. This regional differences can be explained by the weather conditions (like cloud covering and fast changing weather), the sun elevation angle and local area conditions. As shown in the research of [6] there is a relationship between the sky condition and the error of the forecast. It can be said that a long period of clear sky is easier to forecast than a partly covered sky with fast changing irradiation. Furthermore the researches showed that the season also has an impact on the accuracy.

2.3.2 Forecast area

The geographical size of the forecasting area has a significant impact on the forecast accuracy. [17] shows that the average forecast error decreases with the increase of the size of the area under consideration. In order to compare different methods all research papers use a sort of average error. It means the over all error is sum of all part area errors divided by the number of all part areas. It can be explained by the fact that a forecast error of a small part of the forecasting area has not so much impact than the same error in a smaller forecast area. Furthermore, it can be the case that two errors (partly) cancel each other out.

2.3.3 Forecast horizon

In this subsection two factors play a large role. The first is almost the same as in the previous subsection. In a certain time period the accuracy will be increased if the time period also increases, because it is difficult to forecast the movements in the sky. For example a cloud, which was not predicted accurate, covers for 5 min. the sun, has a bigger impact on the result in a 15 min period than in a 1 h period. That means that small faults in the weather prediction can be neglected if the forecast period is big enough. The second factor is that the input values for the PV forecast itself have to be forecast. For example the weather forecast is most accurate in a one to two day period ahead. Whereas for forecasts with historical values mostly stands with the more data available, the better the forecast.

2.3.4 Accuracy metric used

In this subsection special attention is given to define the word accuracy. In different research papers the word accuracy is differently defined. In [16] they use the mean forecast error in order to evaluate their method. Hereby the individual errors represent the maximum error of a day. In another research [4] the normalised root mean square error is the evaluation measure. The error is the normal root mean square error normalised by the average peak power of the PV system. In [9] the method is evaluated with the help of mean absolute percentage error. The error is the deviation of the forecast value from the real value.

What can be concluded from these examples is that for each method or situation different effects or values are important for the evaluation by the user. So not only the method is customised for the specific situation but also the choice for the concrete function giving the error measurement is customised for the situation.

2.4 Results

During the literature research two methods came along quite often. The first is neural network forecasting. Almost 50% of the research was going in this direction. On the other hand regression analysis methods are also much investigated. [2, 5] conclude that a clear trend in the direction of neural networks can be seen in the last decade. But in [2] writes also that many effort is being put in further research in regression analyses methods. So in the following we focus on these two forecast methods.
For the forecast horizon, Section1.1 implies that a forecast of PV production one day ahead is needed, i. e. a STLF forecast. In the area of STLF forecast this research focuses on methods that preferably use both important input variables, which are weather and historical load data.

CHAPTER 3

STATE OF THE ART

In the previous chapter we have focused on the input factors which are used in the forecast methods. In this chapter we now consider the methods them self. As stated in [19], the PV forecasts in the different time periods can broadly be divided in two categories, namely physical and statistical.
In the physical approaches one tries to find (linear) relationships between weather variables (like irradiation or temperature) and the PV production. Mostly they forecast these weather variables a day ahead and use the variables as inputs for PV models or simulations in order to forecast the PV production the next day.
The statistical models rely primary on historical load data in order to train their models. If the training of the model is finished, the achieved model is used to determine the PV production of the next day, in the hope that the weather tomorrow behaves in the same way as in the trainings data.
In the previous chapter it was explained which facts have to be considered to the forecasting models and a decision was made to focus the research in the direction of neural network and regression analysis.

But to the choise of a special method does not only depend on the property of being physical or statistical, it also depends on the information, data and tools available for the given case.

3.1 Neural networks

In this subsection a short introduction in neural networks is given [14]. Neural networks are inspired by the way a human brain handles information. The basis of the network are the neurons. A schematic representation can be found in the first part of Figure 3.1. Each neuron has a number of inputs with different weights. The weights present the priority of the input. Further each neuron has an internal function which calculates based on the values of the input and the weights an output. The simplest implementation is to use only an binary (0 - 1) values for the input and output. As internal function the weighted sum of the inputs is used and a threshold is used to determine the output. If the weighted sum is below the threshold it is a 0 otherwise the output becomes 1.

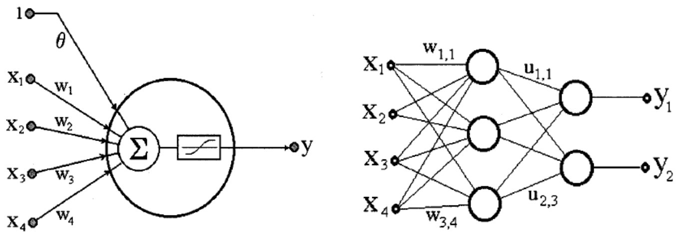


Fig. 1. An artificial neuron.

Fig. 2. A two-layer feed-forward neural network.

Figure 3.1: Short introduction to neural networks [14]

There are many ways to structure the neurons in the network. An example is shown in the right part of Figure 3.1. Often, the network is more or less a matrix. It can consist of x neurons in y layers. These layers are divided in one input layer, a number of hidden layer (at least one) and one output layer. In Figure 3.1 the given network consists of one input layer with four input neurons, a hidden layer with three hidden neurons and one output layer with two output neurons. All neurons of a layer are connected to all neurons of the next layer. The connections are also the places where the "learning" for a neural network takes place. As mentioned, each connection has a weight, that symbolises the influence of the neuron to the result value. In training phase, before the neural network is used for forecasting, a number of known inputs and outputs are provided to the network. In this on "learning" period the weights of the different connections are configured. In such a way, that the network represents the relationship of the trained samples as good as possible, meaning that it ”learns” this relationship. After the trainingsphase the network with the learned weights is ready to being used as forecast method.

3.1.1 Related Work

According to [20] it is possible to forecast PV power with only historical load data as input values. The research describes three different neural networks. The first two approaches are serial meaning that they forecast the PV power simultaneously for all periods of the next day. The third is a iterative one. That means it forecast the power output for time period t+1 (at time t) by using the last twenty output values (t-19, t-18 ... t). The result is then used in the next vector as input value (t-18, t-17 ...,t, t+1) for the next forecast. The methods is tested at the university of Queensland in Australia. The PV consist of 5000 panels on four different places. One of the research results is that the iterative method outperformed the other two. The structure of the iterative method is: twenty neurons in the input layer, one hidden layer (the number of neurons are not mentioned in the research) and one output neuron in the output layer. The network is trained with the 3000 data sets. The training algorithm is the Levenberg Marquardt algorithm. That is a special form of the least square algorithm. The Levenberg Marquardt algorithm is a more stable algorithm and it converges with a high probability even with poor starting conditions.
In [1] the PV power is forecasted by artificial neural networks. The PV plant is a 10 MW power plant in Dhahara, Saudi Arabia. They use only one type of PV panels, which are all directed in the same direction to maximise the power output. Their approach uses weather variables as input data and needs at least two days of historical data in order to train the neural network beforehand. The method tries to forecast the power output directly from the inputs. The two different neural networks are focused on Time Delay Neural Network(FTDNN) and a Distributed Time Delay Neural Network (DTDNN). These networks have time delays between the neurons in order to achieve a time-series input values for each neuron. The base is that every new time slot a new level (row with input-, hidden- and output neurons) is added to the neural network. The difference is that in FTDNN only the input data have time delays in order to get a time series inputs. The DTDNN has also time delays in the middle layer.
In the use case of [9] a radial basis function network is used to forecast a 18kW PV system at the Huazong Unsiverity in China. The PV system consists of sev-

eral 170 W panels. The approach forecast for 24 hours values ahead and uses weather and historical load data. Furthermore, the forecast method is a one layer approach, that means the weather and historical data are input values and the result is a PV production per hour. The system uses an online training, which means that there is a back propagation. Thus the accuracy level is increasing during the forecast cyles until a certain accuracy is achieved. There is a weather station on the area of the university. The weather values that are used in the forecast are: solar irradiation, air temperature, relative humidity, wind speed, wind direction, cloud coverage, sunshine duration and air pressure. These values are forecasted with the help of the meteorological service of Wuhan with a 90% accuracy. The neural network self consists of three layers: input layer, hidden layer and output layer. The network is fully connected. There is no function and no weights between the input and hidden layer and between the hidden and the output layer a function similar to the Gaussian density function is used.
Another method is successfully used in [11]. In the paper, a multilayer preceptron neural network is used to forecast a PV plant in La Rioja (Spain). It predicts solar power production in a hourly resolution using a three step method. The first and second steps are used to predict weather data; surface sensible heat flux, surface latent heat flux, surface downward shortwave radiation, surface downward long wave radiation, top outgoing shortwave radiation, top outgoing long wave radiation and temperature. These weather values plus historical load data are fed in a multilayer preceptron neural network with a back propagation in order to learn from the last forecast. No further information is provided over the structure of the neural network. They have a year (365 days) of recorded data. This period is divided in 217 days to trained the neural network and the rest (148 days) is used to verify the results of the forecast method.
In newer researches, like [3], simpler methods with only a small number of input values are studied. This research forecast a 24h power curve for a PV power plant in region of Puglia Italy. The power plant is built of identical PV panels, which are all pointing in the same direction with the same tilt and a lot of data is available: angle, tilt, shading, the model of the panels etc. But for the predictions they only use the solar irradiation, cell temperature and historical load data. Furthermore the solar irradiation is used to split the weather conditions in three different types: sunny, part cloudy and overcast. The database is also divided in three part. The best forecast method in [3]

is an adaptive feed-forward back-propagation network (AFFNN). Three different AFFNN are trained, one for each weather type. The structure of the AFFNN is as follows: the input layer has three neurons (irradiation, temperature, historical load data), the hidden layer has three vully connected neurons and the output layer has only one neuron (forecast power). The network is trained with a Bayesian Regularization algorithm and approximate 70% of the available data records.
In table 3.1 the properties of the presented methods are summarised.

author	**type of neural network**	**trainings algorithm**	**layout of NN (input-, hidden-, output- layer)**	**region**
[20]	ensemble neural networks	Levenberg Marquardt	i:20, h:?, o:20	Queensland, Australia
[1]	dynamic neural networks	Levenberg Marquardt	i: input values, h:10, o:1	Dhahara, Saudi Arabia
[9]	radial basis function network	online training	i:6, h:15, o:24	Huazong Unsiverity, China
[11]	adaptive neuro-fuzzy	back-propagation	i:11, h:?, o:?	La Rioja, Spain
[3]	autoregressive neural network	Levenberg Marquardt	i:3, h:3, o:1	Puglia, Italy

Table 3.1: Summary of related work

3.2 Regression analysis

In this subsection a short introduction on regression analyses is given. Regression analyses is a mathematical approach for investigation of functional relationships among variables. The relationship is given in a model that connects the response variable and a number of explanatory variables. Normally the response variable is called Y and the explanatory variables X_1, X_2 ... X_p, where p is the number of explanatory variables. Regression analysis includes the following steps:

- Select important predictor variables
- Choosen data collection
- Create a model/function
- Evaluate the model

In this research it is the relationship between predicted weather variables, for example the predicted solar irradiation or historical load data and the PV power production is of interest. For example the ratio between predicted irradiation and power production is point out in a diagram. Then a fitting regression line is calculated, that is a line across all data points with as least distance as possible. An example of such a regression is given in 3.2. For more information see [8].

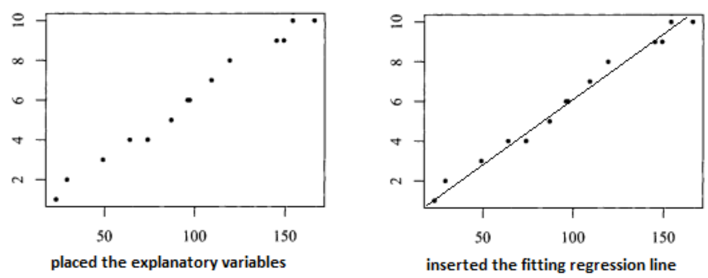


Figure 3.2: Example of regression analysis. [8]

3.2.1 Related Work

As described before, regression analysis is a widespread PV forecast method. Moreno-Munoz et al. [18] prove that the solar radiation can be predicted quit

well in his way. The used forecast method is an auto regression moving average model and the results shown a reliable solar irradiation forecast, which could be used as the start point to forecast PV production.
Kudo et al. [16] propose two methods. These methods are used to forecast the power production of a PV plant in Aichi, Japan. This plant consist of homogeneous PV panels, which are geared in the same tilt and angle to the sun but divided over different locations. The forecast resolution is one hour and they predict 24 hours ahead. The difference between the two methods is that one uses an indirect forecast model and the other a direct forecast model. The indirect model works in two steps. In the first step an irradiation index is calculated. For this purpose the historical irradiation data is divided by the extraterrestrial irradiation in order to get the irradiation index. This irradiation index is a point cloud over which a regression analysis is performed. This process is done for each time slot. In step two, the estimated solar irradiation curve is used as input variable in a PV simulation. In addition to the irradiation curve, the temperature is used to forecast the generated power from the I-V characteristics of the PV cells. In the direct model the power generation is forecasted using weather/power data. To calculate the power index, which is later used to calculate the power output of the PV panels, the actual power values are divided by the corresponding extraterrestrial irradiation. This power index and weather samples are the inputs for a regression analysis. The result of the regression analysis is a forecast equation for each time slot. Then the PV power generation is calculated with the help of the forecast equation and the corresponding irradiation and azimuth/tilt angel.
The direct method with the simplified PV calculation generates better error rates than the indirect method in this research. Furthermore in the direct method a learning effect is obtained due to online back loop in order to modify the forecast equations. Bacher et al. [4] describe a forecast method, which forecast 21 PV systems on rooftops in a village in Denmark. The forecast resolution is one hour, the method predicts 12- 36 hours ahead and the solar panels are not homogeneous. The presented method is also divided in two steps. In the first step the solar is normalized power with the help of a clear sky model with the purpose to have a more stationary time series. The sky model that is used in this method is divided in two components, a clear sky part and a cloud cover part. The cloud cover factor should presents the transmissivity of the clouds and is predicted by using a randomized ARIMA models. The second step is to forecast the generated power with a classical linear

time series methods. With the normalise time series of the solar power from step one the solar power for the next 12 to 36 hours is forecasted.
Hassanzadeh et al. [13] used a three step forecast method in order to forecast the PV generation of a real world solar power plant in Nevada (means that there are 510 identical 175W solar panels). The research are created for a hourly and sub hourly resolution. In the results, it can be clearly seen that the accuracy drops if the time intervals become shorter. The first step of the method is to predict the solar irradiation in a deterministic way. The resulting values are used as input values for a Gaussian noise signal. With the help of these values a flattening calculation is made in the second step. For the flattening calculation the authors try two different manners: a spectral analysis and an ARMA method. As is mentioned in their conclusion, the spectral analysis is better suited for shaping purposes because less processing power is needed and the accuracy is higher than the accuracy of ARMA. The last step is the conversion from solar irradiation to power generation. This is calculated by a Karlman filter. Their research neglects the temperature completely and uses more complicated filtering algorithms than the other methods. However, this only results in a "sufficient" accuracy which is the same or worse than the accuracy of the other methods proposed in this research.
In the work of Bracale et al. [7] the PV production of a 75Kw PV near Denver is forecast. There is no further description of the PV plant in the paper. The forecast method has three steps and a resolution of 15 minutes. The first step is to find a probability density function (pdf) of the predicted power production of the PV panels. This is done by supplying weather data and historical data to an Auto Regression time series model. This pdf value is then used as input for a Bayesian Inference in order to obtain a clearness index of the sky. Finally a Monta Carlo simulation is applied in order to get the PV generation power. This method is the first method that uses both important input values (forecast weather data and historical load data) for the PV power forecast. The advantage of using both input values is that the forecast accuracy seam to increase. The paper promise a forecast accuracy of 14.5% for winter season and 18.0% for the autumn season, which is the best accuracy of all methods considered in this research .
In table 3.2 the properties of the presented methods are summarised.

Author	Pv Power estimation	Input data	region
[16]	conversion from forecast PV index to power production	weather observation, historical PV data, weather forecast	Aichi, Japan
[4]	adaptive recursive least squares algorithm	forecast global irradiation, historical PV data	Jutland, Denmark
[13]	PV system model	solar irradiation, temperature	Nevada
[7]	PV system model	weather observation, forecast clearness index	Denver

Table 3.2: Summary of related work

3.3 Results

With the information of the chapter, it can said that all the methods are standard algorithms that were customised for specific PV systems. This means that they are very difficult to compare. What is certain is that all papers only consider one specific situation. The forecast methods are developed, fitted / trained for a special situation and then tested. No paper shows the situation after one year or later. So there are no long time experience and only one method [3] retains the neural network depending on the season. Further, it can be observed, that older methods that use weather data, mostly have chosen the temperature. However, for the PV panels the solar irradiation is the energy source. This choice may result from the fact that irradiation is much more difficult to forecast. One of the first papers that proposed a reliable irradiation forecast is [18].
All neural network investigated in this research were build in countries with stable intercontinental weather conditions. It seams that the location, where the PV plants were build up, was chosen because of the stable weather conditions. Furthermore it were mostly PV systems which were homogeneous and all panels were in the same location with the same adjustment. This is in contrary to the PV systems in the regression analyses papers. The regression algorithms are used for all kind of PV systems, whereby it is not important if the area has a stable intercontinental or an unstable coastal climate. In addition they also are used not only for PV power plants but also for distributed systems for example in [4].

CHAPTER 4

CONCLUSION

Based on the results of this study it can be said that none of the presented methods is suitable for the project of WESTNETZ. The methods seem to be all customised and specialised. For example [9] expects all PV panels in on ideal situation and all in the same adjustments (same tilled, facing the same direction, no shading effects, etc.).
As an outcome of this literature research the following recommendation can be given. The best of both methods should be combined in a new method suited for the situation of WESTNETZ. The basis method might be a regression analyses because the location of the PV system of WESTNETZ is in the north western part of Germany and has a more unstable coastal climate. Furthermore, the method should use solar irradiation, historical load data as main input variable and temperature, or season as additional inputs. The regression analysis could be improved by the use of a periodical fitting update. The advantage of periodical fitting update is that changes in the environment can be learned. This means that shading effects or impurities of the solar panels would have no effect on the accuracy.
In the second step, where a prediction for a whole week ahead has to be calculated, an iterative process could be considered. In such an iterative method the results of the forecast for the first day are taken as input for the second day, etc.. A further advantage is that the iterative way seam to outperforming the non iterative method in [20]. The faster way is also an advantage if the one day ahead forecast method (from step one) is be used a number of times to forecast a longer period and which effects it has on the accuracy.

Bibliography

[1] Al-Messabi, Li, El-Amin, and Goh. Forecasting of photovoltaic power yield using dynamic neural networks. *The 2012 International Joint Conference on Neural Networks (IJCNN)*, 2012.

[2] Alfares and Nazeeruddin. Electric load forecasting: Literature survey and classification of methods. *International Journal of Systems Science*, 2002.

[3] Almonacid, Pérez-Higueras, Fernández, and Hontoria. A methodology based on dynamic artificial neural network for short-term forecasting of the power output of a pv generator. *Energy Conversion and Management*, 2014.

[4] Bacher, Madsen, and Nielsen. Online short-term solar power forecasting. *Elsevier: Solar Energy*, 2009.

[5] Bakker. *TRIANA: a control strategy for Smart Grids: forecasting, planning and real-time control.* PhD Thesis: University of Twente, 2012.

[6] Beyer, Polo, Suri, Torres, and et al. Report on benchmarking of radiation products. *http://www.mesor.net/deliverables.html*, 2016-01-18.

[7] Bracale, Caramia, Carpinelli, Fazio, and Ferruzzi. A bayesian method for short-term probabilistic forecasting of photovoltaic generation in smart grid operation and control. *Multidisciplinary Digital Publishing Institute: Energies*, 2013.

[8] Chatterjee and Hadi. *Regression Analysis by Example.* Wiley, ISBN 0470905840. 2012.

[9] Chen, Duan, Cai, and Liu. Online 24-h solar power forecasting based on weather type classification using artificial neural network. *Elsevier: Solar Energy*, 2011.

[10] Feinberg and Genethliou. Load forecasting. ISBN 0960-1481. 2005.

[11] Fernandez-Jimenez, Muñoz-Jimenez, Falces, Mendoza-Villena, Garcia-Garrido, Lara-Santillan, Zorzano-Alba, and Zorzano-Santamaria. Short-term power forecasting system for photovoltaic plants. *Renewable Energy*, ISBN 0960-1481. 2012.

[12] Hahn, Meyer-Nieberg, and Pickl. Electric load forecasting methods: Tools for decision making. *Elsevier: European Journal of Operational Research*, 2009.

[13] Hassanzadeh, Etezadi-Amoli, and Fadali. Practical approach for sub-hourly and hourly prediction of PV power output. 2010.

[14] Hippert, Steinherz, Pedreira, Eduardo, Souza, and Castro. Neural networks for short-term load forecasting: A review and evaluation. *IEEE: Power Systems, IEEE Transactions on*, 2001.

[15] Hong and Tao. Short term electric load forecasting. *ProQuest Dissertations and Theses*, ISBN 9781124477725. 2010.

[16] Kudo, Takeuchi, Nozaki, and Sumita Endo. Forecasting electric power generation in a photovoltaic power system for an energy network. *Wiley Online Library: Electrical Engineering in Japan*, 2009.

[17] Lorenz, Hurka, Heinemann, and Beyer. Irradiance forecasting for the power prediction of grid-connected photovoltaic systems. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, ISBN 1939-1404. 2009.

[18] Moreno-Munoz, Rosa, Posadillo, and Pallares. Short term forecasting of solar radiation. *IEEE: International Symposium on Industrial Electronics*, 2008.

[19] Pelland, Remund, Kleissl, Oozeki, and De Brabandere. Photovoltaic and solar forecasting: state of the art. *IEA PVPS*, 2013.

[20] Rana, Koprinska, and Agelidis. Forecasting solar power generated by grid connected pv systems using ensembles of neural networks. 2015.

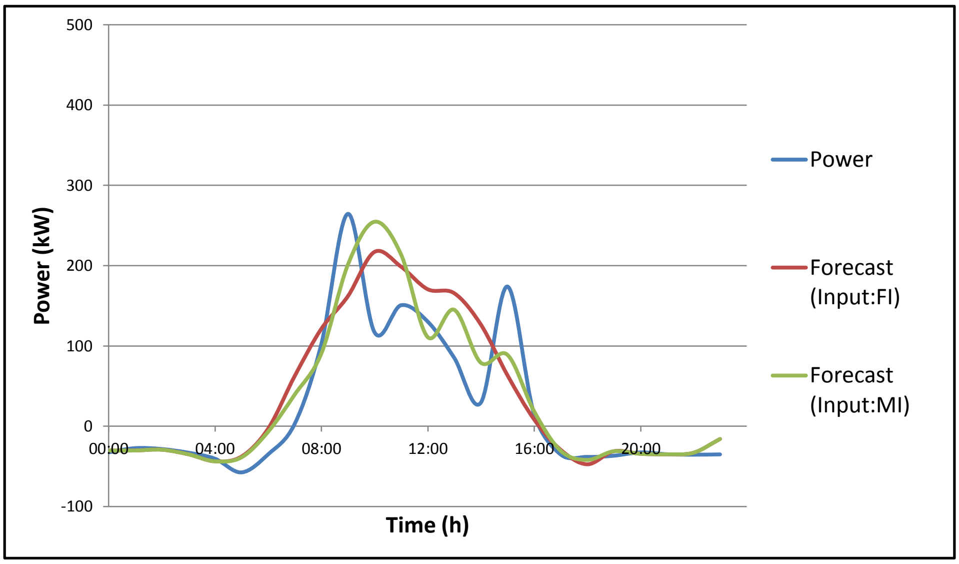
Appendix B

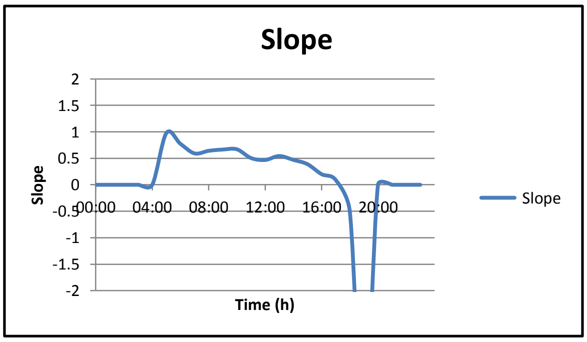
Literature Research

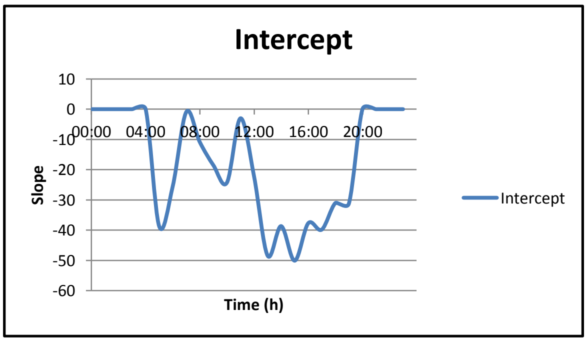
B.1 Regression forecast series per month

08-04-2016

Time (hour)	Power	Forecast (Input:FI)	Forecast (Input:MI)	Slope	Intercept	Error (F)	Error (R)
00:00	-32.589903	-30.33569432	-30.33569432	0	0	-2.25420868	-2.25420868
01:00	-27.319903	-30.23680565	-30.23680565	0	0	2.91690265	2.91690265
02:00	-28.4765703	-29.28323629	-29.28323629	0	0	0.80666604	0.80666604
03:00	-33.0321278	-34.99335976	-34.99335976	0	0	1.96123201	1.96123201
04:00	-40.5010138	-43.73206369	-43.73206369	0	0	3.23104994	3.23104994
05:00	-57.519906	-37.77838668	-38.75444999	0.97606331	-38.75445	-19.7415193	-18.765456
06:00	-35.0343485	-3.030731304	-6.898981764	0.77365009	-25.466584	-32.0036172	-28.1353667
07:00	2.95120125	62.55685322	39.42953607	0.59300813	-0.89501691	-59.605652	-36.4783348
08:00	102.281215	121.2685505	90.46700002	0.64169897	-10.9214369	-18.9873355	11.814215
09:00	264.46288	161.8590424	201.1391136	0.66576392	-18.5629794	102.603837	63.3237659
10:00	117.033996	217.0564705	254.5954011	0.67033805	-24.2652267	-100.022475	-137.561406
11:00	150.668987	198.6689263	213.8327707	0.50546148	-3.01020505	-47.9999398	-63.1637842
12:00	130.347874	170.6116786	111.0305052	0.4691431	-22.2061346	-40.2638048	19.3173686
13:00	85.1300973	165.6276331	144.9820142	0.54330576	-48.4348364	-80.4975359	-59.851917
14:00	29.2623208	126.6897675	79.10775523	0.47110903	-38.6695029	-97.4274468	-49.8454345
15:00	173.957863	63.61603055	88.92793675	0.38941394	-50.0928404	110.341832	85.0299262
16:00	15.5945375	8.697822254	18.94319684	0.2008897	-37.707698	6.89671525	-3.34865934
17:00	-35.1043493	-29.27719976	-30.46812232	0.09160943	-39.812284	-5.82714949	-4.63622693
18:00	-38.2465668	-47.44329561	-41.973172	-0.49728396	-31.0329248	9.19672886	3.72660525
19:00	-36.7776813	-31.21903618	-31.21903618	-4.67197957	-31.2190362	-5.55864507	-5.55864507
20:00	-32.6276798	-34.34379236	-34.34379236	0	0	1.71611261	1.71611261
21:00	-34.9476807	-35.00132275	-35.00132275	0	0	0.053642	0.053642
22:00	-35.4899023	-33.08484117	-33.08484117	0	0	-2.40506108	-2.40506108
23:00	-35.1287905	-15.93890226	-15.93890226	0	0	-19.1898882	-19.1898882
					Average:	-12.1691483	-9.88737092
					RMS:	49.3855212	42.6662251

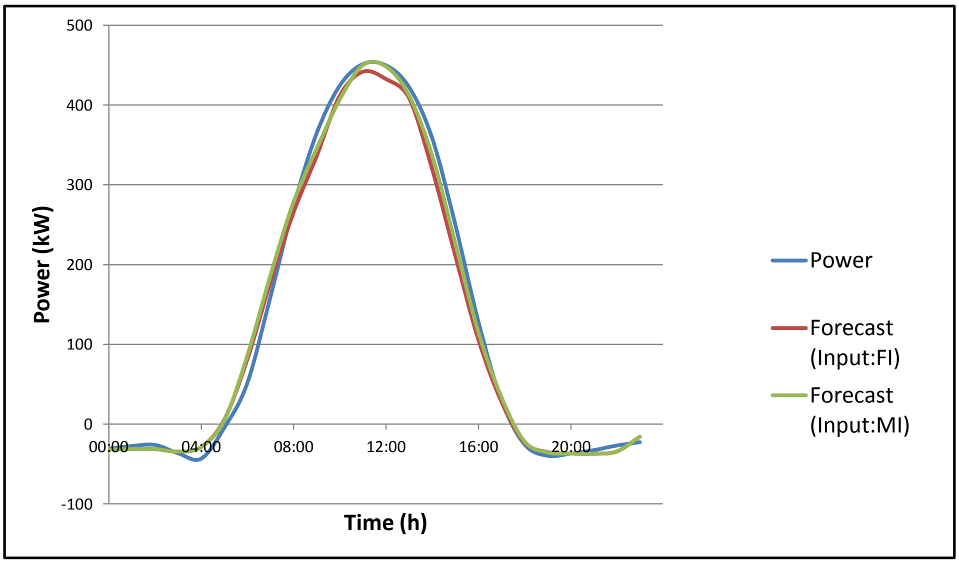


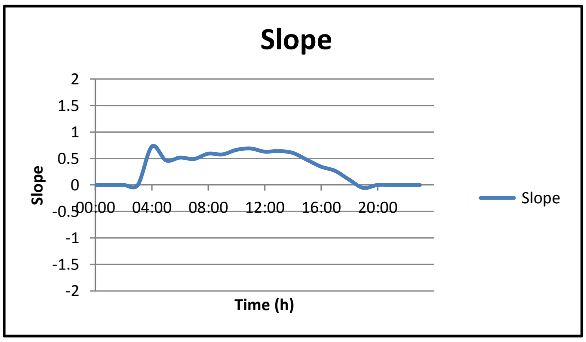


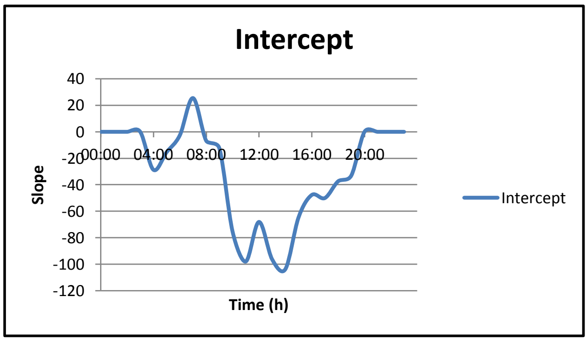


08-05-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-30.8143472	-32.03816342	-32.03816342	0	0	1.22381617	1.22381617
01:00	-27.4365692	-31.20131131	-31.20131131	0	0	3.76474206	3.76474206
02:00	-26.0576807	-31.23649663	-31.23649663	0	0	5.17881588	5.17881588
03:00	-36.472126	-34.35717618	-34.35717618	0	0	-2.11494982	-2.11494982
04:00	-43.302126	-28.6981632	-28.6981632	0.72694794	-28.6981632	-14.6039628	-14.6039628
05:00	-4.58656925	5.40840188	4.482390511	0.46300568	-15.4268539	-9.99497113	-9.06895976
06:00	51.3712098	81.1327475	85.78753035	0.51719809	-2.65334372	-29.7615378	-34.4163206
07:00	159.473435	177.9286519	186.2879502	0.49172343	25.4943879	-18.4552174	-26.8145157
08:00	272.776756	265.2604267	278.2687958	0.59128951	-6.7327461	7.51632929	-5.49203985
09:00	364.333733	335.7366054	344.9610714	0.57652912	-12.4869859	28.5971276	19.3726616
10:00	424.195667	411.3233168	406.681584	0.66310469	-75.3955233	12.8723504	17.5140833
11:00	451.2251	441.776736	450.0390812	0.68852877	-98.0298174	9.44836347	1.18601826
12:00	449.802877	432.6375794	448.3646789	0.62908398	-68.1132711	17.1652979	1.4381983
13:00	422.740938	408.9586907	412.1614415	0.64055016	-96.4353861	13.7822473	10.5794965
14:00	358.980116	320.052238	336.984083	0.60470875	-103.848594	38.9278777	21.9960328
15:00	250.99343	211.8733719	227.5304137	0.47445581	-64.734367	39.1200581	23.4630163
16:00	129.23206	106.6767908	116.0047747	0.34548088	-47.7531638	22.5552687	13.2272848
17:00	30.323151	28.54780283	34.12414869	0.26554028	-50.0521198	1.77534817	-3.80099769
18:00	-25.1768475	-22.63780149	-21.56116515	0.09787603	-37.4170821	-2.53904601	-3.61568235
19:00	-39.601014	-34.97520383	-35.48131275	-0.05623432	-33.0632368	-4.62581017	-4.11970125
20:00	-36.967679	-36.86100347	-36.86100347	0	0	-0.10667553	-0.10667553
21:00	-32.622125	-37.12767022	-37.12767022	0	0	4.50554522	4.50554522
22:00	-26.8343467	-34.26427497	-34.26427497	0	0	7.42992822	7.42992822
23:00	-22.6510125	-15.72889674	-15.72889674	0	0	-6.92211576	-6.92211576
					Average:	5.19745124	0.82515492
					RMS:	16.967208	13.6180286

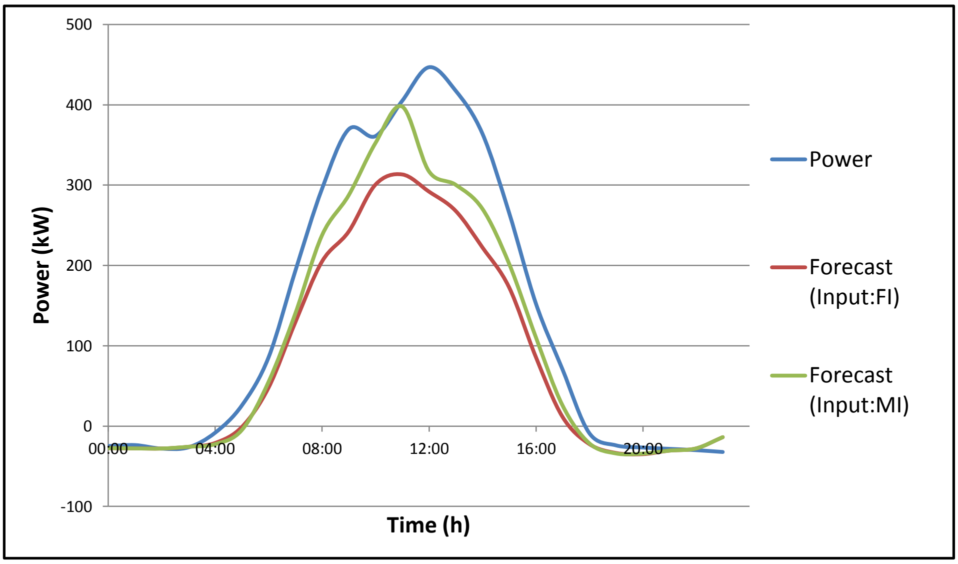


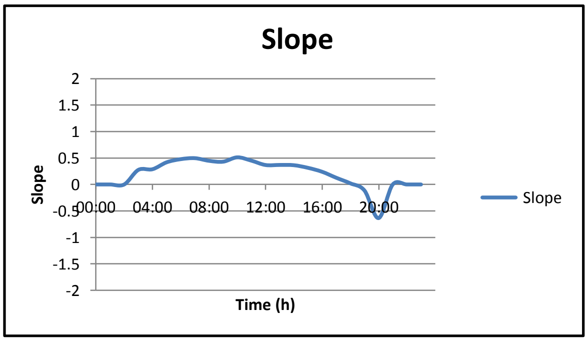


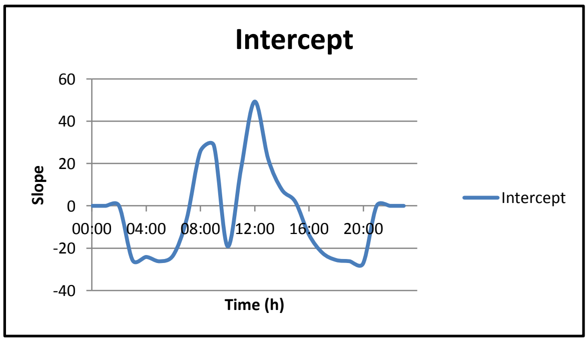


08-06-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-24.7765688	-27.33502606	-27.33502606	0	0	2.55845731	2.55845731
01:00	-23.5810135	-27.70823636	-27.70823636	0	0	4.12722286	4.12722286
02:00	-27.969903	-27.85731029	-27.85731029	0	0	-0.11259271	-0.11259271
03:00	-26.3732345	-25.698726	-25.698726	0.2751905	-25.698726	-0.6745085	-0.6745085
04:00	-8.2254625	-20.98244992	-22.42118983	0.28774798	-24.1476777	12.7569874	14.1957273
05:00	25.7289843	-1.095312255	-4.859464872	0.41823918	-26.189663	26.8242965	30.5884491
06:00	85.5612115	47.88106956	55.04899355	0.4778616	-23.3203088	37.6801419	30.5122179
07:00	192.991215	129.1045815	140.0301595	0.49661718	-5.97529227	63.8866332	52.9610552
08:00	295.295654	204.89344	237.4976361	0.44663282	25.7936781	90.4022142	57.7980182
09:00	369.529843	242.2287355	287.4029971	0.43023106	28.4038972	127.301107	82.1268454
10:00	361.005639	300.5594803	352.2987615	0.51227011	-19.0970694	60.446159	8.70687771
11:00	404.808991	313.3383775	397.8544208	0.44955342	17.5322261	91.4706135	6.95457019
12:00	446.7629	292.058315	317.4043958	0.3673345	49.2502076	154.704585	129.358504
13:00	417.708971	268.0802744	300.5227891	0.36866494	22.1807593	149.628697	117.186182
14:00	364.510954	222.734424	270.7578309	0.36381369	7.72053386	141.77653	93.7531229
15:00	266.096774	173.0523722	202.5695294	0.31401231	1.91566312	93.0444013	63.5272441
16:00	153.267321	86.48679516	111.1843083	0.23978168	-13.5021658	66.7805253	42.0830122
17:00	70.8903855	11.70685167	26.01051636	0.1265811	-22.2168841	59.1835338	44.8798691
18:00	-8.4032435	-22.14250316	-21.16334157	0.02128612	-25.5695687	13.7392597	12.7600981
19:00	-23.8665683	-33.3975275	-33.97168184	-0.11483087	-26.1631828	9.53095925	10.1051136
20:00	-26.574347	-34.86808685	-34.2323413	-0.63574554	-27.2391403	8.29373985	7.6579943
21:00	-28.2554582	-30.47687814	-30.47687814	0	0	2.22141989	2.22141989
22:00	-29.8754588	-27.75595221	-27.75595221	0	0	-2.11950654	-2.11950654
23:00	-32.1532375	-13.70840824	-13.70840824	0	0	-18.4448293	-18.4448293
					Average:	7.05633889	5.74713901
					RMS:	72.6139422	51.1764414

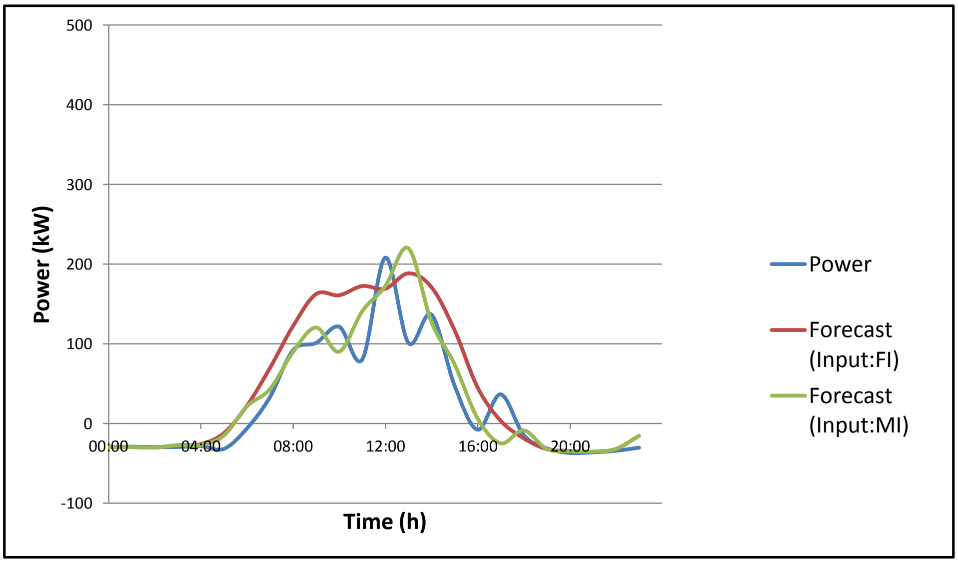


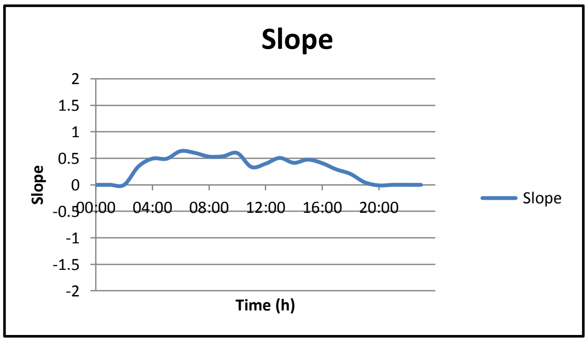


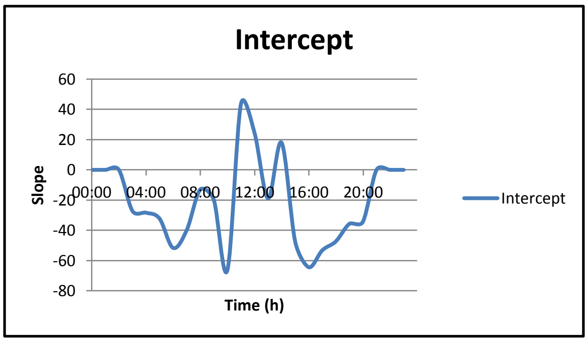


08-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-29.3976813	-29.52748444	-29.52748444	0	0	0.12980319	0.12980319
01:00	-29.0899022	-29.5905091	-29.5905091	0	0	0.50060685	0.50060685
02:00	-29.591014	-30.11742271	-30.11742271	0	0	0.52640871	0.52640871
03:00	-29.4621253	-27.18222092	-27.18222092	0.34416627	-27.1822209	-2.27990433	-2.27990433
04:00	-28.4310137	-25.85152712	-26.84097436	0.49472362	-28.3251452	-2.57948663	-1.59003939
05:00	-31.765459	-12.07701752	-15.03147153	0.492409	-32.2657866	-19.6884415	-16.7339875
06:00	-6.22101625	22.20943594	21.57288721	0.63654873	-51.6302168	-28.4304522	-27.7939035
07:00	33.248989	69.76108622	43.25927206	0.60231396	-39.8600542	-36.5120972	-10.0102831
08:00	91.9600958	122.2909488	89.81497232	0.53239306	-12.9368878	-30.3308531	2.14512343
09:00	101.103436	162.4203637	120.3585474	0.53925406	-19.8475071	-61.3169275	-19.2551111
10:00	121.406765	160.8923348	90.1452908	0.59955122	-66.3375776	-39.48557	31.2614739
11:00	80.3523243	172.4550051	140.886923	0.33583066	43.4960313	-92.1026809	-60.5345987
12:00	207.974277	169.0886968	172.2742281	0.39819141	24.5452167	38.8855807	35.7000494
13:00	101.151208	188.3796365	219.802421	0.5068191	-18.9093768	-87.228429	-118.651213
14:00	136.60233	171.0317779	127.4742948	0.41483317	17.9583373	-34.4294484	9.12803471
15:00	47.8234318	117.2459066	74.41914666	0.47585289	-47.3991927	-69.4224748	-26.5957149
16:00	-7.7410215	45.29743571	6.413612592	0.4093034	-64.3958758	-53.0384572	-14.1546341
17:00	36.6089832	3.481355611	-24.85107344	0.2920869	-53.1835025	33.1276276	61.4600567
18:00	-14.5199043	-18.55255951	-8.626882757	0.20678493	-47.2956651	4.03265526	-5.89302149
19:00	-31.1087933	-32.16236341	-32.06323801	0.0495627	-35.6813151	1.05357016	0.95444476
20:00	-36.9187958	-34.38619347	-34.46153393	-0.01076292	-34.2247496	-2.53260228	-2.45726182
21:00	-36.171015	-35.29538585	-35.29538585	0	0	-0.87562915	-0.87562915
22:00	-34.1898992	-31.89094156	-31.89094156	0	0	-2.29895769	-2.29895769
23:00	-30.2710118	-15.49753878	-15.49753878	0	0	-14.773473	-14.773473
					Average:	-20.794568	-7.58715548
					RMS:	39.0232627	33.2697408



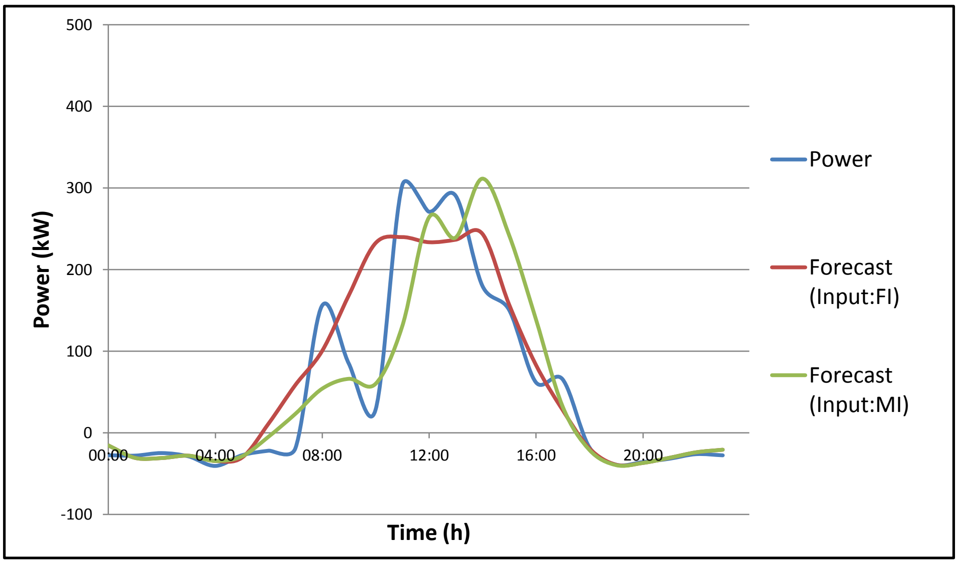


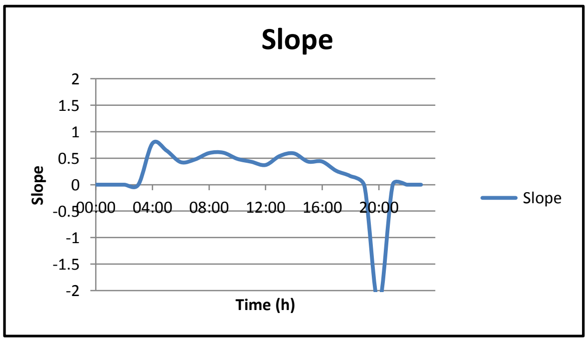


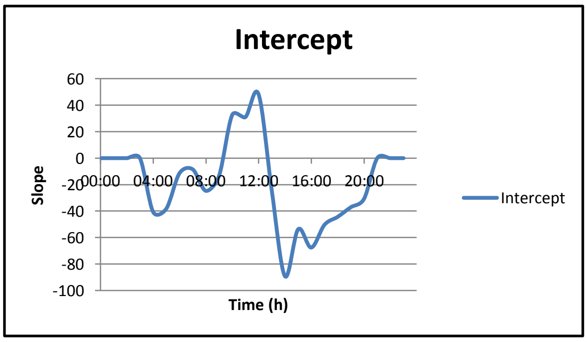
+

08-08-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-27.5610143	-15.55926681	-15.55926681	0	0	3.27048256	3.27048256
01:00	-28.0187903	-30.83149681	-30.83149681	0	0	2.98690435	2.98690435
02:00	-24.905459	-31.0056946	-31.0056946	0	0	3.21338358	3.21338358
03:00	-28.9532353	-28.11884258	-28.11884258	0	0	5.62394044	5.62394044
04:00	-40.6721247	-34.57717569	-34.57717569	0.7809771	-40.6760578	0.00393302	0.00393302
05:00	-27.5732373	-30.52163189	-28.96140132	0.64320174	-38.2017966	2.2669367	0.98053322
06:00	-21.996574	11.32473749	-4.755306043	0.4259417	-11.3840617	-43.4100233	-32.7614808
07:00	-19.1387925	58.47037734	23.11721612	0.4757839	-8.43367028	-88.7336825	-49.2436184
08:00	155.652329	100.0450599	53.89402115	0.5971561	-24.6936576	44.1943948	102.118537
09:00	84.828991	168.2599166	66.07407014	0.60500477	-13.3824889	-100.230086	6.25075439
10:00	27.8278725	232.2324776	59.82308865	0.48825099	32.6747372	-209.912279	-63.925234
11:00	302.932041	239.6931553	130.3249344	0.43253485	31.0045118	88.5327541	185.42056
12:00	270.741764	233.4308199	263.7082591	0.37197773	48.2821416	48.3740433	22.3356021
13:00	290.390665	236.5028742	239.1067184	0.54136532	-24.3515313	40.8113461	37.0217889
14:00	180.121483	243.8352113	311.294965	0.59189734	-89.209163	-17.1476683	-97.645707
15:00	150.60648	157.2894956	242.2533494	0.43655126	-53.7512656	20.5696667	-40.110958
16:00	61.9878735	83.53351867	139.6409412	0.43739078	-67.5557989	-8.67181276	-64.2204413
17:00	65.6534308	28.23278099	32.60668875	0.26197753	-50.374515	58.6548667	56.0350914
18:00	-17.4687932	-18.89442244	-20.77105409	0.16196664	-44.3604615	8.2655044	8.58943769
19:00	-39.0832378	-39.17752896	-39.66342889	-0.02897696	-37.0745583	-1.08141677	-1.16834765
20:00	-35.967682	-37.07455826	-37.07455826	-2.25915178	-30.7624937	-5.2051883	-5.2051883
21:00	-31.8732375	-30.7624937	-30.7624937	0	0	-7.86204914	-7.86204914
22:00	-26.2654585	-24.01118836	-24.01118836	0	0	-5.46507251	-5.46507251
23:00	-27.6732368	-20.80038599	-20.80038599	0	0	-15.5398339	-15.5398339
					Average:	-44.1227388	12.6757542
					RMS:	55.3488648	57.4849347



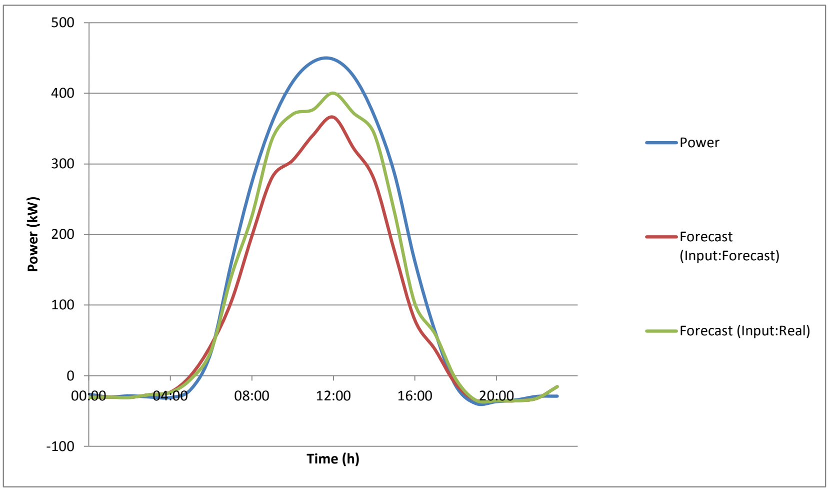




B.2 Regression forecast series per week

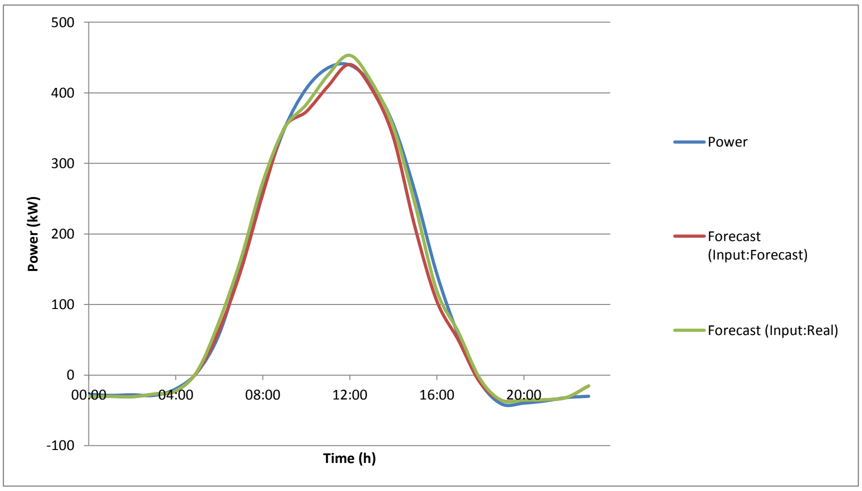
18-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-26.269903	-30.65983039	-30.65983039	0	0	4.38992739	4.38992739
01:00	-30.007681	-30.26513878	-30.26513878	0	0	0.25745778	0.25745778
02:00	-28.42768	-30.7377314	-30.7377314	0	0	2.3100514	2.3100514
03:00	-30.118792	-26.67947775	-26.67947775	0.35479776	-26.6794778	-3.43931425	-3.43931425
04:00	-30.8699035	-23.18388653	-23.60504929	0.42116276	-24.0262121	-7.68601697	-7.26485421
05:00	-19.4987923	0.351409239	-5.00395256	0.44628015	-18.3923571	-19.8502015	-14.4948397
06:00	33.575653	43.56629133	35.39897903	0.58337945	-35.1899344	-9.99063833	-1.82332603
07:00	160.400099	105.5129353	141.0921955	0.52322442	-18.4912511	54.8871637	19.3079035
08:00	273.421204	197.3735582	225.5253077	0.55199509	-6.31262964	76.0476456	47.895896
09:00	359.07897	280.9765192	335.0495654	0.45824615	63.309596	78.1024505	24.0294043
10:00	415.73593	304.8220573	370.1103834	0.38862099	88.3601666	110.913873	45.6255466
11:00	444.529295	340.5045343	376.6500473	0.44079894	48.2548375	104.024761	67.8792477
12:00	448.24317	366.162141	400.245906	0.49396761	16.4330739	82.0810285	47.9972635
13:00	424.066216	322.0425434	371.8383816	0.50298826	-7.41477015	102.023672	52.2278339
14:00	369.085959	278.3022957	343.4475754	0.54287733	-60.4531588	90.7836631	25.6383834
15:00	286.778175	176.9789411	232.1634646	0.46373549	-70.6558112	109.799234	54.6147102
16:00	162.787057	79.37665396	102.7872004	0.23647017	-21.596107	83.4104035	59.9998571
17:00	62.5487005	37.12346149	59.07716926	0.28145779	-47.3138761	25.425239	3.47153124
18:00	-13.301012	-11.0245196	-3.806690857	0.18507253	-44.3375753	-2.2764924	-9.49432114
19:00	-39.2921245	-34.69471649	-34.62893962	0.00411105	-35.0071566	-4.59740801	-4.66318488
20:00	-36.6943483	-35.42211898	-35.5265153	-0.10439632	-34.0649669	-1.27222927	-1.16783295
21:00	-34.1487913	-35.39791658	-35.39791658	0	0	1.24912533	1.24912533
22:00	-29.2532358	-31.93526196	-31.93526196	0	0	2.68202621	2.68202621
23:00	-28.90768	-15.44235311	-15.44235311	0	0	-13.4653269	-13.4653269
					Average:	36.0754206	16.8234652
					RMS:	59.1163088	30.8377099



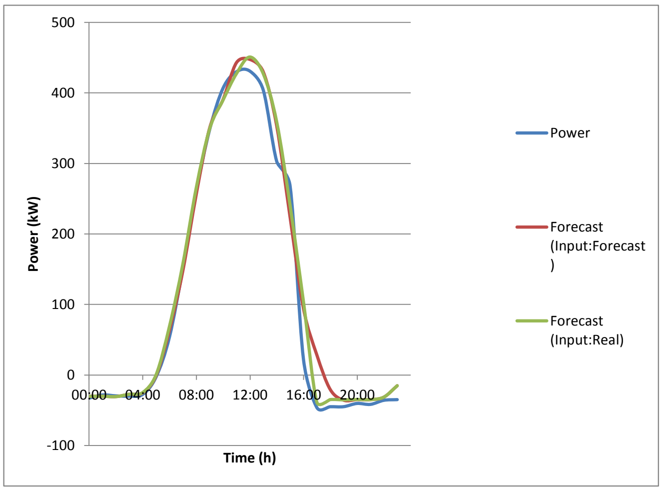
19-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-27.1865688	-30.53705264	-30.53705264	0	0	3.35048389	3.35048389
01:00	-28.8021245	-30.25149682	-30.25149682	0	0	1.44937232	1.44937232
02:00	-27.9410143	-30.70958322	-30.70958322	0	0	2.76856897	2.76856897
03:00	-28.7887928	-26.91143147	-26.91143147	0.41112559	-26.9114315	-1.87736128	-1.87736128
04:00	-19.6032355	-22.64732448	-22.20111882	0.44620566	-23.9859415	3.04408898	2.59788332
05:00	4.6012075	5.01247164	6.231501152	0.60951476	-30.3393842	-0.41126414	-1.63029365
06:00	58.3012115	63.93532445	76.36938601	0.56518462	-28.189768	-5.63411295	-18.0681745
07:00	155.095657	148.5409821	164.8205079	0.54265086	-19.6807847	6.55467488	-9.72485094
08:00	260.238987	255.8481816	273.0011212	0.55332063	-0.33927153	4.39080544	-12.7621342
09:00	348.867863	350.230865	349.8479244	0.38294054	109.744207	-1.36300221	-0.98006168
10:00	405.726508	373.0648755	383.3077287	0.33041462	136.818423	32.6616327	22.4187795
11:00	435.265931	409.1784723	424.9865934	0.46494474	45.1267421	26.0874585	10.2793374
12:00	439.492617	440.2388273	453.2008576	0.49853963	24.9553192	-0.74621057	-13.7082408
13:00	412.52398	406.282067	416.0034594	0.51165223	-3.55137036	6.24191299	-3.47947941
14:00	356.195115	338.288169	352.4450475	0.56627514	-72.2613069	17.9069463	3.7500678
15:00	260.661501	210.750586	243.1331452	0.48332178	-75.3759078	49.9109148	17.5283555
16:00	145.06509	106.0082488	120.5302719	0.30897921	-40.7568777	39.0568412	24.5348181
17:00	57.0131567	49.86591204	61.33988329	0.31872142	-57.8619291	7.14724471	-4.32672654
18:00	-9.71101525	-10.4929501	-5.18335267	0.17698658	-44.2973871	0.78193485	-4.52766258
19:00	-41.1087905	-35.94302017	-36.05782335	-0.01640046	-34.5981828	-5.16577033	-5.05096715
20:00	-39.8321248	-35.55385867	-35.55385867	-0.1178098	-33.9045215	-4.27826608	-4.27826608
21:00	-36.6499052	-35.01131174	-35.01131174	0	0	-1.63859351	-1.63859351
22:00	-31.82879	-31.58526222	-31.58526222	0	0	-0.24352778	-0.24352778
23:00	-30.0732373	-15.36661246	-15.36661246	0	0	-14.7066248	-14.7066248
					Average:	6.88700612	-0.34688742
					RMS:	16.5448366	10.5127004



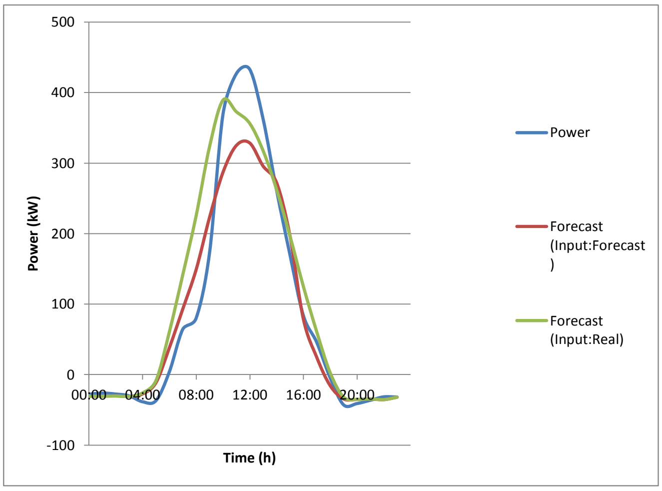
20-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-32.8099003	-30.30328701	-30.30328701	0	0	-2.50661324	-2.50661324
01:00	-28.3399033	-30.19649682	-30.19649682	0	0	1.85659357	1.85659357
02:00	-29.6854588	-30.69217593	-30.69217593	0	0	1.00671718	1.00671718
03:00	-30.0943478	-27.35902838	-27.35902838	0.42507493	-27.3590284	-2.73531937	-2.73531937
04:00	-27.5365685	-25.2994471	-24.86404468	0.43540242	-26.170252	-2.2371214	-2.67252382
05:00	-2.61879475	-0.799183053	0.395983592	0.59758332	-33.6662658	-1.8196117	-3.01477834
06:00	54.1700992	63.84145268	69.28269122	0.54412385	-28.1154786	-9.67135343	-15.112592
07:00	151.760098	148.2257621	157.8519569	0.5347886	-21.3022243	3.53433538	-6.09185943
08:00	260.686764	256.5139906	265.8397348	0.54857319	-2.96112671	4.1727731	-5.15297107
09:00	348.291217	350.4883163	349.3118536	0.39215426	104.607598	-2.1970996	-1.02063683
10:00	406.908979	390.7594219	390.0430877	0.35816711	124.641262	16.1495573	16.8658915
11:00	430.145108	443.0237492	427.4871624	0.47080566	43.78055	-12.8786409	2.65794585
12:00	430.936781	447.5221536	450.9669711	0.49211678	28.7307776	-16.5853729	-20.0301903
13:00	403.988158	429.8394177	427.2483015	0.51822322	1.78703689	-25.8512594	-23.2601433
14:00	303.092051	353.5980408	359.1606441	0.55626033	-57.4783421	-50.5059901	-56.0685934
15:00	268.320364	224.0024712	240.6801546	0.4905201	-78.6484295	44.317893	27.6402097
16:00	22.2503717	94.44761759	103.893317	0.32571377	-46.2607319	-72.1972458	-81.6429452
17:00	-46.2737935	28.38572542	-38.63491703	0.30743414	-56.158663	-74.6595189	-7.63887647
18:00	-45.044346	-20.64638032	-34.9238962	0.16997043	-43.592388	-24.3979657	-10.1204498
19:00	-44.9887915	-35.80963874	-35.26770165	-0.02167748	-34.4439573	-9.17915276	-9.72108985
20:00	-40.4065713	-34.96194897	-34.82143983	-0.14050914	-33.8378759	-5.44462228	-5.58513142
21:00	-41.724346	-34.95631178	-34.95631178	0	0	-6.76803422	-6.76803422
22:00	-35.9521235	-31.48211404	-31.48211404	0	0	-4.47000946	-4.47000946
23:00	-34.9899065	-15.26605699	-15.26605699	0	0	-19.7238495	-19.7238495
					Average:	-11.366288	-9.72121872
					RMS:	27.3786966	23.1623294



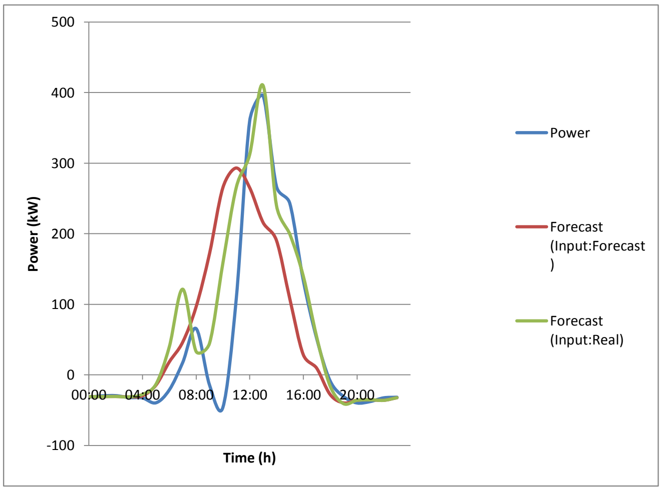
21-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-27.798791	-30.54649674	-30.54649674	0	0	4.13418746	-1.48896401
01:00	-26.171012	-30.54649674	-30.54649674	0	0	5.76196646	-1.86673951
02:00	-27.5799023	-30.27618826	-30.27618826	0	0	4.31449611	-2.63593549
03:00	-30.1243473	-30.80859579	-30.80859579	0	0	2.34887803	-3.72797221
04:00	-38.5010147	-27.3407947	-25.94788376	2.14206669	-31.7466125	-6.75440227	-3.73757674
05:00	-36.9465695	-11.39432225	-8.477121003	0.55128412	-32.5700904	-22.5688549	4.79165875
06:00	4.0167545	38.07387612	60.53444037	0.55151704	-36.7609279	-17.1316064	-8.77433712
07:00	64.2900973	92.95158115	141.4761283	0.53686925	-38.7477692	-11.8521526	0.26063469
08:00	80.0612108	148.8965732	225.3078116	0.57596763	-40.4642025	-84.5190639	17.4345132
09:00	172.796766	222.9503149	323.2783339	0.5855927	-24.8980735	-91.0023593	-23.4485186
10:00	368.71066	286.6928212	389.1812091	0.58295512	-20.9717805	59.1468865	-80.3494619
11:00	426.77705	324.9424047	372.8337699	0.56058578	-34.3493215	101.790885	-101.964774
12:00	432.966214	328.5315587	356.3279476	0.57399527	-52.2531177	115.566377	-29.7740556
13:00	362.480109	295.7004682	317.5247889	0.45556119	47.3131513	49.1192244	-5.66024364
14:00	262.012049	272.596504	262.8006321	0.42900294	55.73986	-12.5193094	13.9847267
15:00	170.441198	197.4966488	196.9645875	0.50951476	-35.801258	-8.2632582	-173.348934
16:00	84.0139895	79.20763739	125.4392322	0.55565163	-108.363424	7.90107274	35.4153113
17:00	45.9034308	24.72260146	60.93212536	0.33322613	-47.6884478	14.9505116	-26.7686974
18:00	-4.239906	-15.45585773	2.91761835	0.27940786	-46.389768	7.22387915	-18.1386339
19:00	-42.763236	-34.38091132	-31.75433907	0.16653162	-42.5772557	-8.84562433	-14.4722302
20:00	-41.1154575	-35.25065509	-35.27815491	-0.02047175	-36.0828554	-4.93024333	-6.82508309
21:00	-36.4043475	-34.51638976	-34.51638976	-0.04624056	-36.2228458	-0.18150167	-6.24240299
22:00	-31.5732377	-35.48884251	-35.48884251	0	0	5.53196306	3.45338551
23:00	-31.826569	-32.10217597	-32.10217597	0	0	1.81776728	0.68005072
					Average:	4.62665493	-18.0501783
					RMS:	42.8541514	53.2253681



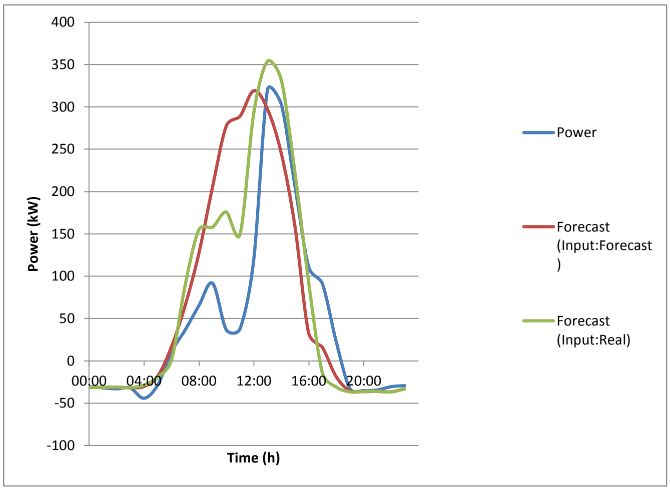
22-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-31.6287913	-30.90575617	-30.90575617	0	0	-0.72303508	-0.72303508
01:00	-29.7976823	-30.90575617	-30.90575617	0	0	1.10807392	1.10807392
02:00	-29.5087925	-30.65476846	-30.65476846	0	0	1.14597596	1.14597596
03:00	-32.1976803	-31.30594126	-31.30594126	0	0	-0.89173899	-0.89173899
04:00	-32.837679	-29.65413392	-27.71669465	1.93743927	-29.6541339	-3.18354508	-5.12098435
05:00	-39.6532355	-14.74020353	-13.46283228	0.42579042	-25.8107543	-24.913032	-26.1904032
06:00	-21.3899025	18.27747766	39.62994664	0.57709376	-33.0838666	-39.6673802	-61.0198491
07:00	17.3934283	46.31994375	121.3704797	0.5559299	-31.5102416	-28.9265155	-103.977051
08:00	65.5900973	96.23681228	33.15099042	0.52571518	-18.3690974	-30.646715	32.4391068
09:00	-14.2710138	171.4990712	44.49215679	0.51419803	12.6118787	-185.770085	-58.7631705
10:00	-46.2699023	265.2058882	158.1972396	0.34297644	129.387219	-311.47579	-204.467142
11:00	107.962413	293.1391485	265.5514719	0.32078694	146.539518	-185.176735	-157.589059
12:00	359.65788	265.2205029	312.1389261	0.47875942	31.107146	94.4373766	47.5189534
13:00	395.560368	215.9497763	410.1236729	0.52479432	-3.9390417	179.610591	-14.5633054
14:00	267.195663	190.5080878	240.0861038	0.50078804	4.21493659	76.6875747	27.1095587
15:00	242.829264	107.4940304	199.3327355	0.55659821	-63.9382193	135.335234	43.4965287
16:00	134.145649	28.6816612	140.2194015	0.49793634	-90.3251242	105.463988	-6.0737525
17:00	51.7823237	9.555179921	54.11503983	0.29706573	-41.8371918	42.2271438	-2.33271608
18:00	-8.24101675	-27.68608223	-15.51349807	0.32898876	-61.5719246	19.4450655	7.27248132
19:00	-30.5543475	-39.74585533	-40.83745793	0.18193377	-47.7509411	9.19150783	10.2831104
20:00	-39.8565682	-36.12264459	-36.12264459	-0.02036569	-36.0411818	-3.73392366	-3.73392366
21:00	-37.9199038	-35.43920873	-35.43920873	-0.06474103	-35.4392087	-2.48069502	-2.48069502
22:00	-32.6265698	-36.17865731	-36.17865731	0	0	3.55208756	3.55208756
23:00	-31.7443463	-32.45112651	-32.45112651	0	0	0.70678026	0.70678026
					Average:	-37.169448	-118.323542
					RMS:	101.771562	61.8224584



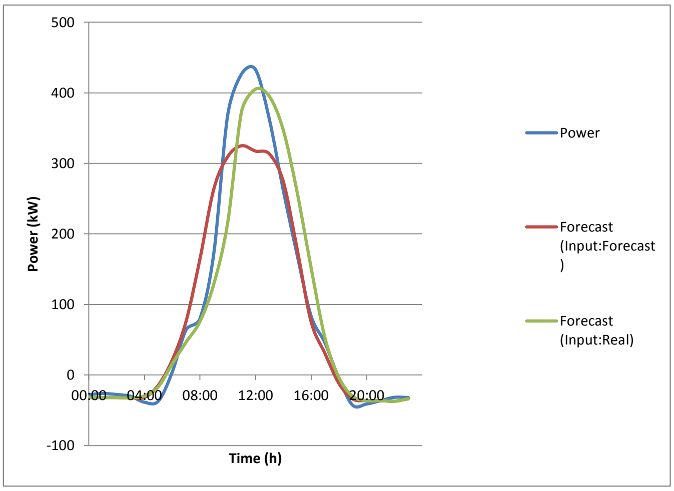
23-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-30.3965697	-31.26939822	-31.26939822	0	0	0.87282847	0.87282847
01:00	-31.862125	-31.26939822	-31.26939822	0	0	-0.59272678	-0.59272678
02:00	-33.0621248	-31.04359582	-31.04359582	0	0	-2.01852893	-2.01852893
03:00	-32.1287913	-31.70297836	-31.70297836	0	0	-0.42581289	-0.42581289
04:00	-44.1832365	-30.28526897	-28.53684931	1.74841967	-30.285269	-13.8979675	-15.6463872
05:00	-28.4299087	-18.00788863	-19.33557077	0.44256071	-29.5144672	-10.4220201	-9.09433798
06:00	10.5267598	16.59508314	0.749616888	0.58686912	-39.7443524	-6.06832339	9.77714286
07:00	36.5300978	65.41030681	89.570018	0.56185375	-39.6563442	-28.8802091	-53.0399202
08:00	65.2445418	127.0344008	154.9200402	0.51640073	-18.0742045	-61.789859	-89.6754985
09:00	91.5212108	205.7955091	157.9433865	0.5500244	-5.96388375	-114.274298	-66.4221758
10:00	36.5212098	277.472414	175.7886132	0.52960313	12.6708495	-240.951204	-139.267403
11:00	38.0512083	288.9652918	149.6528849	0.5047551	9.33096772	-250.914084	-111.601677
12:00	120.048992	319.0607246	292.8977224	0.52326004	-3.26746208	-199.011733	-172.84873
13:00	320.259272	297.2226849	354.0597079	0.53118713	1.35145289	23.0365869	-33.8004361
14:00	303.208981	245.3891314	331.9864098	0.50939576	2.40735623	57.8198491	-28.7774293
15:00	206.403435	158.9456775	222.5791955	0.52158621	-42.9081867	47.4577575	-16.1757605
16:00	111.012328	32.86690664	92.8051499	0.59344795	-133.891968	78.1454214	18.2071781
17:00	91.0134258	15.90338597	-14.34086998	0.36883239	-70.0345608	75.1100398	105.354296
18:00	23.2612035	-18.52770558	-30.85121734	0.32430294	-62.3086026	41.7889091	54.1124208
19:00	-32.5932337	-35.25936841	-36.65117101	0.17397533	-46.0458386	2.66613466	4.05793726
20:00	-35.1587918	-36.26646511	-36.21740791	-0.0245286	-36.1192935	1.10767336	1.05861616
21:00	-34.419905	-36.05475288	-36.05475288	-0.05470016	-36.0547529	1.63484788	1.63484788
22:00	-30.5276808	-36.65563276	-36.65563276	0	0	6.12795201	6.12795201
23:00	-29.2076797	-32.99316346	-32.99316346	0	0	3.78548371	3.78548371
					Average:	-147.423321	-133.59953
					RMS:	90.9118505	62.6118762



24-07-2016

Time (hour)	Power	Forecast (Input:Forecast)	Forecast (Input:Real)	Slope	Intercept	Error (F)	Error (R)
00:00	-27.798791	-31.93297846	-31.93297846	0	0	4.13418746	4.13418746
01:00	-26.171012	-31.93297846	-31.93297846	0	0	5.76196646	5.76196646
02:00	-27.5799023	-31.89439836	-31.89439836	0	0	4.31449611	4.31449611
03:00	-30.1243473	-32.47322528	-32.47322528	0	0	2.34887803	2.34887803
04:00	-38.5010147	-31.74661248	-29.60454579	2.14206669	-31.7466125	-6.75440227	-8.89646896
05:00	-36.9465695	-14.37771455	-16.58285101	0.55128412	-32.5700904	-22.5688549	-20.3637185
06:00	4.0167545	21.14836089	15.63319053	0.55151704	-36.7609279	-17.1316064	-11.616436
07:00	64.2900973	76.14224988	46.61444125	0.53686925	-38.7477692	-11.8521526	17.675656
08:00	80.0612108	164.5802746	75.88125925	0.57596763	-40.4642025	-84.5190639	4.1799515
09:00	172.796766	263.7991255	129.1128055	0.5855927	-24.8980735	-91.0023593	43.6839607
10:00	368.71066	309.5637735	216.2909541	0.58295512	-20.9717805	59.1468865	152.419706
11:00	426.77705	324.9861654	373.7571286	0.56058578	-34.3493215	101.790885	53.0199217
12:00	432.966214	317.3998368	405.2211133	0.57399527	-52.2531177	115.566377	27.7451007
13:00	362.480109	313.3608848	394.9063374	0.45556119	47.3131513	49.1192244	-32.4262282
14:00	262.012049	274.5313579	347.4618572	0.42900294	55.73986	-12.5193094	-85.4498087
15:00	170.441198	178.7044565	259.2077887	0.50951476	-35.801258	-8.2632582	-88.7665905
16:00	84.0139895	76.11291676	152.7928416	0.55565163	-108.363424	7.90107274	-68.7788521
17:00	45.9034308	30.95291911	53.27906988	0.33322613	-47.6884478	14.9505116	-7.37563913
18:00	-4.239906	-11.46378515	-3.081549263	0.27940786	-46.389768	7.22387915	-1.15835674
19:00	-42.763236	-33.91761167	-30.08738449	0.16653162	-42.5772557	-8.84562433	-12.6758515
20:00	-41.1154575	-36.18521417	-36.24662941	-0.02047175	-36.0828554	-4.93024333	-4.86882809
21:00	-36.4043475	-36.22284583	-36.22284583	-0.04624056	-36.2228458	-0.18150167	-0.18150167
22:00	-31.5732377	-37.10520081	-37.10520081	0	0	5.53196306	5.53196306
23:00	-31.826569	-33.64433628	-33.64433628	0	0	1.81776728	1.81776728
					Average:	27.7599296	-4.98118127
					RMS:	44.1663174	46.0937834



B.3 Regression results for the month April

Regression Values for April

Part 1

Date	Slope	Intercept
01.04.2016 01:00	0	0
01.04.2016 02:00	0	0
01.04.2016 03:00	0	0
01.04.2016 04:00	0	0
01.04.2016 05:00	0	0
01.04.2016 06:00	-0.38023142	-36.9611727
01.04.2016 07:00	-0.14218016	-16.9140814
01.04.2016 08:00	-0.15775151	22.5002792
01.04.2016 09:00	-0.25399649	89.5526563
01.04.2016 10:00	-0.37687679	154.040296
01.04.2016 11:00	-0.42074681	187.850755
01.04.2016 12:00	-0.34444089	184.220972
01.04.2016 13:00	-0.32069925	171.942603
01.04.2016 14:00	-0.42688763	177.345817
01.04.2016 15:00	-0.33893204	132.766777
01.04.2016 16:00	-0.26493672	75.2586788
01.04.2016 17:00	-0.0655492	-6.26554914
01.04.2016 18:00	-0.10676904	-44.7344861
01.04.2016 19:00	-0.47710442	-45.9122721
01.04.2016 20:00	0	0
01.04.2016 21:00	0	0
01.04.2016 22:00	0	0
01.04.2016 23:00	0	0
02.04.2016 01:00	0	0
02.04.2016 02:00	0	0
02.04.2016 03:00	0	0
02.04.2016 04:00	0	0
02.04.2016 05:00	0	0
02.04.2016 06:00	0.18360434	-36.6570341
02.04.2016 07:00	-0.23030365	-5.55659578
02.04.2016 08:00	-0.33804588	53.0781589
02.04.2016 09:00	-0.3212045	128.440362
02.04.2016 10:00	-0.25249206	182.593537
02.04.2016 11:00	-0.04706204	181.013912
02.04.2016 12:00	0.07084077	160.464874
02.04.2016 13:00	-0.04657058	171.259418
02.04.2016 14:00	-0.12609673	174.569119
02.04.2016 15:00	-0.07299484	126.754488
02.04.2016 16:00	-0.08407334	72.7122883
02.04.2016 17:00	0.05146254	-9.83730766
02.04.2016 18:00	-0.03027102	-44.1471017
02.04.2016 19:00	-0.36261652	-44.6532831
02.04.2016 20:00	0	0
02.04.2016 21:00	0	0
02.04.2016 22:00	0	0
02.04.2016 23:00	0	0
03.04.2016 01:00	0	0
03.04.2016 02:00	0	0
03.04.2016 03:00	0	0

Part 2

Date	Slope	Intercept
16.04.2016 02:00	0	0
16.04.2016 03:00	0	0
16.04.2016 04:00	0	0
16.04.2016 05:00	1.03010535	-40.6354956
16.04.2016 06:00	0.99498721	-40.8505545
16.04.2016 07:00	0.68612756	-26.0290937
16.04.2016 08:00	0.63016934	-20.0796587
16.04.2016 09:00	0.60056747	-12.9101183
16.04.2016 10:00	0.55322559	0.93759146
16.04.2016 11:00	0.59680071	-37.838329
16.04.2016 12:00	0.58672698	-71.0037927
16.04.2016 13:00	0.54120333	-90.135004
16.04.2016 14:00	0.4766508	-61.4477647
16.04.2016 15:00	0.39229797	-25.8568276
16.04.2016 16:00	0.34526166	-39.6569793
16.04.2016 17:00	0.33492125	-58.0088672
16.04.2016 18:00	0.26079428	-52.0627179
16.04.2016 19:00	-0.03692126	-38.7361051
16.04.2016 20:00	-0.58992248	-33.8768769
16.04.2016 21:00	0	0
16.04.2016 22:00	0	0
16.04.2016 23:00	0	0
17.04.2016 01:00	0	0
17.04.2016 02:00	0	0
17.04.2016 03:00	0	0
17.04.2016 04:00	0	0
17.04.2016 05:00	0.46339497	-39.9495945
17.04.2016 06:00	0.98487372	-41.2241304
17.04.2016 07:00	0.69214586	-26.9065685
17.04.2016 08:00	0.63083351	-21.5820896
17.04.2016 09:00	0.63014323	-19.5750083
17.04.2016 10:00	0.53292425	13.9114099
17.04.2016 11:00	0.54927604	-8.36728178
17.04.2016 12:00	0.54408764	-43.7833357
17.04.2016 13:00	0.58584409	-119.804573
17.04.2016 14:00	0.46363616	-58.3799172
17.04.2016 15:00	0.36762976	-12.9278339
17.04.2016 16:00	0.3179594	-28.0943446
17.04.2016 17:00	0.33479093	-58.397213
17.04.2016 18:00	0.24443192	-50.5238463
17.04.2016 19:00	-0.03787262	-37.537531
17.04.2016 20:00	-0.51539817	-33.4258296
17.04.2016 21:00	0	0
17.04.2016 22:00	0	0
17.04.2016 23:00	0	0
18.04.2016 01:00	0	0
18.04.2016 02:00	0	0
18.04.2016 03:00	0	0
18.04.2016 04:00	0	0

03.04.2016 04:00	0	0	18.04.2016 05:00	2.25006829	-39.9361077
03.04.2016 05:00	0	0	18.04.2016 06:00	0.89289106	-39.8569094
03.04.2016 06:00	0.26673356	-35.2732307	18.04.2016 07:00	0.6993729	-29.0293804
03.04.2016 07:00	-0.12956106	-0.17221475	18.04.2016 08:00	0.63040182	-21.7631709
03.04.2016 08:00	-0.21007055	62.3655589	18.04.2016 09:00	0.6171463	-14.1591983
03.04.2016 09:00	-0.19407762	138.952026	18.04.2016 10:00	0.53644326	10.79604
03.04.2016 10:00	-0.31870294	225.844594	18.04.2016 11:00	0.56838635	-15.9259451
03.04.2016 11:00	-0.30252183	261.759998	18.04.2016 12:00	0.54236313	-25.8546685
03.04.2016 12:00	-0.23214811	254.983578	18.04.2016 13:00	0.60529288	-114.648228
03.04.2016 13:00	-0.16031276	222.451811	18.04.2016 14:00	0.43280157	-31.2264031
03.04.2016 14:00	-0.07512087	178.614167	18.04.2016 15:00	0.33382997	7.90703309
03.04.2016 15:00	-0.02271146	121.435514	18.04.2016 16:00	0.30143587	-17.5325712
03.04.2016 16:00	0.04244394	52.4152743	18.04.2016 17:00	0.35716759	-58.7078521
03.04.2016 17:00	0.13901939	-19.5025402	18.04.2016 18:00	0.26422477	-50.8315667
03.04.2016 18:00	-0.01524522	-43.6528401	18.04.2016 19:00	-0.02653273	-36.6250378
03.04.2016 19:00	-0.29374106	-43.4036596	18.04.2016 20:00	-0.49593177	-32.7079298
03.04.2016 20:00	0	0	18.04.2016 21:00	0	0
03.04.2016 21:00	0	0	18.04.2016 22:00	0	0
03.04.2016 22:00	0	0	18.04.2016 23:00	0	0
03.04.2016 23:00	0	0	19.04.2016 01:00	0	0
04.04.2016 01:00	0	0	19.04.2016 02:00	0	0
04.04.2016 02:00	0	0	19.04.2016 03:00	0	0
04.04.2016 03:00	0	0	19.04.2016 04:00	0	0
04.04.2016 04:00	0	0	19.04.2016 05:00	2.74203226	-38.7594736
04.04.2016 05:00	0	0	19.04.2016 06:00	0.82772377	-35.8305032
04.04.2016 06:00	0.20882892	-36.3934287	19.04.2016 07:00	0.6716458	-24.2280111
04.04.2016 07:00	0.00578647	-3.55553758	19.04.2016 08:00	0.62944383	-21.2866971
04.04.2016 08:00	-0.06845778	55.2015053	19.04.2016 09:00	0.6127911	-19.1803146
04.04.2016 09:00	-0.14727867	140.168244	19.04.2016 10:00	0.47284455	32.3337698
04.04.2016 10:00	-0.30523729	242.99221	19.04.2016 11:00	0.47172649	30.7762127
04.04.2016 11:00	-0.32740285	307.414839	19.04.2016 12:00	0.55286922	-34.9128923
04.04.2016 12:00	-0.29831033	317.688219	19.04.2016 13:00	0.61692528	-121.847242
04.04.2016 13:00	-0.25974868	291.645029	19.04.2016 14:00	0.397986	-9.50214122
04.04.2016 14:00	-0.20449222	247.023215	19.04.2016 15:00	0.32356172	11.4413314
04.04.2016 15:00	-0.093898	155.531149	19.04.2016 16:00	0.31242196	-25.2514194
04.04.2016 16:00	0.01559839	65.1675389	19.04.2016 17:00	0.36964557	-60.7025213
04.04.2016 17:00	0.13730158	-16.7970672	19.04.2016 18:00	0.27641671	-53.5936116
04.04.2016 18:00	0.01962774	-42.2718531	19.04.2016 19:00	-0.05006418	-36.0804157
04.04.2016 19:00	-0.26645929	-41.9480708	19.04.2016 20:00	-0.50613372	-32.1956886
04.04.2016 20:00	0	0	19.04.2016 21:00	0	0
04.04.2016 21:00	0	0	19.04.2016 22:00	0	0
04.04.2016 22:00	0	0	19.04.2016 23:00	0	0
04.04.2016 23:00	0	0	20.04.2016 01:00	0	0
05.04.2016 01:00	0	0	20.04.2016 02:00	0	0
05.04.2016 02:00	0	0	20.04.2016 03:00	0	0
05.04.2016 03:00	0	0	20.04.2016 04:00	0	0
05.04.2016 04:00	0	0	20.04.2016 05:00	1.81277163	-37.5412307
05.04.2016 05:00	0	0	20.04.2016 06:00	0.79486801	-35.6168699
05.04.2016 06:00	1.38726258	-44.2500081	20.04.2016 07:00	0.6903888	-26.1460306
05.04.2016 07:00	0.51253494	-18.1191719	20.04.2016 08:00	0.6278647	-19.9850303
05.04.2016 08:00	0.11283917	52.0171098	20.04.2016 09:00	0.62139484	-20.2816632
05.04.2016 09:00	0.15016455	107.415632	20.04.2016 10:00	0.48033816	26.4716052
05.04.2016 10:00	0.11627488	159.167799	20.04.2016 11:00	0.44169221	44.8343276

05.04.2016 11:00	-0.0085166	234.571164	20.04.2016 12:00	0.48914344	3.64479454
05.04.2016 12:00	-0.09446895	272.326361	20.04.2016 13:00	0.60328385	-112.582899
05.04.2016 13:00	-0.02974898	229.108125	20.04.2016 14:00	0.40014367	-16.3497738
05.04.2016 14:00	-0.0016105	200.000893	20.04.2016 15:00	0.31773777	11.1656009
05.04.2016 15:00	-0.0603869	169.310313	20.04.2016 16:00	0.3527337	-36.0589159
05.04.2016 16:00	0.03470321	69.6585815	20.04.2016 17:00	0.36930282	-61.8477713
05.04.2016 17:00	0.17752022	-23.5555432	20.04.2016 18:00	0.24663047	-51.2427122
05.04.2016 18:00	0.06353983	-43.2161089	20.04.2016 19:00	-0.04256661	-35.7286562
05.04.2016 19:00	-0.25225073	-40.4828972	20.04.2016 20:00	-0.50852328	-31.5723724
05.04.2016 20:00	0	0	20.04.2016 21:00	0	0
05.04.2016 21:00	0	0	20.04.2016 22:00	0	0
05.04.2016 22:00	0	0	20.04.2016 23:00	0	0
05.04.2016 23:00	0	0	21.04.2016 01:00	0	0
06.04.2016 01:00	0	0	21.04.2016 02:00	0	0
06.04.2016 02:00	0	0	21.04.2016 03:00	0	0
06.04.2016 03:00	0	0	21.04.2016 04:00	0	0
06.04.2016 04:00	0	0	21.04.2016 05:00	2.0337942	-38.9445763
06.04.2016 05:00	0	0	21.04.2016 06:00	0.80174155	-37.4990759
06.04.2016 06:00	0.77849778	-42.7104932	21.04.2016 07:00	0.72341971	-35.9642105
06.04.2016 07:00	0.47191597	-18.6731397	21.04.2016 08:00	0.60386647	-26.6189643
06.04.2016 08:00	0.18732882	40.0936613	21.04.2016 09:00	0.64495759	-34.4707178
06.04.2016 09:00	0.13321546	94.3315512	21.04.2016 10:00	0.50984046	21.3472747
06.04.2016 10:00	0.23536896	96.7624647	21.04.2016 11:00	0.48383905	31.7887232
06.04.2016 11:00	0.37687658	78.8431063	21.04.2016 12:00	0.5953827	-38.4132837
06.04.2016 12:00	0.29881235	99.1896245	21.04.2016 13:00	0.71871295	-158.457315
06.04.2016 13:00	0.24360302	95.2976916	21.04.2016 14:00	0.46589473	-33.4361198
06.04.2016 14:00	0.20285255	98.977117	21.04.2016 15:00	0.3859631	-4.39053986
06.04.2016 15:00	0.15225536	81.1265743	21.04.2016 16:00	0.40707002	-52.7889084
06.04.2016 16:00	0.17846251	20.2314164	21.04.2016 17:00	0.37985796	-65.1684975
06.04.2016 17:00	0.23346995	-36.6681099	21.04.2016 18:00	0.23957885	-50.5756804
06.04.2016 18:00	0.11465552	-45.7592248	21.04.2016 19:00	-0.05169272	-34.8235562
06.04.2016 19:00	-0.25009267	-38.9475315	21.04.2016 20:00	-0.46208914	-31.1460731
06.04.2016 20:00	-2.43526357	-35.1157512	21.04.2016 21:00	0	0
06.04.2016 21:00	0	0	21.04.2016 22:00	0	0
06.04.2016 22:00	0	0	21.04.2016 23:00	0	0
06.04.2016 23:00	0	0	22.04.2016 01:00	0	0
07.04.2016 01:00	0	0	22.04.2016 02:00	0	0
07.04.2016 02:00	0	0	22.04.2016 03:00	0	0
07.04.2016 03:00	0	0	22.04.2016 04:00	0	0
07.04.2016 04:00	0	0	22.04.2016 05:00	1.66739397	-38.4468131
07.04.2016 05:00	0	0	22.04.2016 06:00	0.76967301	-36.9777548
07.04.2016 06:00	1.19517107	-46.0956399	22.04.2016 07:00	0.73061305	-37.2218352
07.04.2016 07:00	0.9634135	-40.0313904	22.04.2016 08:00	0.61406905	-28.2346197
07.04.2016 08:00	0.80282562	-32.4846412	22.04.2016 09:00	0.65420622	-37.0588024
07.04.2016 09:00	0.72486453	-31.1582952	22.04.2016 10:00	0.52219798	16.6678593
07.04.2016 10:00	0.77679151	-63.7356496	22.04.2016 11:00	0.49171481	28.316793
07.04.2016 11:00	0.74898989	-62.8502623	22.04.2016 12:00	0.60240748	-41.4367163
07.04.2016 12:00	0.59550878	-33.1110257	22.04.2016 13:00	0.72974561	-163.048148
07.04.2016 13:00	0.57434421	-52.4257545	22.04.2016 14:00	0.47978264	-38.1143154
07.04.2016 14:00	0.64723971	-89.0963218	22.04.2016 15:00	0.40067941	-8.35598922
07.04.2016 15:00	0.54374887	-67.7433351	22.04.2016 16:00	0.42439995	-57.1888313
07.04.2016 16:00	0.4868791	-75.312596	22.04.2016 17:00	0.39105664	-67.7425
07.04.2016 17:00	0.34081724	-62.60085	22.04.2016 18:00	0.22927885	-49.7715293

07.04.2016 18:00	0.21258139	-53.0802239
07.04.2016 19:00	-0.32291437	-37.3110854
07.04.2016 20:00	-0.81567397	-35.0753418
07.04.2016 21:00	0	0
07.04.2016 22:00	0	0
07.04.2016 23:00	0	0
08.04.2016 01:00	0	0
08.04.2016 02:00	0	0
08.04.2016 03:00	0	0
08.04.2016 04:00	0	0
08.04.2016 05:00	0	0
08.04.2016 06:00	1.30568869	-47.2371664
08.04.2016 07:00	0.86242589	-34.8133784
08.04.2016 08:00	0.74081433	-23.4041354
08.04.2016 09:00	0.66966549	-21.7103781
08.04.2016 10:00	0.74108479	-49.815513
08.04.2016 11:00	0.72219832	-49.1376275
08.04.2016 12:00	0.52711022	-16.0778974
08.04.2016 13:00	0.53168913	-52.2314648
08.04.2016 14:00	0.66568616	-100.575288
08.04.2016 15:00	0.5451731	-63.7398742
08.04.2016 16:00	0.50852925	-82.9730357
08.04.2016 17:00	0.31236373	-59.5189981
08.04.2016 18:00	0.24038852	-54.1764733
08.04.2016 19:00	-0.3064452	-37.4841461
08.04.2016 20:00	-0.69736974	-35.193646
08.04.2016 21:00	0	0
08.04.2016 22:00	0	0
08.04.2016 23:00	0	0
09.04.2016 01:00	0	0
09.04.2016 02:00	0	0
09.04.2016 03:00	0	0
09.04.2016 04:00	0	0
09.04.2016 05:00	0	0
09.04.2016 06:00	1.23001078	-47.321466
09.04.2016 07:00	0.85200175	-35.0446478
09.04.2016 08:00	0.74551143	-23.7306007
09.04.2016 09:00	0.67269335	-15.7578238
09.04.2016 10:00	0.66462085	-23.948546
09.04.2016 11:00	0.68944567	-46.7465058
09.04.2016 12:00	0.52556164	-15.7155987
09.04.2016 13:00	0.52864311	-51.3068939
09.04.2016 14:00	0.68818776	-114.819313
09.04.2016 15:00	0.59794858	-86.8643702
09.04.2016 16:00	0.55420166	-98.703193
09.04.2016 17:00	0.29377776	-57.8389345
09.04.2016 18:00	0.22434343	-52.8679828
09.04.2016 19:00	-0.3161765	-37.0895675
09.04.2016 20:00	-1.01906583	-34.8719499
09.04.2016 21:00	0	0
09.04.2016 22:00	0	0
09.04.2016 23:00	0	0
10.04.2016 01:00	0	0
22.04.2016 19:00	-0.04031606	-35.2778031
22.04.2016 20:00	-0.42057896	-31.31427
22.04.2016 21:00	0	0
22.04.2016 22:00	0	0
22.04.2016 23:00	0	0
23.04.2016 01:00	0	0
23.04.2016 02:00	0	0
23.04.2016 03:00	0	0
23.04.2016 04:00	0	0
23.04.2016 05:00	1.80206847	-36.271735
23.04.2016 06:00	0.78858659	-32.7515836
23.04.2016 07:00	0.68978956	-27.3429048
23.04.2016 08:00	0.62270319	-21.965786
23.04.2016 09:00	0.64094624	-26.0967232
23.04.2016 10:00	0.52872225	14.6197726
23.04.2016 11:00	0.51109555	23.406648
23.04.2016 12:00	0.60407182	-38.6400189
23.04.2016 13:00	0.72093988	-158.997559
23.04.2016 14:00	0.4781949	-38.3876739
23.04.2016 15:00	0.41376554	-7.23337349
23.04.2016 16:00	0.52142176	-82.2308935
23.04.2016 17:00	0.41247743	-73.2655886
23.04.2016 18:00	0.22083147	-49.677182
23.04.2016 19:00	-0.05111207	-34.3249351
23.04.2016 20:00	-0.55543959	-30.6148933
23.04.2016 21:00	0	0
23.04.2016 22:00	0	0
23.04.2016 23:00	0	0
24.04.2016 01:00	0	0
24.04.2016 02:00	0	0
24.04.2016 03:00	0	0
24.04.2016 04:00	0	0
24.04.2016 05:00	1.83683696	-36.3388361
24.04.2016 06:00	0.7690037	-33.0251357
24.04.2016 07:00	0.68386144	-31.9268216
24.04.2016 08:00	0.64355402	-33.8493816
24.04.2016 09:00	0.66203882	-35.3467308
24.04.2016 10:00	0.53281366	13.5885431
24.04.2016 11:00	0.52068262	17.5103295
24.04.2016 12:00	0.60398866	-42.9430525
24.04.2016 13:00	0.66934184	-127.573197
24.04.2016 14:00	0.44289824	-12.3701959
24.04.2016 15:00	0.39944727	8.54067882
24.04.2016 16:00	0.54827238	-86.0727166
24.04.2016 17:00	0.46249289	-87.5350054
24.04.2016 18:00	0.24772086	-53.8397089
24.04.2016 19:00	-0.03888402	-34.7853991
24.04.2016 20:00	-0.55911054	-30.9147384
24.04.2016 21:00	0	0
24.04.2016 22:00	0	0
24.04.2016 23:00	0	0
25.04.2016 01:00	0	0
25.04.2016 02:00	0	0

10.04.2016 02:00	0	0	25.04.2016 03:00	0	0
10.04.2016 03:00	0	0	25.04.2016 04:00	0	0
10.04.2016 04:00	0	0	25.04.2016 05:00	1.8110612	-35.2655896
10.04.2016 05:00	0	0	25.04.2016 06:00	0.74345307	-31.8310019
10.04.2016 06:00	1.22000941	-47.551132	25.04.2016 07:00	0.70529871	-33.8581519
10.04.2016 07:00	0.7893122	-32.5977027	25.04.2016 08:00	0.62827696	-30.7855104
10.04.2016 08:00	0.71525784	-21.4625835	25.04.2016 09:00	0.66627165	-38.2292613
10.04.2016 09:00	0.65261812	-12.6355323	25.04.2016 10:00	0.51953886	17.7426339
10.04.2016 10:00	0.61997761	-14.1342497	25.04.2016 11:00	0.46283442	36.5706529
10.04.2016 11:00	0.6673629	-43.7000247	25.04.2016 12:00	0.48179499	25.211978
10.04.2016 12:00	0.52529039	-11.6876443	25.04.2016 13:00	0.56970377	-44.981191
10.04.2016 13:00	0.52270681	-46.2745213	25.04.2016 14:00	0.46454979	3.52210991
10.04.2016 14:00	0.68021254	-109.421231	25.04.2016 15:00	0.41736337	17.7371753
10.04.2016 15:00	0.62063501	-92.2418676	25.04.2016 16:00	0.53995823	-78.233229
10.04.2016 16:00	0.53919833	-96.2322423	25.04.2016 17:00	0.47227717	-89.9430402
10.04.2016 17:00	0.32058529	-60.9616761	25.04.2016 18:00	0.26254583	-55.8435628
10.04.2016 18:00	0.24905389	-54.4993181	25.04.2016 19:00	-0.01990225	-35.4545666
10.04.2016 19:00	-0.22747236	-37.9619004	25.04.2016 20:00	-0.43921315	-31.3931498
10.04.2016 20:00	-2.61670402	-34.6965085	25.04.2016 21:00	0	0
10.04.2016 21:00	0	0	25.04.2016 22:00	0	0
10.04.2016 22:00	0	0	25.04.2016 23:00	0	0
10.04.2016 23:00	0	0	26.04.2016 01:00	0	0
11.04.2016 01:00	0	0	26.04.2016 02:00	0	0
11.04.2016 02:00	0	0	26.04.2016 03:00	0	0
11.04.2016 03:00	0	0	26.04.2016 04:00	0	0
11.04.2016 04:00	0	0	26.04.2016 05:00	1.68210156	-33.7558641
11.04.2016 05:00	0	0	26.04.2016 06:00	0.71680712	-27.4219414
11.04.2016 06:00	1.25003666	-45.4452658	26.04.2016 07:00	0.67261713	-25.5725662
11.04.2016 07:00	0.80359857	-27.3878008	26.04.2016 08:00	0.62330241	-23.6821245
11.04.2016 08:00	0.68558429	-11.8415001	26.04.2016 09:00	0.70942289	-54.1044688
11.04.2016 09:00	0.663899	-17.2626263	26.04.2016 10:00	0.45215676	52.6733505
11.04.2016 10:00	0.62268211	-20.7716623	26.04.2016 11:00	0.41224501	65.5182664
11.04.2016 11:00	0.63111984	-34.5085722	26.04.2016 12:00	0.41984666	61.8343944
11.04.2016 12:00	0.47278485	7.73925466	26.04.2016 13:00	0.5360574	-22.4341495
11.04.2016 13:00	0.45837535	-22.9693345	26.04.2016 14:00	0.47903916	-2.87391195
11.04.2016 14:00	0.58108942	-76.0804582	26.04.2016 15:00	0.46142989	-4.6634979
11.04.2016 15:00	0.53087525	-63.6553201	26.04.2016 16:00	0.55413993	-81.4280436
11.04.2016 16:00	0.53471536	-94.2864056	26.04.2016 17:00	0.43810391	-76.5508667
11.04.2016 17:00	0.33092174	-61.7185015	26.04.2016 18:00	0.23754373	-50.8323394
11.04.2016 18:00	0.2429104	-54.8427126	26.04.2016 19:00	-0.02322244	-34.4776915
11.04.2016 19:00	-0.17380126	-39.0713365	26.04.2016 20:00	-0.41277518	-31.2464701
11.04.2016 20:00	-3.1029396	-34.5523903	26.04.2016 21:00	0	0
11.04.2016 21:00	0	0	26.04.2016 22:00	0	0
11.04.2016 22:00	0	0	26.04.2016 23:00	0	0
11.04.2016 23:00	0	0	27.04.2016 01:00	0	0
12.04.2016 01:00	0	0	27.04.2016 02:00	0	0
12.04.2016 02:00	0	0	27.04.2016 03:00	0	0
12.04.2016 03:00	0	0	27.04.2016 04:00	0	0
12.04.2016 04:00	0	0	27.04.2016 05:00	0.9267364	-32.2190782
12.04.2016 05:00	0	0	27.04.2016 06:00	0.67701098	-27.1823089
12.04.2016 06:00	1.15215104	-44.7895873	27.04.2016 07:00	0.68904092	-30.387018
12.04.2016 07:00	0.73913339	-25.1231878	27.04.2016 08:00	0.59410473	-14.8085938
12.04.2016 08:00	0.66249144	-10.4305967	27.04.2016 09:00	0.73065603	-72.5662277

12.04.2016 09:00	0.65144665	-15.673918
12.04.2016 10:00	0.6149846	-19.8095575
12.04.2016 11:00	0.62119414	-32.4114215
12.04.2016 12:00	0.47973307	1.29175759
12.04.2016 13:00	0.46694034	-31.3532901
12.04.2016 14:00	0.54995363	-68.1760153
12.04.2016 15:00	0.50311477	-56.1598217
12.04.2016 16:00	0.51538095	-89.6500297
12.04.2016 17:00	0.33733432	-62.7013604
12.04.2016 18:00	0.24386524	-54.4040291
12.04.2016 19:00	-0.11453784	-39.0941347
12.04.2016 20:00	-1.72118497	-34.1097659
12.04.2016 21:00	0	0
12.04.2016 22:00	0	0
12.04.2016 23:00	0	0
13.04.2016 01:00	0	0
13.04.2016 02:00	0	0
13.04.2016 03:00	0	0
13.04.2016 04:00	0	0
13.04.2016 05:00	-3.97391749	-42.7454005
13.04.2016 06:00	0.94848108	-45.3540123
13.04.2016 07:00	0.71031826	-31.0974626
13.04.2016 08:00	0.61264574	-13.0848095
13.04.2016 09:00	0.62434017	-15.2660621
13.04.2016 10:00	0.57798384	-11.6403964
13.04.2016 11:00	0.57323016	-20.9166294
13.04.2016 12:00	0.44988357	7.8264249
13.04.2016 13:00	0.45818975	-29.959989
13.04.2016 14:00	0.54567593	-66.3243971
13.04.2016 15:00	0.47284043	-47.7382357
13.04.2016 16:00	0.42560819	-67.5888004
13.04.2016 17:00	0.33177372	-61.3961541
13.04.2016 18:00	0.25510988	-54.3352955
13.04.2016 19:00	-0.10834989	-39.1463925
13.04.2016 20:00	-1.73467625	-34.0847107
13.04.2016 21:00	0	0
13.04.2016 22:00	0	0
13.04.2016 23:00	0	0
14.04.2016 01:00	0	0
14.04.2016 02:00	0	0
14.04.2016 03:00	0	0
14.04.2016 04:00	0	0
14.04.2016 05:00	1.10876558	-42.2424342
14.04.2016 06:00	1.02868246	-43.2496409
14.04.2016 07:00	0.71683072	-25.7020599
14.04.2016 08:00	0.61436782	-8.80614718
14.04.2016 09:00	0.59459621	-6.25849309
14.04.2016 10:00	0.5738068	-12.1178684
14.04.2016 11:00	0.58083655	-30.2714709
14.04.2016 12:00	0.45469929	3.16421079
14.04.2016 13:00	0.45472097	-29.0180259
14.04.2016 14:00	0.53933165	-65.8730018
14.04.2016 15:00	0.47617955	-48.2332534

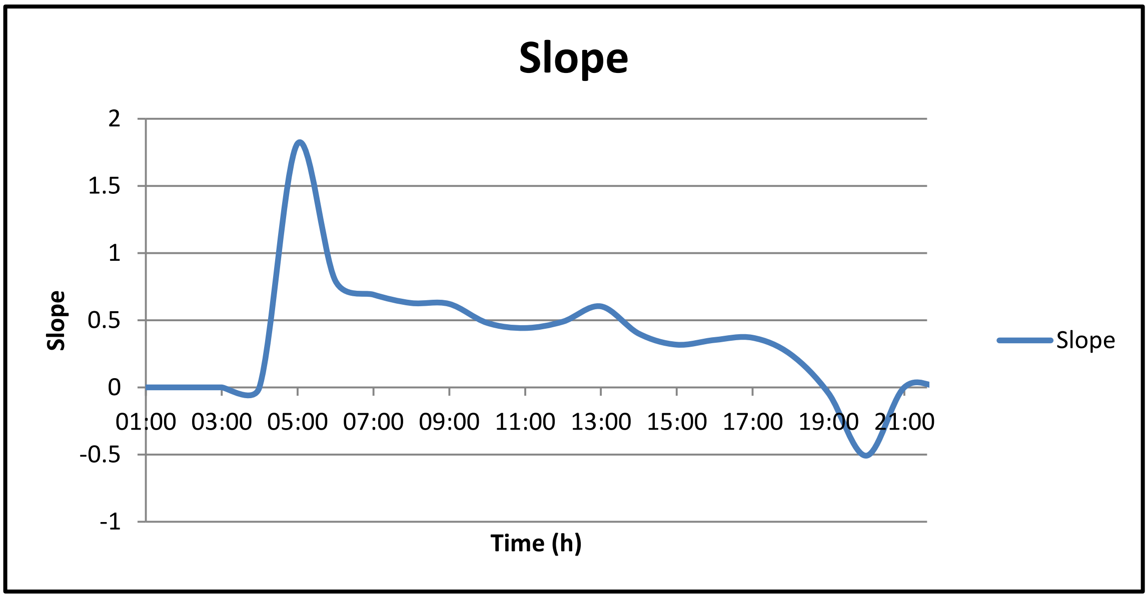
27.04.2016 10:00	0.5700985	-12.2816498
27.04.2016 11:00	0.48253156	14.6197531
27.04.2016 12:00	0.4734377	21.399602
27.04.2016 13:00	0.49534523	17.2519211
27.04.2016 14:00	0.46673414	14.7144432
27.04.2016 15:00	0.46006772	-6.0533845
27.04.2016 16:00	0.56115743	-84.4326479
27.04.2016 17:00	0.42764487	-72.5532745
27.04.2016 18:00	0.23572452	-49.6295466
27.04.2016 19:00	-0.0143551	-34.8710233
27.04.2016 20:00	-0.36342152	-31.6137394
27.04.2016 21:00	0	0
27.04.2016 22:00	0	0
27.04.2016 23:00	0	0
28.04.2016 01:00	0	0
28.04.2016 02:00	0	0
28.04.2016 03:00	0	0
28.04.2016 04:00	0	0
28.04.2016 05:00	0.445751	-32.2486216
28.04.2016 06:00	0.69721595	-29.6533559
28.04.2016 07:00	0.69355672	-32.3365148
28.04.2016 08:00	0.61010345	-21.0850142
28.04.2016 09:00	0.73851989	-71.7912611
28.04.2016 10:00	0.55763963	-5.37365771
28.04.2016 11:00	0.48982425	-5.94384509
28.04.2016 12:00	0.48458701	-2.24069735
28.04.2016 13:00	0.49598643	12.5762303
28.04.2016 14:00	0.50635775	-12.5938256
28.04.2016 15:00	0.49134478	-21.7029012
28.04.2016 16:00	0.51865536	-61.5836077
28.04.2016 17:00	0.36074589	-53.368975
28.04.2016 18:00	0.19850529	-43.76654
28.04.2016 19:00	-0.01541735	-35.1428956
28.04.2016 20:00	-0.37714111	-31.6878636
28.04.2016 21:00	0	0
28.04.2016 22:00	0	0
28.04.2016 23:00	0	0
29.04.2016 01:00	0	0
29.04.2016 02:00	0	0
29.04.2016 03:00	0	0
29.04.2016 04:00	0	0
29.04.2016 05:00	0.63867766	-32.3334245
29.04.2016 06:00	0.72398289	-29.3250858
29.04.2016 07:00	0.69189455	-26.2643611
29.04.2016 08:00	0.5350827	2.72573557
29.04.2016 09:00	0.76511791	-81.6246578
29.04.2016 10:00	0.66773172	-52.6039784
29.04.2016 11:00	0.58253413	-39.4629904
29.04.2016 12:00	0.52788545	-6.92385354
29.04.2016 13:00	0.46792256	39.6988386
29.04.2016 14:00	0.50825769	-14.4096467
29.04.2016 15:00	0.50468519	-32.3507579
29.04.2016 16:00	0.49667596	-53.2417981

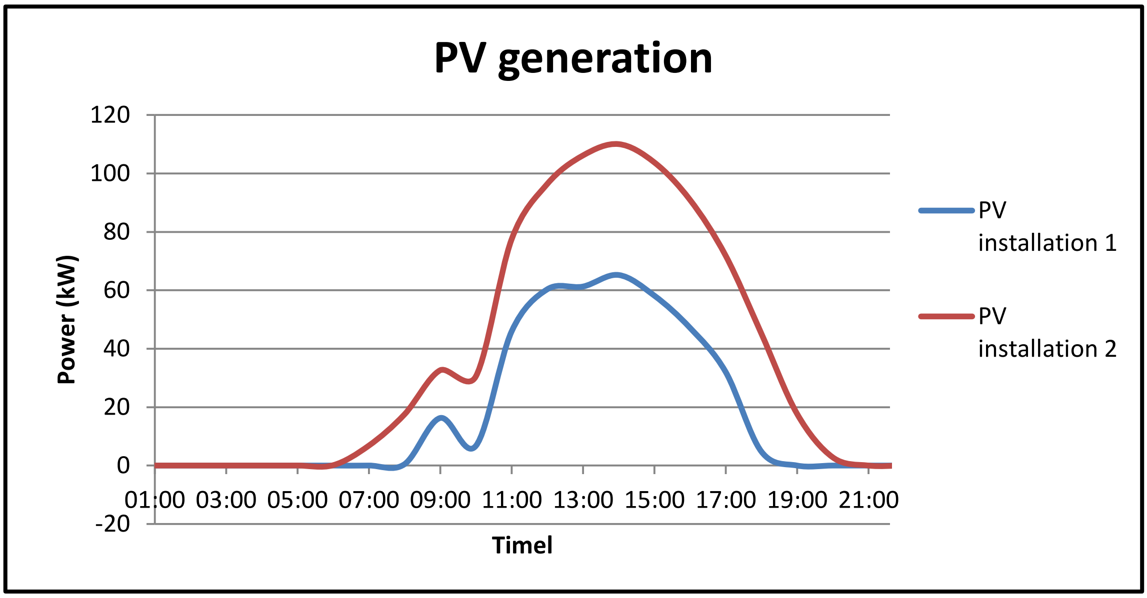
14.04.2016 16:00	0.41969319	-60.103604
14.04.2016 17:00	0.35079663	-59.5384862
14.04.2016 18:00	0.26497352	-53.6222249
14.04.2016 19:00	-0.10551386	-38.676037
14.04.2016 20:00	-1.18564565	-34.2060292
14.04.2016 21:00	0	0
14.04.2016 22:00	0	0
14.04.2016 23:00	0	0
15.04.2016 01:00	0	0
15.04.2016 02:00	0	0
15.04.2016 03:00	0	0
15.04.2016 04:00	0	0
15.04.2016 05:00	1.89386717	-42.0480077
15.04.2016 06:00	1.02941976	-41.8107124
15.04.2016 07:00	0.66775577	-22.5108904
15.04.2016 08:00	0.60532272	-13.1227672
15.04.2016 09:00	0.60839683	-16.3600357
15.04.2016 10:00	0.58790787	-17.414387
15.04.2016 11:00	0.61200593	-46.0072899
15.04.2016 12:00	0.54942937	-47.0227639
15.04.2016 13:00	0.49575806	-60.9602035
15.04.2016 14:00	0.49286211	-68.4566111
15.04.2016 15:00	0.44985397	-53.2094139
15.04.2016 16:00	0.39293387	-55.9168637
15.04.2016 17:00	0.33727513	-56.1535241
15.04.2016 18:00	0.27013777	-52.0327956
15.04.2016 19:00	-0.05258452	-38.6010095
15.04.2016 20:00	-0.43986678	-34.0917807
15.04.2016 21:00	0	0
15.04.2016 22:00	0	0
15.04.2016 23:00	0	0
16.04.2016 01:00	0	0

29.04.2016 17:00	0.33826066	-45.1084446
29.04.2016 18:00	0.19792846	-40.7837729
29.04.2016 19:00	0.01948625	-35.5436281
29.04.2016 20:00	-0.3040872	-31.8953655
29.04.2016 21:00	0	0
29.04.2016 22:00	0	0
29.04.2016 23:00	0	0
30.04.2016 01:00	0	0
30.04.2016 02:00	0	0
30.04.2016 03:00	0	0
30.04.2016 04:00	0	0
30.04.2016 05:00	0.70337893	-31.2268127
30.04.2016 06:00	0.6544695	-23.5201056
30.04.2016 07:00	0.60515386	-12.8505973
30.04.2016 08:00	0.49912599	8.7483477
30.04.2016 09:00	0.81376004	-107.401044
30.04.2016 10:00	0.70985281	-75.3263833
30.04.2016 11:00	0.62714356	-70.0819481
30.04.2016 12:00	0.61611419	-64.880331
30.04.2016 13:00	0.5211362	10.2343078
30.04.2016 14:00	0.54585559	-28.1332049
30.04.2016 15:00	0.55706952	-50.7830876
30.04.2016 16:00	0.50754629	-55.1092666
30.04.2016 17:00	0.33698427	-43.831079
30.04.2016 18:00	0.21420501	-41.453869
30.04.2016 19:00	0.02835606	-35.8426853
30.04.2016 20:00	-0.28152577	-32.1988657
30.04.2016 21:00	0	0
30.04.2016 22:00	0	0
30.04.2016 23:00	0	0

B.4 Comparison between regression Slope and PV generation

Date	Slope	PV installatior	PV installation 2
01:00	0	0	0
02:00	0	0	0
03:00	0	0	0
04:00	0	0	0
05:00	1.81277163	0	0
06:00	0.79486801	0	0.1075
07:00	0.6903888	0	6.8
08:00	0.6278647	0.45	17.49425
09:00	0.62139484	16.28	32.62275
10:00	0.48033816	6.725	30.511
11:00	0.44169221	45.85	77.37625
12:00	0.48914344	60.34	96.38825
13:00	0.60328385	61.285	106.16675
14:00	0.40014367	65.245	110.06175
15:00	0.31773777	58.19	103.8155
16:00	0.3527337	47.165	91.00225
17:00	0.36930282	32.05	71.8555
18:00	0.24663047	4.8	45.18725
19:00	-0.04256661	0	17.728
20:00	-0.50852328	0	2.80825
21:00	0	0	0
22:00	0	0	0
23:00	0	0	0





PV generation
Power (kW)
120
100
80
60
40
20
0
-20
01:00
03:00
05:00
07:00
09:00
11:00
13:00
15:00
17:00
19:00
21:00
Timel
PV installation 1
PV installation 2

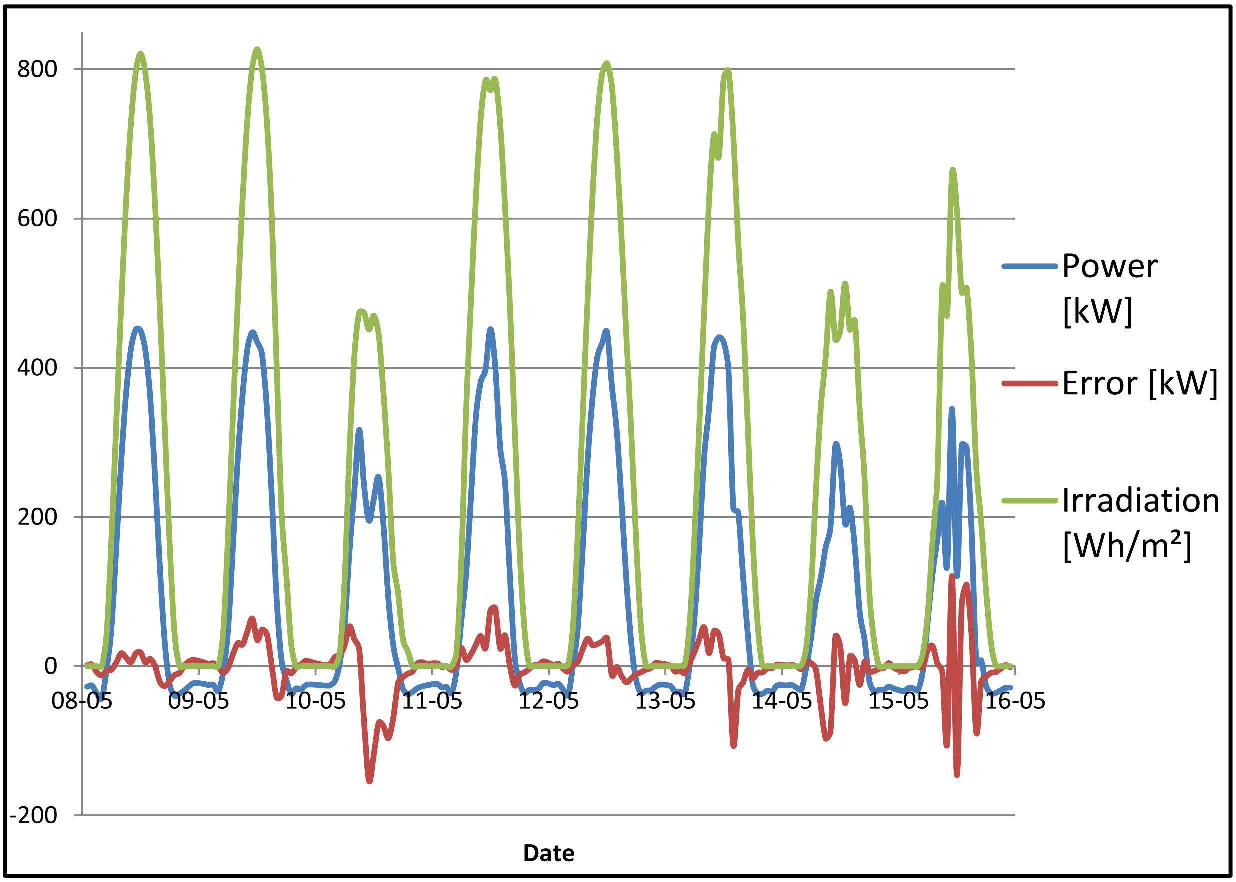
B.5 Comparison between power flow and forecast accuracy

Date	Power [kW]	Error [kW]	Irradiation [Wh/m²]
08.05.2016 01:00	-27.4365692	1.30580258	0
08.05.2016 02:00	-26.0576807	2.02086361	0
08.05.2016 03:00	-36.472126	-8.29845806	0
08.05.2016 04:00	-43.302126	-12.2587662	0
08.05.2016 05:00	-4.58656925	-6.001785	43
08.05.2016 06:00	51.3712098	-4.79437137	171
08.05.2016 07:00	159.473435	4.99458839	327
08.05.2016 08:00	272.776756	17.3573561	482
08.05.2016 09:00	364.333733	11.5022927	620
08.05.2016 10:00	424.195667	5.31994083	727
08.05.2016 11:00	451.2251	16.9395056	796
08.05.2016 12:00	449.802877	18.3053553	821
08.05.2016 13:00	422.740938	4.90162742	794
08.05.2016 14:00	358.980116	9.90138449	729
08.05.2016 15:00	250.99343	-0.33733726	616
08.05.2016 16:00	129.23206	-21.5819057	474
08.05.2016 17:00	30.323151	-26.6783147	317
08.05.2016 18:00	-25.1768475	-19.9143549	162
08.05.2016 19:00	-39.601014	-11.8308038	43
08.05.2016 20:00	-36.967679	-9.19080596	0
08.05.2016 21:00	-32.622125	0.6722225	0
08.05.2016 22:00	-26.8343467	6.5141366	0
08.05.2016 23:00	-22.6510125	8.36938424	0
09.05.2016 01:00	-23.7087925	5.14709782	0
09.05.2016 02:00	-25.355458	2.84185174	0
09.05.2016 03:00	-24.9165703	3.85969032	0
09.05.2016 04:00	-33.4232333	-1.07530551	0
09.05.2016 05:00	-7.865461	-8.61850036	45
09.05.2016 06:00	48.9145432	-2.44436724	176
09.05.2016 07:00	159.685658	15.6783677	334
09.05.2016 08:00	277.494545	30.9017045	489
09.05.2016 09:00	364.407863	29.034808	626
09.05.2016 10:00	426.210414	47.1731885	734
09.05.2016 11:00	447.51095	63.8349693	803
09.05.2016 12:00	434.373424	34.9479825	827
09.05.2016 13:00	418.002601	49.1309511	800
09.05.2016 14:00	344.373711	42.8260029	729
09.05.2016 15:00	227.256484	0.5205514	603
09.05.2016 16:00	90.4439923	-41.8869009	404
09.05.2016 17:00	8.57314675	-39.4240978	210
09.05.2016 18:00	-18.0032375	-7.28173392	122
09.05.2016 19:00	-37.0510168	-9.69552421	30
09.05.2016 20:00	-29.863237	-2.10528133	0
09.05.2016 21:00	-31.3599013	2.16407578	0
09.05.2016 22:00	-25.5610128	7.44734721	0
09.05.2016 23:00	-24.4654575	5.82370468	0
10.05.2016 01:00	-25.5010135	2.57932133	0
10.05.2016 02:00	-25.925458	1.65592589	0
10.05.2016 03:00	-25.5743483	2.8966655	0

10.05.2016 04:00	-19.628791	12.3345688	0
10.05.2016 05:00	4.4145355	15.0446635	17
10.05.2016 06:00	56.5178798	28.0117116	117
10.05.2016 07:00	154.516766	53.4415721	288
10.05.2016 08:00	234.71899	35.9613835	416
10.05.2016 09:00	316.732875	22.520126	474
10.05.2016 10:00	242.194553	-74.924551	474
10.05.2016 11:00	195.023442	-153.534931	451
10.05.2016 12:00	224.278999	-118.244015	470
10.05.2016 13:00	253.166783	-75.9490273	445
10.05.2016 14:00	188.213436	-80.4804603	365
10.05.2016 15:00	91.1234268	-96.4566693	264
10.05.2016 16:00	28.1556538	-69.4525739	141
10.05.2016 17:00	-2.46768775	-22.4819325	98
10.05.2016 18:00	-30.028791	-14.734825	36
10.05.2016 19:00	-37.427682	-10.0267274	20
10.05.2016 20:00	-34.308794	-7.06897183	0
10.05.2016 21:00	-29.398792	3.77586392	0
10.05.2016 22:00	-27.0876803	5.1358645	0
10.05.2016 23:00	-25.5887918	3.38388868	0
11.05.2016 01:00	-23.7965698	3.77302433	0
11.05.2016 02:00	-28.494348	-1.14376661	0
11.05.2016 03:00	-28.1965705	-0.00814928	0
11.05.2016 04:00	-36.0799027	-5.01845651	0
11.05.2016 05:00	-6.9254575	0.82556301	18
11.05.2016 06:00	60.031211	24.4533619	140
11.05.2016 07:00	123.870098	8.50713353	343
11.05.2016 08:00	226.752339	16.0314682	490
11.05.2016 09:00	333.134271	28.4474107	627
11.05.2016 10:00	380.942059	40.3812144	734
11.05.2016 11:00	397.509554	24.3099797	785
11.05.2016 12:00	451.755402	74.449285	772
11.05.2016 13:00	401.076215	77.553984	786
11.05.2016 14:00	294.074539	24.0725178	727
11.05.2016 15:00	246.395668	41.1869155	617
11.05.2016 16:00	122.789272	0.60919352	485
11.05.2016 17:00	13.2909298	-25.9603982	320
11.05.2016 18:00	-22.098795	-12.1498432	157
11.05.2016 19:00	-36.136572	-8.34511184	50
11.05.2016 20:00	-31.8276812	-3.77433896	1
11.05.2016 21:00	-32.2276805	1.20543244	0
11.05.2016 22:00	-29.5699027	2.47246915	0
11.05.2016 23:00	-22.2610145	6.554382	0
12.05.2016 01:00	-25.345459	1.63777706	0
12.05.2016 02:00	-23.628792	3.15333285	0
12.05.2016 03:00	-31.5165705	-3.68259364	0
12.05.2016 04:00	-38.409904	-7.26240844	2
12.05.2016 05:00	1.012315	1.76544895	54
12.05.2016 06:00	53.9878755	6.03289425	182
12.05.2016 07:00	158.820105	22.9005149	336

12.05.2016 08:00	275.261192	36.9305312	492
12.05.2016 09:00	358.234542	28.3508509	629
12.05.2016 10:00	413.950931	29.6777431	735
12.05.2016 11:00	432.895931	33.3709405	794
12.05.2016 12:00	447.811472	37.4878873	808
12.05.2016 13:00	375.756233	-12.1888584	777
12.05.2016 14:00	315.647872	-1.0023096	688
12.05.2016 15:00	219.289283	-13.3754592	573
12.05.2016 16:00	113.46094	-21.6227504	440
12.05.2016 17:00	30.0537128	-16.2213305	312
12.05.2016 18:00	-18.7565715	-10.8023255	167
12.05.2016 19:00	-35.9776805	-8.02361364	51
12.05.2016 20:00	-32.8043515	-4.7185123	1
12.05.2016 21:00	-32.2210133	-2.50975501	0
12.05.2016 22:00	-27.4143462	4.17475404	0
12.05.2016 23:00	-24.6899022	3.64666714	0
13.05.2016 01:00	-26.505459	0.70493764	0
13.05.2016 02:00	-34.0387933	-7.2350016	0
13.05.2016 03:00	-34.1221255	-5.91586454	0
13.05.2016 04:00	-36.7387933	-8.93741812	2
13.05.2016 05:00	1.03120275	4.75313873	56
13.05.2016 06:00	64.4767713	19.1546432	176
13.05.2016 07:00	165.298991	36.3465214	325
13.05.2016 08:00	280.456776	52.1288957	478
13.05.2016 09:00	345.542326	17.5424079	625
13.05.2016 10:00	427.127049	46.9908596	712
13.05.2016 11:00	440.828436	42.8950159	683
13.05.2016 12:00	434.534838	10.2952226	787
13.05.2016 13:00	396.279543	8.16296612	798
13.05.2016 14:00	211.803996	-106.537988	710
13.05.2016 15:00	206.735113	-33.1047515	570
13.05.2016 16:00	120.298712	-21.8338568	468
13.05.2016 17:00	40.5489838	-4.85212441	317
13.05.2016 18:00	-24.4865698	-16.2739661	168
13.05.2016 19:00	-36.841015	-8.85079202	56
13.05.2016 20:00	-36.8943475	-8.364308	1
13.05.2016 21:00	-32.8787915	-2.91079135	0
13.05.2016 22:00	-34.1265688	-2.43660435	0
13.05.2016 23:00	-25.9599027	2.18061717	0
14.05.2016 01:00	-25.7632373	1.02691246	0
14.05.2016 02:00	-25.1399023	1.72475369	0
14.05.2016 03:00	-28.7032375	-0.085001	0
14.05.2016 04:00	-31.1165692	-3.81751978	1
14.05.2016 05:00	-2.02212475	4.92654674	25
14.05.2016 06:00	38.6212077	4.10921691	105
14.05.2016 07:00	88.054543	-4.81498414	236
14.05.2016 08:00	119.060098	-53.5770134	347
14.05.2016 09:00	159.342323	-97.1288293	414
14.05.2016 10:00	186.748147	-86.6475942	502
14.05.2016 11:00	295.614543	39.2508325	438

14.05.2016 12:00	270.884543	26.443184	449
14.05.2016 13:00	191.106769	-49.63298	513
14.05.2016 14:00	212.237052	12.8978178	451
14.05.2016 15:00	158.923985	7.13647592	463
14.05.2016 16:00	73.1712105	-25.1520199	344
14.05.2016 17:00	35.52343	6.19244144	252
14.05.2016 18:00	-20.4743493	-7.01413707	99
14.05.2016 19:00	-34.0032368	-6.40842079	33
14.05.2016 20:00	-31.5932373	-3.48466569	0
14.05.2016 21:00	-31.3876795	-2.25227515	0
14.05.2016 22:00	-27.4454585	4.08555504	0
14.05.2016 23:00	-30.0021248	-1.99944443	0
15.05.2016 01:00	-33.4621243	-7.09660411	0
15.05.2016 02:00	-29.5421255	-2.86067936	0
15.05.2016 03:00	-29.6510153	-1.05129726	0
15.05.2016 04:00	-31.8410143	0.34457881	0
15.05.2016 05:00	-6.207686	-1.63260402	17
15.05.2016 06:00	59.917876	21.4950069	70
15.05.2016 07:00	124.010104	27.0533135	168
15.05.2016 08:00	170.250933	3.53489478	255
15.05.2016 09:00	218.56176	-7.95512769	508
15.05.2016 10:00	134.531491	-103.600036	471
15.05.2016 11:00	345.020369	120.737508	660
15.05.2016 12:00	120.813153	-146.007322	612
15.05.2016 13:00	296.413991	81.9786725	501
15.05.2016 14:00	293.256755	109.426268	507
15.05.2016 15:00	186.70566	43.1464852	418
15.05.2016 16:00	5.653419	-89.2786457	266
15.05.2016 17:00	7.99454075	-21.5118045	194
15.05.2016 18:00	-25.8910135	-14.2396168	102
15.05.2016 19:00	-36.3632353	-8.95304879	33
15.05.2016 20:00	-35.8832398	-7.96391186	1
15.05.2016 21:00	-32.3087913	-3.75319082	0
15.05.2016 22:00	-29.0999013	1.35234693	0
15.05.2016 23:00	-28.7499038	-1.31401358	0



800
600
400
200
0
-200
08-05
09-05
10-05
11-05
12-05
13-05
14-05
15-05
16-05
Date
Power [kW]
Error [kW]
Irradiation [Wh/m²]