Wind Power Forecasting Considering Icing

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Abstract

A considerable amount of wind energy developments are situated in regions with a potential for atmospheric icing. The goal of this master’s thesis is to investigate the potential of wind energy forecasting considering icing. The forecast system consists of the atmospheric model WRF using a Kalman filter post-processing and an icing algorithm. The system is applied and verified for a test-site in Switzerland which encounters frequent icing during winter. The Kalman-filtered model output of wind speed has a RMSE (root mean square error) of 2.05m/s. The icing model predicting the occurrence of most icing events with a Probability of Detection of 0.94 vs. a False Alarm Ratio of 0.34. The power forecast considering icing reduced the normalized RMSE to 22% compared to 27% without taking icing into account.
## Contents

Abstract i  
Contents ii  

1 Introduction 1  
  1.1 Wind power forecasting 2  
  1.2 Atmospheric Icing and its prediction 3  
  1.3 Goals 4  
  1.4 Outline 5  

2 Test site St.Brais 6  
  2.1 Overview 6  
  2.2 Ultrasonic-anemometer on gondula 10  
  2.3 Ice and Cloud Classification 12  

3 The model system 17  
  3.1 The atmospheric model WRF 18  
  3.2 Kalman filter 20  
  3.3 Power curve 21  
  3.4 Icing algorithm 22  

4 Results 25  
  4.1 Evaluation protocol 25  
  4.2 Direct model output from WRF 26  
    4.2.1 Wind Speed Evaluation 26  
    4.2.2 Temperature Evaluation 29  
    4.2.3 Cloud Water Evaluation 31  
  4.3 Kalman filter verification 31  
  4.4 Icing forecasts 33  
    4.4.1 Evaluation 33  
    4.4.2 Sensitivity studies 34  
  4.5 Power forecasts and icing 36  

5 Conclusions and Outlook 40  

Glossary 41  
Bibliography 43
1 Introduction

The number of wind farms in cold climate regions increases, e.g. in Scandinavia, North America and the European Alps. The wind potential in cold climate regions is generally high (Laakso et al. 2010; Baring-Gould et al. 2010) but icing is a limiting factor (Westerhellweg and Mönnich 2010). Laboratory studies and simulations show that power production is being significantly reduced due to aerodynamic losses caused by icing (Jasinski et al. 1998; Wang et al. 2007; Barber et al. 2009). Besides loss of aerodynamic efficiency of the blades under the influence of ice there are also significant safety concerns. On the one hand there is the risk of ice throw (Seifert et al. 2003) (see figure 1.1). On the other hand there is the problem of turbine fatigue due to additional loads and imbalance caused by ice (Frohboese and Anders 2007). These factors normally enforce the operator to switch off the Wind Turbine (WT) when icing is experienced. As soon as the WT is on idle, either a heating system is started or the WT remains idle until the ice melts off due to changing atmospheric conditions. It has been shown, that blade heating reduces the loss compared to a complete shutdown (Cattin 2010). To forecast electricity production from a WT, icing conditions in addition to wind conditions have to be predicted.

Figure 1.1: Ice fragment thrown from a wind turbine. (Photo taken by the author)
1.1 Wind power forecasting

Proper wind power forecasts are vital for an efficient integration of wind energy into the electricity market. A challenge of the network operator is to fit the amount of energy production to the demand. Since buffer capacities in energy grid systems are either limited or do not exist, the gap between wind energy production and energy demand has to be bridged by other suppliers, such as nuclear power plants. There are different time frames used for wind power forecasting for a range of purposes. The shortest extends up to one day. This timescale is important for the intra-day energy market. The intermediate timescale usually forecasts 1-2 days and is used on the energy market for trading the next day’s energy demands. This is the timescale this thesis will focus on. Forecasts with longer time horizons are mainly used for maintenance planning. For the 1-2 day time horizon, numerical weather models are usually used as the basis for wind power predictions.

Much effort has been spent on wind power forecasts in flat terrain (Monteiro et al. 2009; Costa et al. 2008; Landberg et al. 2003) and some on forecasting in complex terrain (Dierer et al. 2009; Parkes and Tindal 2004; Marti et al. 2003). There are many approaches using Numerical Weather Prediction (NWP) model outputs for wind power forecasting. Due to sub-grid features the direct model output does usually include a systematic error, called bias. This is especially true in complex topography. There are two downscaling approaches to lower this model bias. One is a dynamic downscaling using either fine resolved NWP models or Computational Fluid Dynamics (CFD) models (Dierer et al. 2009; Kanohgi et al. 2007; Giebel 2006) to resolve the fine topographic features. For the latter, a CFD model is usually run for different wind directions and atmospheric stabilities resulting in a multiplication factor for each direction. A overview of dynamic downscaling approaches is given in Giebel et al. 2006. The other approach is statistical downscaling. An overview of statistical downscaling methods is given in Nielsen et al. 2006. For that, empirical relations of the forecast error to different predictors are studied. The most common way of doing that is using a NWP model in combination with computer learning algorithm (e.g. neuronal network) (von Bremen 2007). The downside of that approach is a need for an extensive learning data set in order to set up the model. In the current work, a recursive statistical approach is used instead. The major reason for that being the lack of training data and the promising results with this specific method in past studies (Crochet 2004).

The prognostic variable that stands in direct relation with the wind power is the horizontal wind speed. Formula 1.1 (taken from Ramakrishnan and Srivatsa (2010)) explains the relation between wind speed and the available power to a WT. It is called Betz’ law. Since the produced power is directly proportional to the kinetic
1.2 Atmospheric Icing and its prediction

Atmospheric icing on structures, such as power-lines, cable-cars, rotor blades of a WT etc, occurs if freezing rain, wet snow or super-cooled cloud droplets get in contact with their surfaces. Figure 1.2 shows the different stages during an icing process on structures like a WT. Initially the atmospheric conditions change to allow icing, meaning that the temperature drops to subzero temperatures and cloud droplets are available. This sets the beginning of the meteorological icing. At this initial stage structures exposed to the onset of icing conditions may still be too warm to allow ice nucleation on their surface. This leads to a time lag between start of meteorological icing and the onset of instrumental icing which is defined by the formation of ice crystals on the structure’s surface. This lag time is called incubation time. The same is true for the time when the meteorological icing conditions stop. At that stage, there will usually still be ice on the structures, before either the atmospheric temperatures reach above-zero temperatures, longwave radiation becomes stronger or an active heating mechanism sets in. This time is called recovery time. Power-losses due to icing obviously occur during times of instrumental icing only.

energy acting on the rotor blades, the air density has to be taken into account when calculating production values from wind speeds. ($\rho$ stands for the air density, $A$ for the cross section of the rotor blades and $v$ for the wind speed).

$$P = C_p \frac{1}{2} \rho A v^3$$  \hspace{1cm} (1.1)

The WT can capture only about 59% of the energy available theoretically (Betz 1920). Therefore an efficiency factor $C_p$ has to be added to the formula above. Furthermore, there is of course an upper limit of power production and wind speed in which the WT can operate. If the upper wind threshold value is reached, the pitch control of the WT usually turns the blades slightly out of the wind. The resulting relation is described by a power curve which characterises a WT and it is usually provided by the manufacturer. The power curve provided by the manufacturer may in some cases differ from the empirically derived power curve. This is due to the fact, that the designer’s power curve has to be established for clearly defined conditions (IEC:61400-12-1 2005), which may not apply at the deployment site of the turbine.
1.3 Goals

The aim of this study is to investigate the potential of forecasting wind power, with special focus on icing. Investigations are based on information from two WT

In order to forecast icing there are different approaches. There are physical and statistical models. Statistical approaches simulate the empirical relationships between icing as predictant and multiple predictors. Physical models on the other hand try to capture all processes that lead to icing and incorporate the physical relation into one model. The algorithm used in this work is a physical approach.

To the author’s knowledge, none of the wind power forecasting systems takes care of the icing problem. The icing modeling itself however has been explored independently in some studies. Seifert (2010) uses a neuronal network to model the icing. Prodi et al. 1994 uses a ballistic model to simulate the ice accretion on a cylinder. In this model the angular position of the impinging droplet on the cylinder is stochastically determined. In this study, a physical model approach, based on the icing algorithm by Makkonen (2000), is used. Dierer et al. 2009 showed that this accretion model is suitable to predict the occurrence and the duration of icing events. The same study demonstrated for the Swiss Jura region a 2-3km NWP model resolution is sufficient to get acceptable results. Comparing their simulations with ice-load sensors showed the maximum ice-load not being captured accurately enough. They explained this failure by the cloud droplet concentration being unknown. A similar physical algorithm was developed by Szilder et al. 1988 with the focus on the resulting shape of the ice accretion.

Figure 1.2: Different stages during icing episodes. Based on Heimo et al. (2009)
that are operating in Switzerland in a region with frequent icing. Wind power forecasts are calculated using the weather forecast model Weather Research and Forecasting (WRF) coupled with a Kalman filter (Kalman 1960) and an icing algorithm (Makkonen 2000). The Kalman filter corrects the bias of the wind speed calculated by the WRF model. It is based on the method described in Crochet (2004). The model system is set-up and icing and wind power forecasts are simulated for the winter 2009/2010. The performance of the individual parts of the modeling system (WRF model, Kalman filter and the icing algorithm) will be tested against measurements using statistical scores. The ability of the model system to predict wind power under icing conditions will be evaluated. Statistical scores shall show whether the consideration of icing improves the forecast quality.

1.4 Outline

The following section (Section 2) will give an overview of the test site, used for the evaluation of the forecasting system. It will also explain why it was chosen as test site. Section 3 will focus on the methodology used in this thesis. First it provides an overview of the forecasting system and the interaction of its components. This is followed by details of the individual components. The wind power forecasts are based on the results of the WRF atmospheric model (Section 3.1) which are post-processed using a Kalman filter (Section 3.2). Icing forecasts are calculated separately (Section 3.3).

In the ‘Results’ section (Section 4) some specific results of the forecasting system as a whole will be presented, and a discussion of those added. The performance of each part of the forecasting system will also be discussed. WRF (Section 4.1), Kalman filter (Section 4.2), and the icing algorithm (Section 4.3). At the end the performance of the complete system is evaluated (Section 4.4).

A ‘Conclusion’ section (Section 5) will focus on the question whether wind power forecasting with special consideration of icing is feasible, and what kind of problems have to be expected. The ‘Outlook’ will focus on potential extensions of the system.


2 Test site St.Brais

2.1 Overview

To study the feasibility of wind energy forecasts considering icing, an appropriate test site has to be found. In this case, it was already chosen and set up prior to the master thesis. This is due to the fact that another ongoing research project imposes the same requirements to its test site. The requirements are the following:

Existence of a WT and access to its production data, wind speed measurements at hub-height and some data to verify the icing simulations. Equally important is the general validity to the majority of other sites facing the icing problem, hence not specific. The following data was provided from the other research project: webcam pictures (subsection 2.3), wind measurements (subsection 2.2) and production data of the WT. The other research project extends over the period of two winters: 09/10 and 10/11, from which the first winter 09/10 is used in this master thesis. The test site St.Brais with two WT is situated in the Swiss Jura (lat=47.30; lon=7.10) at an elevation of 1049m a.m.s.l. (ground level) on top of a foothill (figure 2.1). The topography around St.Brais can be regarded as complex in terms of modeling. This site is exposed to frequent icing and may be representative for many sites either in planning stage or in operation already. According to Switzerland’s icing map (figure 2.2) 14-16 days per year with prevailing icing conditions can be expected at 100m above ground level.
2.1 Overview

Figure 2.1: The spatial location of the test site St.Brais (red circle) and the surrounding topography based on SRTM3 digital elevation model.

Figure 2.2: Map of icing frequency at 100m height above ground (Dierer et al. 2010)

Two Enercon WT (E-82) are installed on the test site (figure 2.3). Both of them are equipped with blade heating systems. Once power generated by the WT drops below the potential output, calculated with the measured wind and the power
curve, the turbine stops due to assumed icing of the blades. The halt of the WT operation is followed by a heating cycle of 3 hours before the WT is re-started. The heating system of WT1 (figure 2.3) was deactivated from 06/01/10 until 08/02/10. Without blade heating, a restart after icing requires the atmospheric temperature to be above 2°C. Wind speed, atmospheric temperature and humidity are measured at hub-height using a Ultra Sonic Anemometer (USA) and temperature and humidity sensors respectively. There are also two webcams monitoring icing on blades and on the structure on which the USA is mounted to. All these components are installed on the nacelle (figure 2.4), 78m above ground level.

In addition Laser Detection and Ranging (LIDAR) measurements with a Leosphere Windcube were carried out in January 2010 in order to establish undisturbed wind speed measurements. The outcomes were used to validate the USA’s measurements at the nacelle location. The LIDAR was located 100m to the south-east of WT1 (figure 2.3) on a elevation of 1030m a.m.s.l. The range gates were set to 20m and the 80m level was used for the evaluation. The measurements were logged as 10minutes mean values. The data availability at the 80m level was 91% during the period. The reduction is mostly due to precipitation. Albers and Janssen (2008) evaluated the accuracy of the Windcube LIDAR compared to a cup anemometer at 98.7m and came up with a standard deviation between the measurements of 0.24 m/s, or 2.2% in terms of 10minute averaged wind speed. In order to verify the power forecasts, 10 minute production data was made available for that study. To sum up, the test site in St.Brais meets the requirements imposed on it.
Figure 2.3: Positions of the two WT and the LIDAR measurement. Topography based on SRTM3 digital elevation model. One cell is three-arc-second (about 90 meters) wide and high.
2.2 Ultrasonic-anemometer on gondula

LIDAR measurements were available for a three weeks only. This is why the USA attached to the nacelle was used to verify and train the Kalman filter. However, wake effects and wind shadow of the rotor blades influence the USA measurements. LIDAR measurements from 2010-01-05 to 2010-01-27 were used to identify the correlation between undisturbed wind measurements and wind measurements disturbed by the blades. The mean wind speed during that period was $0.4 \text{m/s}$ on WT1 and $0.8 \text{m/s}$ on WT2 lower than the one measured at the same height by the LIDAR. The standard deviation between the measurements from the LIDAR and the USA was $0.9 \text{m/s}$ for WT1 and $1.1 \text{m/s}$ for WT2. The offset can be explained via Betz’ law (formula 1.1). The mean wind speed measured by the LIDAR during that was $4.9 \text{m/s}$ and that measured by the USA on WT1 consequently $4.5 \text{m/s}$ and that on WT1 $4.1 \text{m/s}$. The Betz factor for an ideal turbine is $0.59$, meaning it extracts $59\%$ of the kinetic energy of the oncoming wind. The remaining energy reaches the USA behind the WT. In this example a factor of $0.5$ for a real turbine is assumed. Accord-
ing to Betz’ law (formula 1.1), 50% of the available kinetic energy are proportional to $f f_{USA}^3$. The available kinetic energy itself is proportional to $(1 \cdot f f_{USA}^3)/0.5$ and the wind speed in front of WT1 can therefore be calculated by:

$$f f_{LIDAR} = \left( \frac{1 \cdot f f_{USA}^3}{0.5} \right)^{(1/3)} = \left( \frac{1 \cdot 4.1 m/s^3}{0.5} \right)^{(1/3)} = 5.2 m/s \quad (2.1)$$

For this study the measurements have not been adjusted with the offset. However the method used to calculated the power values from the wind speed was trained with data from the USA (subsection 3.3) and therefore is not affected by this offset. Furthermore it is still being investigated whether LIDAR data can be taken as reference in complex topography (El Kasmi et al. 2010).

Figure 2.5 shows that the predominant wind-direction in January 2010 was from the sector south-west. The gondola position shows a similar pattern as that measured by the LIDAR. The dominant wind direction measured by the LIDAR is $210^\circ$. The dominant position of the gondola from WT2 spreads over a wider angle. The reason for that is a channeling effect between the WT1 and the Trees in to the South of the LIDAR (figure 2.3) or due to the different response times of LIDAR compared to the gondola position.

![Figure 2.5: Wind roses of the LIDAR measurement at 80m and the position of the gondola of WT2](image)

Figure 2.6 shows that the measurements of the LIDAR are generally of lower magnitude than the USA measurements when the wind direction is between $210^\circ$ to $160^\circ$. In the complementary, south-west, sector the opposite is true. This is due to the fact, that to the south-west of the LIDAR, there are trees with a height of about 30 meters (figure 2.7). In the south-western direction relative to WT1 there
are fewer trees. In addition, the LIDAR is positioned about 20m below the ground elevation at WT1. This results in more turbulence for the LIDAR, when the wind is blowing from the south. At around 50° the wake of WT2 is visible in the reduced wind speed of the LIDAR compared to WT1.

![Figure 2.6](image)

**Figure 2.6:** USAs wind speed measurements (on WT1) compared with the LIDAR measurements at 80m Level. Both times-series are averaged to 10min intervals.

![Figure 2.7](image)

**Figure 2.7:** Panorama around the LIDAR. (Photo taken by Meteotest) Direction is not linear!

### 2.3 Ice and Cloud Classification

No measurements of ice load are available for winter 09/10. This is why a rough classification of ice load during the icing events, based on webcam observation, has been introduced. Two webcams on WT1 automatically take pictures every half hour of the blades (webcam1) and the USAs (webcam2), respectively. Both cameras keep
working during night hours but in infrared mode. Webcam1 uses motion control to capture the blade at an ideal angle to see icing on its leading edge. Webcam2 was used as basis for the classification. The first reason for that choice was, that the sensors observed by webcam2 are not moving. Hence the quality of these images is much better than that of the images of the blades. This is even more accentuated during nighttime and during cloudy conditions and this is when the icing usually sets in. Another reason for choosing Webcam2 as basis for the classification is the following: Since icing data of blades, captured by the webcam1, include heating signals this renders such data unsatisfactory.

The images were classified based on the amount of ice built-up, icing peaks (time between ice growth and reduction) observed, and if structure is in-cloud (figure 2.9).

The amount of icing has been classified as follows:

- 0 Does not have any ice at all.
- 1 Ice on parts of the structure; beginning of icing, or melting of ice stuck to the structure.
- 2 Solid ice cover along the whole windward side of the structure.
- 3 Ice extending towards the windward side and around the structure.
- 4 The whole structure is covered in ice, no icefree metal surface visible.

Figure 2.8 shows examples of the different icing categories.
2.3 Ice and Cloud Classification

![Figure 2.8: Examples for the icing classes 1-4. Windward site on the left.](image)

![Figure 2.9: Examples of in-cloud classification.](image)

To aid the manual icing classification, overview figures were assembled (figure 2.10). They consisted of a picture of the USA, an image of the blade and a satellite picture from within 30 min of the event.
Figure 2.10: Classification cockpit consisting of the sensor camera picture, blade camera picture, a satellite image and a data-field.

During winter 09/10 (2009-11-28 to 2010-03-15) six major icing events of the sensors reaching at least class 3 were observed and documented. They lasted over a total 1270 hours (figure 2.11), which is 50% of the time. The intermediate moment between a growing- and shrinking-phase of the ice mass is called peak. This is marked in red, where it was distinguishable on the webcam pictures.
The test site was in-cloud (fog) 912 hours (36% of the time) in the time from 2009-11-28 to 2010-03-15. (figure 2.12).

Figure 2.11: Icing classification based on the webcam pictures directed towards the USA on WT1

Figure 2.12: Cloud classification based on the webcam pictures on WT1. Grey areas mark the time when the turbine was in-cloud.
3 The model system

The power production at the test site is simulated with the model system shown in figure 3.1. First the numerical weather prediction model WRF is run. The Direct Model Output (DMO) of wind speed (ff), cloud water content (Q CLOUD) and the temperature (T) for the test-site are then post-processed. Power forecasts are calculated from Kalman filter post-processed wind speed combined with an empirical relation of measured wind vs. produced power. Icing forecasts are calculated with a physical icing algorithm based on the Kalman filter post-processed wind speed and the DMO of cloud water and temperature. The power forecast and the icing forecast are subsequently combined with a simple algorithm into power forecast considering icing. The respective parts of the model system are discussed in the following subsections.

Figure 3.1: Schematic overview of modeling system. Algorithms and programs are marked green, output variables are marked yellow and measurements are marked blue. QCLOUD = cloud water content, ff = wind speed, T=temperature.
3.1 The atmospheric model WRF

For the atmospheric simulations, the WRF model with the Advanced Research WRF (ARW) dynamic solver in the version 3.2 is used. It is a mesoscale model with fully compressible non-hydrostatic equations. The Global Forecast System (GFS) data with 0.5° resolution initialized at 12 UTC are used to calculate the boundary conditions. The initial 12 hrs are not used to allow for model spin-up. A forecast for the next day (12h-36h forecast time) and one for the day after (36h-60h forecast time) is calculated. They are subsequently assembled into long time series with linearly interpolated point values in space, from 28.11.2009 to 15.03.2010. The focus is on the first forecast day (12h-36h forecast time). The second forecast day (36h-60h) is only used for sensitivity studies.

The biggest domain in WRF has a grid spacing of 12km and consists of 100x100 grid boxes in east-west and north-south direction. The nesting is shown in figure 3.2. The model time-step was 10s.

![Nested WRF model domains with horizontal mesh with of 12, 4 and 1.33km respectively. The position of the St.Brais test site is marked by a red dot.](image)

**Figure 3.2:** Nested WRF model domains with horizontal mesh with of 12, 4 and 1.33km respectively. The position of the St.Brais test site is marked by a red dot.
3.1 The atmospheric model WRF

The model system

SRTM3 reference Topography

Latitude (deg E)  Longitude (deg N)

7 7.1 7.2

47.2

47.3

47.4

1.33km Model Grid

Latitude (deg E)  Longitude (deg N)

7 7.1 7.2

47.2

47.3

47.4

Elevation [m a.m.s.l]

500

600

700

800

900

1000

1100

1200

1300

Sub-grid scale physical processes are parameterised using the following schemes: Turbulence is calculated with the Mellor-Yamada-Janjic Turbulence Kinetic Energy (TKE) scheme (Janjic 2002). The surface layer is parameterized using a Moning-Obukhov scheme. The land surface is calculated with the unified Noah land surface scheme (Chen and Dudhia 2001). Cumulus convection parameterization is only applied to the outer model domains at 4km and at 12km because at 1.3km convection can be simulated directly (Petersen et al. 2009). The cloud microphysics are parameterized with the (Thompson et al. 2008) scheme. It is a two moment (mass and number concentration) scheme, which is considered to be important for the prediction of supercooled water in the atmosphere. Its predicted mass variables are Qc (cloud water), Qi (cloud ice), Qr (rain), Qs (snow) and Qg (graupel). Its predicted
number variables are ice and rain number concentration. Radiation is simulated using the RRTM longwave radiation scheme (Mlawer et al. 1997) and the Dudhia (Dudhia 1989) shortwave radiation scheme.

For evaluation the model results need to be interpolated to hub-height. The question arises whether it is more realistic to use real height above sea level or height above ground. The second approach conserves the boundary layer properties, hence the wind profile. Since this is the most important variable for the wind power forecasting, height above ground is used to interpolate the data to the position of the Nacelle at 78m above ground. The real terrain height of the test site is 1049m a.m.s.l. In domain 3 with the 1.33km resolution, the terrain elevation at this point is 911m a.m.s.l. Assuming a lapse rate of 0.65°C this would lead to a temperature bias of less than a 1°C. In the domain with 4km resolution, the terrain height at this point is 863m a.m.s.l.

First the iteration time steps were set to 30s which in some cases became unstable. Therefore the time-step was decreased to 10s.

3.2 Kalman filter

The resolution of the WRF simulations is too worse to capture the details of the topography and associated flow. This leads to systemic error of the wind velocity profiles close to the ground. There are different approaches to take care of this problem. A discrete Kalman filter algorithm is used here. This filter algorithm is based on a dynamic linear regression model, represented in formula 3.1, simulating the error of the wind forecast. The forecast error $\hat{\text{err}}_{ff}$ is the sum of the systematic offset ($x_1$), an error ($x_2$) that is proportional to the forecasted wind speed $f f_{MOD}$ and the uncertainty of this model ($\eta_{ff}$).

$$\hat{\text{err}}_{ff}(t) = x_1(t) + x_2(t) \cdot f f_{MOD}(t) + \eta_{ff} \tag{3.1}$$

The algorithm iteratively predicts the linear regression coefficients $x_1$ and $x_2$ for every forecast hour of the following day. It uses the forecast error of the current day to forecast the regression coefficients of the following day. Thereby the algorithm extracts the systematic error from the forecast error of the current day and uses this information to predict the error of the following day, hence recursive. It works like a predictor corrector algorithm because it first corrects the linear regression coefficients predicted on the previous day and then as the next step predicts the regression coefficients for the following day. However in this algorithm the prediction is a copy of the corrected regression coefficients only. The initial values of the variances are set to a predefined signal to noise ratio of both regression coefficients. They were taken from a previous project (Dierer et al. 2009). Tests
confirmed, that the values lead to the best results in this case. The formulas of the iterative algorithm are applied according to Crochet (2004).

The setup enables the filter to capture diurnal fluctuations in the systematic error. However, if any rapid changes in the synoptic situation take place, this would not be captured by the algorithm, since it directly applies the linear regression coefficients of the previous day.

The Kalman filter can also be applied directly to the power instead of wind speed. However since the logged power values include icing information this procedure would lead to errors once icing status changes.

### 3.3 Power curve

The power production is calculated from the wind speed by using the empirical power curve plotted as blue line in figure 3.4. This power curve had been calculated with time series of power production and wind speed measured at hub-height during the icefree period of Summer 2010 (2010-04-01 to 2010-08-01) and is considered to be representative for the the local conditions. As the wind speed measurement at the nacelle is located behind the rotor blades, the values are generally too low compared to the real conditions. Furthermore, the air density at at 1049m a.m.s.l. (1.112kg/m3) does not correspond to standard conditions. For these two reasons, the empirical power curve does not necessarily fit exactly with the manufacturers curve (ENERCON 2010).
3.4 Icing algorithm

The icing algorithm (Makkonen 2000) simulates the accretion of ice mass, the duration of the icing and the removal of the icing due to melting. It approximates the ice accretion due to in-cloud icing for a freely rotating cylindrical structure instead of the actual one. The diameter of the cylinder is adjustable. The types of icing permitted are either rime or clear ice. The algorithm takes into account cloud droplets and freezing drizzle but not wet snow nor hoar frost. Freezing drizzle is not very frequent, but reaches very high ice-masses if it occurs. Wet snow was not considered since it was very seldom observed on the webcam pictures. Ronsten (2008) wrote: "Wet snow can stick to a surface if the temperature is between 0°C and 3°C. This is due to the snow having some liquid water present, which allows the snow crystals to bind together when they come in contact on the surface. Wet snow often has a low binding strength while forming, but can become very hard and strongly bound if the temperature subsequently falls below 0°C." The icing due to hoar frost produced by the Bergeron process is usually negligible (Makkonen 1984). The icing algorithm accounts for the time of instrumental icing and not meteorological icing (figure 1.2).

Not all processes that lead to removal of ice mass are captured in this algorithm. It only reduces the ice mass when atmospheric temperatures are above 0°C and the
energy balance of the ice is being positive. Other processes for the removal of ice mass are:

- Melting
  - Longwave radiation due to cloud cover
  - Blade heating system

- Sublimation
  - Solar irradiation (UV)
  - Blade heating system

- Shedding
  - Vibration of the WT
  - Erosion by wind
  - Centrifugal forces when WT is turning

Formula 3.2 shows the basic equation of the icing algorithm with \( w \) being the water mass concentration in the atmosphere (cloud and rain water), \( v \) is the wind velocity normal to that surface and \( A \) is the projected area of the structure surface. The product of \( w \) and \( v \) equals the flux density. The \( \alpha_n \) are factors which account for the efficiency of different processes in the icing process. They vary from 0 to 1. The \( \alpha_1 \) (Figure 3.5) factor compensates for the collision efficiency. It describes the fact that small cloud droplets and ice particles tend do follow the streamlines due to their tiny inertia. Not all cloud droplets and ice particles stick to the surface after the hit. Some of them bounce off. This collection efficiency is described via \( \alpha_2 \). The last correction factor, \( \alpha_3 \), describes the accretion efficiency. It accounts for the fact that freezing cloud droplets release latent heat to the icing surface. If the heat transfer away from the surface is not able to compensate for that heating, a liquid layer will persist. In that case some water may escape via run-off.

\[
\frac{dM}{dt} = \alpha_1 \alpha_2 \alpha_3 w v A \quad (3.2)
\]
The cloud droplet concentration strongly influences the accreted ice mass. It had to be prescribed as a constant factor because it is not a forecasted variable of the microphysic scheme (Thompson et al. 2008) used for this study. A value of 200 cm$^{-3}$ was chosen for this work. This value for the cloud droplet concentration is used by the algorithm to calculate the median volume droplet size. Gultepe and Isaac (2004) suggest a value between 100 cm$^{-3}$ and 600 cm$^{-3}$ over land. Isaac et al. (2001) made in-situ measurements in a winter storm and came up with a mean of 144 cm$^{-3}$. Therefore a reasonable number seemed to be 200 cm$^{-3}$. Another tunable variable is the initial diameter of the freely rotating cylinder. Sensitivity studies, while setting up the modeling system, have shown that these variables affect the ice mass only but not the time when icing sets in. However the ice mass has influences the duration of the icing event.

Figure 3.5: Collision efficiency for the flow around a cylindrical obstacle From Makkonen (2000)
4 Results

The forecasted values of ice mass, wind and power were verified with production data from the WT, with the wind and temperature measurements taken on the nacelle, with the classified webcam pictures, with LIDAR taken at the test-site, atmospheric soundings from Payerne weather observation and Automatic Measurement Network of Swiss Weather stations (SwissMetNet) Stations close to the test-site. Icing classification derived from observations with the webcams was used as reference for icing forecast. In addition, the differences between theoretical power output of the WT and power actually delivered by the WT were used as indicators for icing onset. The theoretical power production is the look up value of the measured wind in the power-curve. Finally the temperature forecasts have been compared and verified.

There are three different time windows under investigation. The WRF model data covers the time-window from 2009-11-28 to 2010-03-15 in order to include all icing events and includes some initial time for the Kalman filter to adjust. From now on it will be referred as long TS1 (timeseries 1). The LIDAR data are available from 2010-01-05 to 2010-01-27, time-series TS2. From 2010-01-04 to 2010-02-02 the heating system of WT1 was switched off. This time-series is used for evaluations of the icing algorithm in combination with power predictions. It is referred to as TS3.

- TS1: 2009-11-28 to 2010-03-15
- TS2: 2010-01-05 to 2010-01-27
- TS3: 2010-01-04 to 2010-02-04

Unless mentioned otherwise the modeling domain with the 1.3km grid size is used for the forecasting horizon from 13h to 36h.

4.1 Evaluation protocol

To allow for comparison of the performance of this model system with other wind prediction systems, a standardized protocol (Madsen et al. 2005) was used. For this, the following notation will be used:

\( k \) Prediction horizon
\( N \) Number of data used for the model evaluation
\( t \) Time of model model initiation
\( e(t + k|t) \) Error (difference between prediction and measurement) corresponding to time \( t + k \) for the prediction made at time origin \( t \)
The systematic error, called the bias, can be calculated with equation 4.1. However this measure does not incorporate the random error and therefore does not describe the correlation.

\[
\text{BIAS}(k) = \mu_e(k) = \frac{1}{N} \sum_{t=1}^{N} e(t + k|t) = \frac{1}{N} \sum_{t=1}^{N} \bar{e}(k) = 1
\] (4.1)

The standard deviation (SD) of the error distribution (see equation 4.2) on the other hand only accounts for the random error.

\[
\text{SDE}(k) = \left( \frac{\sum_{t=1}^{N} (e(t + k|t) - \bar{e}(k))^2}{N - 1} \right)^{\frac{1}{2}}
\] (4.2)

Criteria that include both the systematic and the random error are Mean Absolute Error (MAE) (equation 4.3) and Root Mean Square Error (RMSE) (equation 4.4).

\[
\text{MAE}(k) = \frac{1}{N} \sum_{t=1}^{N} |e(t + k|t)|
\] (4.3)

\[
\text{RMSE}(k) = \sqrt{\text{MSE}(k)} = \sqrt{\frac{\sum_{t=1}^{N} (e(t + k|t))^2}{N - 1}}
\] (4.4)

The BIAS and MAE are directly related to the error of the prediction. RMSE and STD on the other hand account for the variance of the error. Usually these quality measures are expressed in percent normalised to the maximal capacity of the installed WT. Thus the measures are termed nBIAS, nSTD, nMAE and nRMSE. In the result tables, the quality measures are presented as mean values for the whole forecast horizon.

### 4.2 Direct model output from WRF

#### 4.2.1 Wind Speed Evaluation

The model results for wind speed have been verified with the Payerne sounding (figure 4.1), which is about 56km away from St.Brais. Evaluation was performed for the model domain at 4km grid size because the one at 1.3km does not cover Payerne. However the 1.3km resolution was verified with the LIDAR measurements in St.Brais (figure 4.2). At 925hPa, 850hPa, 700hPa and 500hPa the DMO output, for a prediction horizon of 12-36h, has a correlation of 0.75, 0.80, 0.79 and 0.88 respectively. The weakest correlation at the lowest level is due to the fact that it is often within the planetary boundary layer and therefore affected by the surface.
4.2 Direct model output from WRF

Figure 4.1: Wind speed scatterplot: sounding vs. 4km domain (12-36h prediction horizon) at different pressure levels during TS1. The green line represents the least square linear regression.

The LIDAR measurements only cover the first 200m and are therefore also influenced by the surface. In figure 4.2 it can be seen, that high winds within the first 200m are generally overestimated by the model. The correlation reaches again higher values as the distance to the surface increases. Figure 4.3 shows this increase and indicates that the inversion height during this time might often have been around 120m above ground.
4.2 Direct model output from WRF

Figure 4.2: Wind speed scatterplot: LIDAR vs. 1.3km domain (12-36h prediction horizon) at different height levels above ground during the 3 week TS2 period. The green line represents the least square linear regression.
4.2 Direct model output from WRF

RESULTS

Figure 4.3: Correlation of the different LIDAR heights above ground to the corresponding model output of the 1.3km domain during TS2.

Finally a verification with the anemometer measurements on top of the WT1 has been done. In there a sensitivity study with another PBL-parameterisation scheme was performed. Instead of the Mellor-Yamada-Janjic scheme (Eta operational scheme with local closure), the Yonsei University scheme (non-local closure) (Hong et al. 2006) was used. Table 4.1 shows that the Yonsei University scheme, got better scores for wind forecasts during the TS2.

<table>
<thead>
<tr>
<th>PBL closure</th>
<th>1.3km</th>
<th>4km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bias</td>
<td>MAE</td>
</tr>
<tr>
<td>TKE (Mellor-Yamada-Janjic)</td>
<td>1.68</td>
<td>2.50</td>
</tr>
<tr>
<td>K (Yonsei University)</td>
<td>1.29</td>
<td>2.19</td>
</tr>
</tbody>
</table>

Table 4.1: Bias, Mean absolute error (MAE), root mean square error (RMSE) for wind speed, forecasts during TS2 for a 12-36 forecast horizon. Forecasts were verified against anemometer measurements on top of the WT1.

4.2.2 Temperature Evaluation

Since Temperature is an important input parameter for the icing algorithm its forecast quality of the DMO was verified with the 2m temperature of 4 SwissMetNet stations in close proximity to the test site (figure 4.4). For that, the DMO of the 2m temperature was interpolated to the corresponding station. The systematic error at Fahy and Payerne is less than 1°C (see table 4.2). At Neuchatel, on the other hand, the systematic offset is relatively high with 3.6°C. An explanation might be that Lake Neuchatel is closer to the test site in the model than in reality. This leads to a warming effect in winter. Comparing the 1.3km model resolution with the 4km model resolution by the RMSE values, the forecast for most sites improves little with the higher resolution. The forecast for Chasseral even became worse.
4.2 Direct model output from WRF

![Temperature: SwissMetNet stations vs. 1.3km domain interpolated to stations location during TS1. The green line represents the least square linear regression.](image)

**Figure 4.4:** Temperature: SwissMetNet stations vs. 1.3km domain interpolated to stations location during TS1. The green line represents the least square linear regression.

<table>
<thead>
<tr>
<th>Site</th>
<th>1.3km Bias</th>
<th>MAE</th>
<th>RMSE</th>
<th>Std</th>
<th>4km Bias</th>
<th>MAE</th>
<th>RMSE</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chasseral</td>
<td>1.50</td>
<td>1.86</td>
<td>2.16</td>
<td>1.55</td>
<td>2.18</td>
<td>2.43</td>
<td>2.74</td>
<td>1.55</td>
</tr>
<tr>
<td>Fahy</td>
<td>-0.45</td>
<td>1.38</td>
<td>1.77</td>
<td>1.71</td>
<td>-0.30</td>
<td>1.33</td>
<td>1.72</td>
<td>1.69</td>
</tr>
<tr>
<td>Neuchatel</td>
<td>3.64</td>
<td>3.66</td>
<td>4.10</td>
<td>1.90</td>
<td>2.73</td>
<td>2.84</td>
<td>3.35</td>
<td>1.94</td>
</tr>
<tr>
<td>Payerne</td>
<td>-0.77</td>
<td>1.80</td>
<td>2.24</td>
<td>2.10</td>
<td>-0.46</td>
<td>1.68</td>
<td>2.16</td>
<td>2.11</td>
</tr>
</tbody>
</table>

**Table 4.2:** Bias, Mean absolute error (MAE), root mean square error (RMSE) for temperature during TS1 (2009-11-28 to 2010-03-15). Forecasts (12-36h prediction horizon) were verified with 4 SwissMetNet stations.
4.2.3 Cloud Water Evaluation

Another important input parameter for the icing algorithm is the cloud water content. Since this parameter was not measured in the field, the model output was verified with a visual judgement of the webcam images on whether the WT is in-cloud or not. The result has been plotted in figure 4.5. There are two episodes when the model simulated clouds around the WT but there were no clouds observed. These are at the beginning of December 2009 and at the beginning of March 2010. To quantify the quality of the forecast, the prognostic cloud water content of the model was transformed into binary values with a threshold of greater 0kg/m equals clouds. When comparing the resulting binary time series with the closest webcam image in terms of time, a False Alarm Ratio of 0.21 and a Probability of Detection of 0.56 result.

![Figure 4.5: Cloud water content: Webcam images vs. WRF output of the TS1](image)

4.3 Kalman filter verification

In table 4.3 it can be seen, that the Kalman filter significantly reduces the bias, MAE, RMSE and standard deviation for both domains and forecast horizons. The systematic offset, expressed with the bias, becomes virtually zero with Kalman filter. The standard deviation only reduces by about 30%. Since the Kalman filter uses the past information of the systematic offset for the filtering, this is the expected
4.3 Kalman filter verification

behaviour. The standard deviation can not be reduced to zero, since the white noise processes can not be predicted.

<table>
<thead>
<tr>
<th>model resolution</th>
<th>forecast horizon</th>
<th>DMO</th>
<th>KF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bias</td>
<td>MAE</td>
<td>RMSE</td>
</tr>
<tr>
<td>1.33km</td>
<td>2.59</td>
<td>3.17</td>
<td>4.12</td>
</tr>
<tr>
<td>1.33km</td>
<td>2.70</td>
<td>3.26</td>
<td>4.21</td>
</tr>
<tr>
<td>4km</td>
<td>2.18</td>
<td>2.88</td>
<td>3.76</td>
</tr>
<tr>
<td>4km</td>
<td>2.28</td>
<td>2.94</td>
<td>3.83</td>
</tr>
</tbody>
</table>

Table 4.3: Bias, Mean absolute error (MAE), root mean square error (RMSE) for wind speed. Statistical quality measures of the TS1. Forecasts have been verified with anemometer measurements on top of the WT1. All values are in m/s.

It was already discussed in subsection 4.2.1 that high wind speeds are overestimated by the model. For wind speed, figure 4.6 shows that the systematic overestimation of wind speed by the model is corrected by the Kalman filter.

![Wind speed scatterplot: DMO vs. Kalman filtered DMO for 1.33km domain](image)

Figure 4.6: Wind speed scatterplot: DMO vs. Kalman filtered DMO for 1.33km domain

When evaluating the look-ahead times separately, the results are similar throughout all of the look-ahead periods and do not significantly decrease in quality. (figure 4.7)
4.4 Icing forecasts

4.4.1 Evaluation

Figure 4.8 shows the performance of the icing algorithm. Comparing the difference between the theoretical and real power with the modeled icing load, one can see that they correlate. There are few occasions when the difference of theoretical and real power production gets zero even if icing occurs. These periods are characterized by very weak wind speeds. The duration of the icing events is simulated well. The onset of all major 5 icing events in the simulations compared to reality had a time offset of less than a day. 2 of these events were even modeled within about one hour. There is a slight tendency to overestimate the recovery time. This is due to the incomplete implementation of ice removal processes in the icing algorithm (see 3.4). The result is an overestimation of the total icing period by 20% (without the miss-forecasted icing event in March 10). One false alarm event was simulated in March when no icing occurred in reality. There the WRF model simulated boundary layer clouds at the test site, however the webcam images proved that to be wrong. This can be seen in figure 4.5. The WT was not in-cloud when the icing algorithm simulated the most intense ice growth. In reality the cloud base was mostly above the WT. To quantify
the quality of the forecast, the simulated ice load was transformed into binary values with a threshold of greater 0 equals ice. The icing classification based on the webcam pictures was transformed the same way. When comparing the two resulting binary time series, a False Alarm Ratio of 0.43 and a Probability of Detection of 0.94 result. When excluding the false alarm event in March, a False Alarm Ratio of 0.34 and a Probability of Detection of 0.94 result.

![Image of graph](image.png)

**Figure 4.8:** Simulated ice load (blue), ice mass from the webcam images (grey) and additionally the difference between the nominal power (power value relating to the measured wind speed in the WT’s power curve) and the actually produced power on WT2 (green) during TS1. All values are normalized with their maximum.

### 4.4.2 Sensitivity studies

**Mesh size**  The simulated ice mass based on WRF results at 1.33km grid size and 4km grid size are compared in figure (figure 4.8). It can be seen that onset and duration of the icing events are simulated very similar. Only the ice load differs somewhat. Since cloud water values become ”smeared” using lower model resolutions it impacted rather on the mass of simulated ice than on real ice onset. With higher resolution the cloud water concentration in boundary layer becomes more confined to the hill top sites leading to higher simulated icing loads. This is due to the orographic lifting at the hill sides. This result suggests that 4km grid size is sufficient to describe wind as well as clouds in the area of St.Brais.
4.4 Icing forecasts

**Figure 4.9:** Simulated ice load for the 1.33km domain (blue) vs. the 4km domain (green) and ice mass from the webcam images during TS1. All values are normalized with the maximum simulated ice mass of both simulations.

**Microphysical scheme**  The microphysical scheme in use is responsible for the predicted cloud water content. In the basic run, the Thompson scheme (Thompson et al. 2008) was used. It was developed for the prediction of icing and therefore keeps hydrometeors longer in the atmosphere. As sensitivity test the WDM6 scheme (Lim and Hong 2010) was used. This provides cloud droplet number concentration as a prognostic variable. When adjusting the icing algorithm with this value, the ice accretion and removal get a jump like pattern. The temporal correlation is about the same using the WDM6 scheme. However, with the WDM6 less ice is simulated in the example and therefore it needs less time to melt it. Unfortunately, no ice load measurements are available for winter 09/10 in order to evaluate those differences.
4.5 Power forecasts and icing

This subsection combines power forecasts together with the icing forecasts. Figure 4.11 shows the wind power forecasting without the consideration of icing in green and the real production in red. Figure 4.12 on the other hand shows the wind power forecasting with the consideration of icing in green and again the real production in red. To study this, the TS3 has been used, when heating system was most of the time switched off on WT 1. This allows to study an undisturbed behavior of ice accretion and ice removal. There are only two heating events at the beginning and at the end of TS3. These heating events had to be incorporated because otherwise the two simulated icing events would not be completely within the timeseries. Figure 4.11 shows that as the power produced decreases to 0kW in the beginning of January 2010, there should still be production according to the power simulation. The production went in fact to 0kW, due to the WT sensing icing. About one day earlier, the icing algorithm starts to model ice accretion with a maximum of 0.4kg/m. Shortly after the icing algorithm has reached this maximum, the WT was already producing again. It took the icing algorithm about two more days to get rid of the ice. The second icing event according to the icing algorithm was simulated
with a very low mass. This event, if even present, had no effect on the WT. The last event was also simulated about one day earlier.

![Image of power forecasts and icing](image)

**Figure 4.11:** Produced power (red), simulated power with 4km domain (green) and simulated ice load with 4km domain (blue) during TS3. This plot shows a verification of the icing algorithm and the simulated power production compared to the real power production of WT1.

Figure 4.12 shows a promising result for wind energy forecasting with the consideration of icing. The power forecast considering icing is considerably better than the one without considering icing showing an nRMSE of 22% compared to an nRMSE of 27%. However this example only covers one month, one test site and for a case with no heating. Here again the recovery time was much longer in the simulation compared to reality. The reason for that has most probably be intense solar radiation with clear sky during the day (figure 4.13).
4.5 Power forecasts and icing

Figure 4.12: The same as figure 4.12 but with power-production set to zero when a threshold of 0.05kg/m ice-mass is reached in the simulation.

Figure 4.13: Classification cockpit for 2010-01-02

The statistical quality measures with the consideration of icing and without are
listed in table 4.4. Virtually all of the measures were improved by the consideration of icing, which is an encouraging result but based on a small sample size.

<table>
<thead>
<tr>
<th>model resolution</th>
<th>forecast horizon</th>
<th>nBias</th>
<th>nMAE</th>
<th>nRMSE</th>
<th>nStd</th>
<th>nBias</th>
<th>nMAE</th>
<th>nRMSE</th>
<th>nStd</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.33km</td>
<td>13-36h</td>
<td>0.08</td>
<td>0.16</td>
<td>0.27</td>
<td>0.25</td>
<td>-0.07</td>
<td>0.09</td>
<td>0.22</td>
<td>0.21</td>
</tr>
<tr>
<td>1.33km</td>
<td>37-60h</td>
<td>0.08</td>
<td>0.15</td>
<td>0.25</td>
<td>0.24</td>
<td>-0.05</td>
<td>0.10</td>
<td>0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>4km</td>
<td>13-36h</td>
<td>0.08</td>
<td>0.16</td>
<td>0.27</td>
<td>0.26</td>
<td>-0.04</td>
<td>0.12</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>4km</td>
<td>37-60h</td>
<td>0.07</td>
<td>0.15</td>
<td>0.25</td>
<td>0.23</td>
<td>-0.04</td>
<td>0.11</td>
<td>0.24</td>
<td>0.23</td>
</tr>
</tbody>
</table>

**Table 4.4**: Bias, mean absolute error (MAE), root mean square error (RMSE) and standard deviation for produced power during TS3. All values are normalized to the maximal capacity of the WT1. Forecasts have been verified with production data of WT1.
5 Conclusions and Outlook

To sum up, there is a potential to improve wind power forecasts by additionally forecasting icing. Both the icing algorithm and the Kalman filter show very promising results. The simple approach used in subsection 4.5 to couple the power forecast with the icing forecast already reduce the nRMSE of the 12-36 hours forecast from 27% to 22%. This is a reasonable result when comparing it to other forecasting systems in complex topography. Examples are Parkes and Tindal 2004 with an nRMSE of 24% and Nielsen et al. 2006 with 25%. These examples are not calculated under icing conditions. They study the the time horizon 24-48 hours. In this study, the 37-60 hour forecast reached a value of 23%.

A next step would have to look at improving forecast of recovery time by adding further ice removal processes to the icing algorithm. The icing algorithm could also be adapted to more complicated structures than the rotating cylinder. The challenge remains to couple the routines to get a final power output forecast when a heating system is in use. An approach to do that could be to incorporate a self learning algorithm and to use the current dataset as a learning dataset. The predictors would be the output from the icing algorithm, the ice-mass change over time, the Kalman-filtered wind and maybe some output variables (wind-direction) from the direct model output, too. However, the question might be raised, why not use the DMO variables directly as predictors. This would have to be evaluated. The problem with a self learning system approach would certainly be, that it would be rather site specific and sensitive to changes within the system. A change in pitch control of the WT for example would have a huge impact on the system’s response. Last but not least, a very important feature would be the incorporation of uncertainties, to provide a better decision guidance from such models.
### Glossary

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
<th>Symbol</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARW</td>
<td>Advanced Research WRF</td>
<td></td>
<td>18</td>
</tr>
<tr>
<td>Bergeron process</td>
<td>The basis of this theory is the fact that the equilibrium vapor pressure of water vapor with respect to ice is less than that with respect to liquid water at the same subfreezing temperature. Thus, within an admixture of these particles, and provided that the total water content were sufficiently high, the ice crystals would gain mass by vapor deposition at the expense of the liquid drops that would lose mass by evaporation. (AMS-Glossary)</td>
<td></td>
<td>22</td>
</tr>
<tr>
<td>CFD</td>
<td>Computational Fluid Dynamics</td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>DMO</td>
<td>Direct Model Output</td>
<td>17, 26,</td>
<td>29, 32,</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>33</td>
</tr>
<tr>
<td>GFS</td>
<td>The Global Forecast System, is a global numerical weather prediction computer model run by NOAA</td>
<td></td>
<td>18</td>
</tr>
<tr>
<td>hub-height</td>
<td>The height from the foundation of the WT to the nacelle. In St.Brais this is 78m.</td>
<td>6, 8,</td>
<td>20, 21</td>
</tr>
<tr>
<td>LIDAR</td>
<td>Laser Detection and Ranging, is an optical remote sensing technology that measures properties of scattered light to find range and/or other information of a distant target.</td>
<td>8, 10–</td>
<td>12, 25,</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>27</td>
</tr>
<tr>
<td>nacelle</td>
<td>The gondula where the blades the generator is situated and the blades are mounted to.</td>
<td>8, 10,</td>
<td>25, 41</td>
</tr>
<tr>
<td>Notation</td>
<td>Description</td>
<td>Symbol</td>
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<td>----------</td>
<td>-----------------------------------------------------------------------------</td>
<td>--------</td>
<td>-----------</td>
</tr>
<tr>
<td>NWP</td>
<td>Numerical Weather Prediction</td>
<td></td>
<td>2, 4</td>
</tr>
<tr>
<td>St.Brais</td>
<td>A rural town in the Swiss Jura which is situated beside the hill upon which</td>
<td></td>
<td>6–8, 34,</td>
</tr>
<tr>
<td></td>
<td>the two WT are built.</td>
<td></td>
<td>41</td>
</tr>
<tr>
<td>SwissMetNet</td>
<td>Automatic Measurement Network of Swiss Weather stations</td>
<td></td>
<td>25, 29, 30</td>
</tr>
<tr>
<td>TKE</td>
<td>Turbulence Kinetic Energy</td>
<td></td>
<td>19</td>
</tr>
<tr>
<td>USA</td>
<td>Ultra Sonic Anemometer</td>
<td></td>
<td>8, 10, 11,</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>14, 16</td>
</tr>
<tr>
<td>WRF</td>
<td>The Weather Research and Forecasting Model, is a next-generation mesoscale</td>
<td></td>
<td>5, 17, 18,</td>
</tr>
<tr>
<td></td>
<td>numerical weather prediction system designed to serve both operational</td>
<td></td>
<td>20, 25, 33,</td>
</tr>
<tr>
<td></td>
<td>forecasting and atmospheric research needs. (WRF Homepage)</td>
<td></td>
<td>34</td>
</tr>
<tr>
<td>WT</td>
<td>Wind Turbine</td>
<td></td>
<td>1–4, 6–8,</td>
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<td></td>
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<td>10–12, 23,</td>
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<td>41, 42</td>
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