Evaluation and development of normal year correction methodologies for icing climatology in wind farm applications

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Photo: Benjamin Klintström

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Abstract

Wind power developments in cold and icing conditions pose new challenges to the wind power industry. Icing of wind turbines cause safety hazards, production losses and increased loads. This means that there is a need to develop a technique to quantify the icing climatology and corresponding effects on wind turbines to enable large scale wind power developments in the windy, sparesly populated areas of northern Sweden.

This thesis is focused on evaluating the possibilities to estimate the long term icing climatology using mesoscale meteorological models in combination with existing ice models. The basis for the study were long term, low resolution time series from WRF and COAMPS in combination with high resolution, short term time series for the same geographical area, with the aim to find a method for normal year correction of the icing climatology. A number of different methodologies for normal year correction of icing climatology were developed and evaluated using a few criteria: plausibility of the results, site dependency, sensitivity to data set used and sensitivity to the length of the time series used as reference. The ice modeling was performed using an implementation of the Makkonen algorithm for ice accretion. The normal year correction was performed using different theoretical reasoning and at different steps in the modeling. Linear regression of time series of standard meteorological parameters as well as of active ice hours and ice loads were tested. A method using iterative height adjustment of the parameters was developed as well as a basic method directly relating the high resolution modeled ice load to the low resolution modeled ice load. A method using averaged values for the different ice model input parameters was also tested.

The evaluation showed promising results for the linear regression method. The different implementations showed feasible results and the outcome was not sensitive to the length of the correction basis. The height adjustment method was difficult to evaluate and was sensitive to the time series used as correction basis. The method using basic relations between high and low resolution parameters was extremely sensitive to the correction basis and the method based on averaged values did not show feasible results. Using active ice hours as basis for the normal year correction was shown to be preferable compared to using ice load.

The conclusion drawn was that linear regression in combination with height adjustment to relate low resolution modeled icing climatology to high resolution icing climatology may be a promising tool. Development of the ice models used to estimate icing of wind turbines is needed, preferably a way to model ice directly on the wind turbine blades compared to the standard cylinder used in the Makkonen algorithm. Also, more reliable means to measure ice accretion are needed to enable further evaluation of the methods compared to the real icing climatology.

Keywords: ice modeling, normal year correction, icing of wind turbines, mesoscale meteorological models

Contents

List of Figures

List of Tables

1 Introduction

The fastest growing energy source in Europe today is wind energy. As of 2011, over 21 % of the newly installed power capacity was wind power. Today contributing to around 6 % of Europe's annual electricity consumption, the goal set by the European Wind Energy Association is 20 % by 2020 [1]. To reach this goal, large-scale developments, both onshore and offshore, will be needed. This means that the wind power industry will have to face new challenges, building wind power plants in demanding conditions in remote areas. As for Sweden, the hilly, sparsely populated northern parts offer such opportunities, and since the area is subject not only to high winds but also to cold climate and icing conditons, one of the challenges lies in developing solutions and techniques to cope with ice, snow and low temperatures. The risks of ice throw, increased noise levels as well as increased loading on the turbines and lowered production poses a need for new solutions. Wind power developments in cold climate being a fairly new industry, the methods to address icing issues are not fully developed. A reliable way to detect ice on the wind turbine blades is still to be found, and the existing models for ice accumulation have limitations. Estimating production losses due to icing is related to large uncertainties. For the wind industry to be able to harness the endless wind resources of northern Sweden, these problems need to be solved. Reliable means to model, detect and mitigate ice, as well as turbines robust enough to cope with extreme conditions, need to be developed.

The prevailing wind direction in large parts of the north of Sweden is from south west to west, which means that the Scandinavian mountains to some extent shelter the area from icing conditions. This giving a slightly less severe icing climate, the local terrain still has the largest impact and as opposed to sites in inner Russia or Mongolia, the main problem in northern Sweden is not extremely low temperatures but ice accumulation [2] [3]. Unfortunately, hilly terrain does not only offer high wind speeds but also increased icing severity [4].

This thesis is focused on modeling of icing climatology using meteorological models and ice accumulation models. The aim is to asses the possibilities to use this methodology to estimate the long-term icing climatology at sites in northern Sweden suitable for wind power utilization. To achieve this, a number of normal year correction methods are developed and evaluated.

1.1 Method and scope

To assess the possibilities to use meteorological mesoscale models and ice accumulation models to estimate the icing climatology, firstly, a literature study has been performed. The state-of-the art wind power in cold climate in terms of ice accumulation models, anti-icing (for definition see chapter 3.2), ice detection and meteorological modeling is described with up-to-date literature and reports on the subject forming the foundation. Thereafter, time series for the icing climatology, resulting from mesoscale meteorological models, has been compared and analysed, with focus on long term correction. Different methodologies for normal year correction of the icing climatology has been developed and analysed by the author.

The time series analysed are results from simulations made by Company C, Company A and Company B Vindteknikk for Vattenfall Vindkraft. The simulations have been made using meteorological mesoscale models together with existing ice accumulation models, for different sites in northern Sweden interesting for Vattenfall (see chapter 5). All meteorological parameters from the model output are included in the time series, as well as calculated ice parameters from all three companies and production losses from Company B and Company A.

The thesis does not include thorough analysis of ice measurements. The focus is on the possibilities to use meteorological models to estimate ice parameters, such as active ice hours and ice load, and to compare different methodologies for normal year correction of the icing climatology. The modeled production losses have been compared to actual production losses. No modeling of production losses has been performed within the study.

2 Ice accumulation

2.1 Types of ice

It is often claimed that inuits have several hundred words for snow. Whether this should be considered as far too many may be discussed, but it is a fact that a distinction between different types of snow and ice is necessary for modeling of icing climatology and estimating effects on wind power production.

The source of natural ice may be cloud droplets, water vapour, snow or rain drops [5]. Depending on the source, the wind speed and other atmospheric parameters, the ice formed on a structure will be of different types. What is normally referred to as ice, the opaque and colourless structure, is defined as glaze ice. Glaze ice will be formed during *wet growth* (see Figure 2.1), which means that the rate with which droplets hit an object is larger than the rate at which they freeze to the surface [6]. This in turn means that a part of the mass flux will leave the surface of the structure as run-off. A liquid layer will be formed on the surface and freezing will take place underneath, hence the definition wet growth. Glaze ice has the highest density of the common types of ice (ρ = 0.7 - 0.9 g/cm^3).

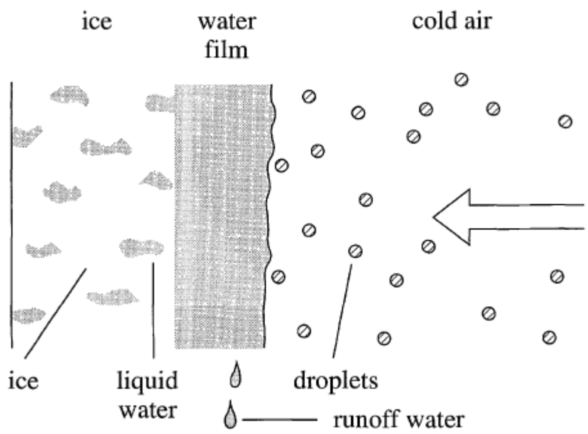


Figure 2.1: Wet growth of glaze ice [5]

When there is no liquid layer and no run-off, the ice accumulation is called *dry growth* (see Figure 2.2). This type of ice is called rime ice. Rime usually forms at temperatures lower than glaze ice. It is less dense than glaze ice at temperatures below -10°C (ρ = 0.3 - 0.4 g/cm^3) but the characteristics are more similar to those of glaze when the temperature is closer to 0°C. Rime ice incorporate air pockets, which means that the volume is often larger than for glaze ice. A third type of ice is hoar frost, which forms from sublimation of water vapour. Hoar frost is slower to accumulate and have lower adhesion strength. Hoar frost can appear in relatively clear weather with little wind. Although contamination with hoar frost or wet snow is less common than glaze and rime ice, it can pose a problem on certain locations with specific climatic conditions [7].

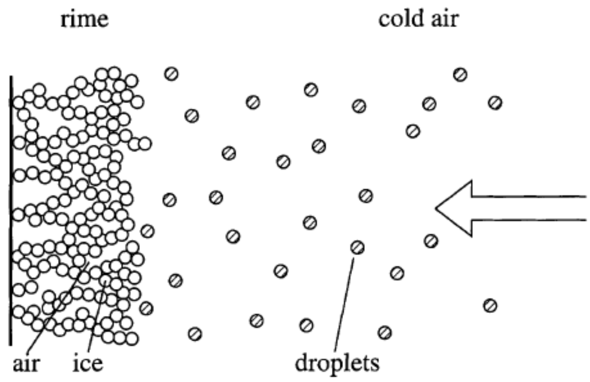


Figure 2.2: Dry growth of rime ice [5]

A fourth type of accumulation on structures is wet snow, which can be formed during periods of heavy snow fall [5]. Different types of ice form at different conditions. Formation of glaze ice typically occurs when the wet bulb temperature is less than 0°C and there is liquid precipitation, whereas rime ice generally is formed when the air temperature is less than 0°C and the cloud-base is below the elevation at the studied location. Wet snow is formed when the wet-bulb temperature is above 0°C, which means that the heat flux is from the air to the snow surface. Rapid changes in wind speed, cloud cover and humidity will often lead to intermediate types of ice being formed, with physical and chemical properties between those of rime and glaze. Moving structures, such as aeroplanes and wind turbines, are known to accumulate harder types of rime or even glaze compared to stationary structures at the same ambient conditions, since a hardening of the ice is induced by the movement [6]. The droplet mass flux to the surface increases which can lead to a transition from dry to wet growth. Combinations of glaze ice, hard and soft rime can often be found on structures after longer periods with icing conditions [6].

Different types of ice are common in different areas. In Canada, for instance, freezing precipitation is a significant problem, causing damages to the transmission net. In northern Scandinavia, in-cloud rime icing is the by far most common type of ice accumulation [8]. It is important to distinguish between active and passive icing of structures. Active icing refers to the period during which meteorological conditions for ice accumulation are favourable. Passive icing, refers to the time an instrument or structure remains iced, the time after which the meteorological conditions do not favour icing any longer. Instrumental icing refers to the whole time period during which the structure remains iced. Incubation time refers to the time between the onset of meteorological icing and instrumental icing, and recovery time to the time between the end of the meteorological icing and the end of instrumental icing, see figure 2.3 [9].

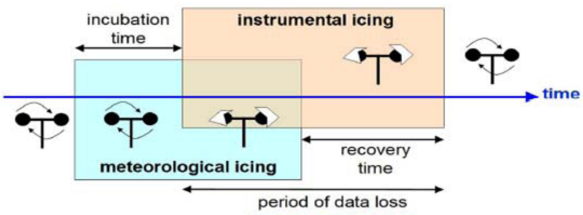


Figure 2.3: Active and passive icing [9]

2.2 Modeling of ice accretion and accumulation

Although estimation of icing on aeroplanes, wind turbines and other important structures can be crucial, no undisputed model has so far been developed. Due to non-linear relationships between parameters affecting ice accretion, most models include empirical formulas and none can be solved analytically. The most widely used model of today is Makkonen's algorithm for ice accretion, described in this chapter. The Makkonen model is originally developed for modeling of ice accretion on overhead power lines, and therefore models ice accretion on a cylinder resembling a power line.

Irrespective of what kind of particles, liquid or solid, that cause ice on an object, the accumulation rate will be dependent of the flux density, in other words the cross-sectional area of the object, the velocity of the particles and the mass concentration of particles in the air. Since not all particles will collide with the object and not all particles that do collide will stick or accrete, three efficiency coefficients need to be introduced [5].

$$\frac{dM}{dt} = \alpha_1 \alpha_2 \alpha_3 w v A \tag{2.1}$$

where α_1 is the collision efficiency, α_2 is the sticking efficiency, α_3 the accretion efficiency, w the flux density, v the particle velocity relative to the object and A the cross-sectional area relative to the particle velocity. The Makkonen equation can easily be used to model ice load and ice accretion rate. It is common to give the ice load and ice accretion rate in kg/m and kg/m/hr, which refers to per meter of the cylinder used in the model. The ice accretion rate is sometimes presented in terms of active ice hours, which refers to hours with ice accretion rate above a pre-defined threshold, commonly 10 g/m/hr [10].

2.2.1 The collision coefficient, α_1

The collision coefficient, α_1 is the ratio of the flux density of particles hitting the object to the total flux density. α_1 decreases from 1 when particles are forced around the object instead of hitting it. Small droplets, large cross-sections and low wind reduce α_1. The droplet trajectory is determined by the aerodynamic drag and the inertia. For a small droplet, the inertia will be small and it will tend to follow the streamlines around the object instead of hitting it. If the inertia and drag forces are known, the collision coefficient can be calculated theoretically by numerically calculating droplet trajectories. Since this is computationally expensive, Makkonen [5] suggests the simplification to assume a cylindrical object, and to use an empirical equation for α_1,

$$\alpha_1 = A - 0.028 - C(B - 0.0454) \tag{2.2}$$

where

$$\left.\begin{aligned} A &= 1.066K^{0.00616} e^{-1.103K^{-0.688}} \\ B &= 3.641K^{0.498} e^{-1.497K^{-0.694}} \\ C &= 0.00637(\phi - 100)^{0.381} \end{aligned}\right\} \tag{2.3}$$

where K and ϕ are dimensionless parameters

$$\phi = \frac{Re_d^2}{K} \tag{2.4}$$

where Re is the droplet Reynold's number based on the free stream velocity and given by

$$Re_d = \frac{\rho_a d v}{\mu} \tag{2.5}$$

and

$$K = \frac{\rho_w d^2 v}{9 \mu D} \tag{2.6}$$

where d is the droplet diameter and D the cylinder diameter, ρ_w the water density, μ the absolute viscosity of air and ρ_a the air density.

Since α_1 depends on the droplet size, one can safely assume $\alpha_1 = 1$ for wet snow and freezing rain as long as the structure studied is not extremely large [5]. This means that α_1 normally needs to be calculated only for occasions with in-cloud icing with small droplets.

2.2.2 The sticking coefficient, α_2

The sticking efficiency coefficient, α_2, is the ratio between the droplets that stick to the surface to the total amount of droplets that collide with the object. For liquid droplets it can normally be assumed that they do not bounce and hence α_2 equals 1. As soon as there is a liquid layer on the surface, combined with favourable conditions, basically all droplets will stick to the surface. For ice and snow particles, the ratio of particles that bounce off the object can be a significant share. For solid particles, such as dry snow, α_2 is close to or equal to 0. So far, no valid equation for α_2 has been developed [5]

2.2.3 The accretion coefficient, α_3

The accretion efficiency coefficient, α_3, is the ratio of icing to the flux density of droplets sticking to the object's surface. During dry growth (see chapter 2.1) α_3 equals 1 since there is no run-off. During wet growth, glaze icing, there is a liquid film on the adhesion surface and α_3 will be less than 1 [6]. The freezing rate will then be determined by the rate with which latent heat from freezing can be transported away from the surface. A heat balance over the surface of the object can be used to determine the portion that will freeze [11].

$$Q_f + Q_v = Q_c + Q_e + Q_l + Q_s \tag{2.7}$$

where Q_f is the latent heat of freezing of the water, Q_v is the frictional heating of the air, Q_c is the sensible heat lost to the air, Q_e is the heat loss due to evaporation, Q_l is the heat needed to heat the supercooled water droplets to the freezing temperature and finally, Q_s the heat loss due to radiation. The terms of the heat balance equation can be parametrized, for equations see for instance Makkonen [5]. For Q_f, unfrozen water incorporated into the ice structure need to be taken into account. The fraction of liquid can usually be given a constant value, since studies have shown that it is rather insensitive to the growth conditions. Q_v is usually a small term except for very high speeds [7]. Q_c and Q_e can be parametrized using several different relations, developed by for example Makkonen [7] for a cylinder. Q_l is parametrized using the specific heat for water and the temperature difference between the droplets and the surface of the object. The heat loss due to radiation, Q_s, is very hard to parametrize. Makkonen [5] suggest that only the long-wave radiation be taken into account, neglecting short-wave radiation from the sun. This can be justified by the assumption that icing occurs during cloudy weather, which is valid for the general case [11].

α_3 will be equal to 1 during dry growth without run-off. If α_3 is less than 1, this means that run-off occurs, the surface is to some degree covered in liquid film and the collision efficiency is therefore not important (see 2.2.1). During rime formation (dry growth) when α_3 equals 1, α_1 will instead be the dominant factor determining the efficiency. As the object accumulates rime ice, its area will increase and hence deflecting the air flow to a higher degree and lowering the collision efficiency [6]. Also, when the ice accumulation starts as wet growth with α_3 less than 1, the reduction of the collection efficiency α_1 due to the growing structure may cause a transition to dry growth with α_3 equal to 1 at constant atmospheric conditions [7]. This being said, it is important to distinguish between the ideal, modeled ice accretion and the ice accretion that will occur in reality. The accretion rate as well as the shape of the ice will be determined by many factors, of which only a few are considered in the above described model.

2.2.4 Limitations of the model

Although Makkonen's model for ice accumulation is widely used, it is limited by the fact that it models ice accretion on a cylinder. To translate the ice load on an ideal cylinder to a complex structure such as a lattice tower or a wind turbine is computationally expensive and so far not possible for the general case. To model ice accumulation on a wind turbine, one needs to break down the structure into small elements, still taking into consideration shadowing effects from other elements and ice growing elements together to form a single element.

One of the more practical problems is that the liquid water content, LWC, of the air, the cloud droplet density and the median volume droplet size, MVD, in the air are required values. These parameters are not routinely measured nor does there exist a satisfactorily way to measure them [6]. The average droplet diameter has to be approximated, and the average number of droplets in-cloud has to be known. The liquid water content can be modeled (see chapter 4.1), but the result has a high uncertainty. There is an uncertainty in the model when α_1, the collision efficiency, is small, since α_1 depend on the droplet diameter and errors are introduced estimating MVD. Also, the effects of droplet trajectory angle on the collision efficiency are poorly known, which means that the effects of wind direction and rotational speed of a wind turbine are uncertain. Another uncertainty regarding α_1 are low velocities introducing uncertainties in Reynolds number and flow patterns [5].

Modeling of ice accretion also requires modeling of the ice density, since the icing rate depends on the dimensions of the iced object. The density of the ice can be modeled using ballistic models, but for rime-ice best-fit equations have been developed in wind-tunnel experiments [5].

$$\rho = 0.378 + 0.425log(R) - 0.823log(R)^2 \tag{2.8}$$

where R is the Macklin parameter, a dimensionless density parameter.

$$R = -(v_0 d_m / 2t_s) \tag{2.9}$$

where v_0 is the droplet impact speed, d_m is the droplet median diameter and t_s is the surface temperature. t_s can be approximated to the air temperature. To solve the equation, the impact speed must first be calculated from the heat balance equation. A difficulty with solving the heat balance equation is the convective heat transfer coefficient. Even assuming a simple structure such as a cylinder, to determine the heat transfer coefficient is complicated. The roughness of the surface has a large impact, and factors that determine it are poorly known. The be able to determine the shape of the ice structure it is furthermore necessary to perform local heat balances [12].

A limitation of the model is that it takes into account only accumulation of ice. Ice will be removed only due to the sign of the heat balance. Melting is not included, neither is shedding of ice nor sublimation. The energy available for melting can be calculated according to equation (2.10) below:

$$Q_m = Q_h + Q_e + Q_n + Q_v + Q_w + Q_q \tag{2.10}$$

where Q_m is the available energy for melting the ice, Q_h is the sensible heat transfer from air to the melting ice, Q_e is the latent heat transfer from the air, Q_n is the net radiation, Q_v is the friction, Q_w is the conduction due to warm droplets and finally, Q_g is the flux of heat from the inner of the iced object [11]. Q_v, Q_w and Q_g are small terms and are sometimes neglected [13].

Melting of ice can relatively easily be incorporated into the model for ice accumulation, but sublimation poses larger problems. It occurs in situations with dry air and the rate increases with wind speed, which means that it is a more important process for rotating objects, such as wind turbines, than for stationary structures [13]. The sublimation rate can be calculated by evaluating the energy balance between latent heat released from the sublimation process and long wave radiation [14]. Ice shedding is another process that need to be taken into account and that is not incorporated in the model. Measurements show that shedding can contribute to a large share of the ice removal from structures, especially moving structures such as wind turbines. A statistical approach has been suggested, but a satisfying way of modeling shedding is yet to be found [14].

3 Wind power in cold climate

One differentiation important to make when dealing with wind power in cold climate is the one between cold climate and icing climate. Cold climate areas refer to areas where the temperature occasionally go below the operational limits of standard wind turbines, and/or icing conditions occur. Areas with only low temperatures are referred to as low temperature climate, and areas with only icing conditions as icing climate [9].

Icing of a wind turbine can lead to increased static and dynamic loads. Since ice accumulation is dependent on the wind speed relative to the object (see equation (2.1)), a moving rotor blade will accumulate more ice than stationary structures. During an icing event, ice typically builds up on the leading edge of the blade, reducing the aerodynamic lift forces and the torque and increasing the drag forces. Even a light icing event can increase the roughness of the blade to a large extent, leading to power loss [15]. Recent studies have shown the production losses to be correlated to the onset of meteorological icing conditions, active ice hours, to a higher extent than to ice loads. Apart from this, during long and severe icing events, the turbine will eventually stop, due to either loss of torque, increased vibrations due to aerodynamic imbalance or simply by being shut down for de-icing (see 3.2). Analysis of the production from wind turbines at sites subject to icing have has shown clear effects on power production during the winter season [16].

Ice accumulating may lower the resonance frequency, which increases the risk of higher loads on gearbox and drive train. Regarding the aerodynamics, simulations and wind tunnel experiments by e.g Homola et al. [17] have shown a significantly lower power coefficient, c_p, for an iced blade compared to a clean one (Figure 3.1). The power curve for the iced blade differed significantly, with 27% lower production for wind speeds between 8 and 10 m/s for the studied 5MW turbine. Other studies have come to similar conclusions. Pitch-controlled turbines will counteract the reduced aerodynamic performance by a smaller pitch angle than at normal conditions, which will lead to higher than normal bending moments on blades and tower. This probably leads to increased stress and fatigue and a reduction in turbine lifetime [17]. For stall controlled wind turbines, the decreased aerodynamic performance can lead to overloading due to delayed stall [18].

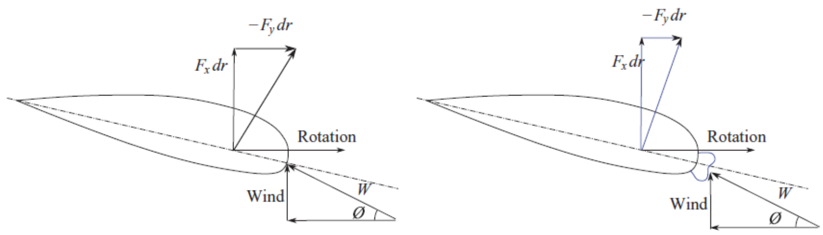


Figure 3.1: Airfoil without and with ice, and difference in aerodynamic performance [18]

Modeling of ice accumulation on aeroplane wings has been performed the last few decades, and lately this proficiency has been applied to wind turbine blades. It has been shown that a different type of ice can be formed on the tip of the rotor blade compared to the root, due to the fact that the icing rate and type depend on the velocity as well as on the object size [3]. Overall, the tip sections of the blades are generally more subjected to icing, due to their higher velocity and smaller cross-sectional area (see 2.2.1).Larger wind turbines have been found to collect less rime ice relative to their size compared to smaller turbines in wind tunnel experiments and simulations. This is mainly due to the collection efficiency decreasing with larger area, and the larger the turbine the dimensionally thicker the blades. This is only valid for the case of rime icing, since it is dependent on the droplets being small and easily deflected. Also, without taking the taller towers and hence the increased risk of the turbine being in-cloud, one can not safely say that larger turbines equals lower icing risk [18].

TURBICE is a software commonly used to model ice accumulation on wind turbine blades. It is a numerical model simulating ice accretion on a two-dimensional airfoil. The results from the simulations have been compared to real cases and found to agree well, and the model can simulate both glaze and rime icing [19]. Another software used to model ice accretion is LEWICE, which can model the shape of the ice accumulation. It models both rime and glaze icing, and LEWICE can also incorporate a thermal anti-icing procedure [19].

3.1 Ice detectors

To be able to estimate the icing climatology in an area or in a wind power park, reliable means to measure wind speed and ice accumulation are needed. One of the problems with sites experiencing icing conditions is that traditional wind anemometers have difficulties giving reliable results during extremely cold weather or icing conditions, especially combined with very high or low winds [19]. Research has shown that even small amounts of ice on anemometers can lead to errors in wind measurements [20]. Since icing and high winds cause higher loads on met height and hence introducing another uncertainty masts, wind measurements are sometimes performed at a low height above ground level, which causes a need for extrapolating to the accurate height. If the anemometers are not able to measure the correct wind speed it is impossible to relate icing to production loss. It is unfortunately common that anemometers accumulate ice and show too low wind speed. When analysing production data for an ice event, this error will lead to areas with overproduction when the wind turbines in reality are under-producing. Studies in Sweden, Norway and Finland show a significant percentage of overproduction during the winter months, which probably can be explained to iced anemometers [21].

Ice build-up need to be measured fast and accurately to minimize related losses. There exist a number of different types of ice detectors on the market, none of which is considered completely reliable. Many of the techniques for ice detection are originally developed for aviation applications, and are not easily adapted to wind turbine purposes. During tests, different ice sensors showed significantly different results [22]. The ice detectors measure ice build-up directly or indirectly. Directly means detecting a property change caused by ice accretion, such as changes in mass, conductivity or inductance. Indirect detection refers to detecting changes in weather conditions leading to icing or effects of icing such as deviation from the normal power curve [19]. Some detectors are designed to measure ice load, others to detect onset of icing events or the ice accumulation rate.

A common type of ice detectors detect ice by measuring accretion on a thin wire or a cylinder, resembling the standard cylinder from Makkonen's algorithm (see chapter 2.2). When ice is detected a heating cycle begins, aiming to melt the accreted ice and making the detector ready to accumulate and detect new ice formation. A problem with this approach is that the heating can be insufficient, letting partly melted ice freeze again after finished heating cycle. Another problem is that the response time can be long, which means that if the detection of ice is coupled to a de-icing process, this can begin too late to be efficient [19]. Initiating the de-icing process too late means a higher energy consumption (see 3.2). Due to the problems with uncertainties using existing ice detectors a number of other solutions are being tested by the industry. The combination of an ice detector with temperature and humidity sensors is one of the techniques being tested. Simplifying, icing takes place when the relative humidity is close to or above 100 % and the temperature is below zero degrees. By coupling these informations some uncertainty is erased. Unfortunately, evaluation of this method has shown that it did not detect icing at the same time as other ice detectors. Studies showed several events with temperatures below zero degrees and relative humidity above 95 % without icing occurring [22].

Another solution is to use two traditional anemometers, one with a heating system and one without. The difference in output between the two can then be used as an indication for icing [19]. Another straight-forward way is to measure the deviation from the normal power curve to detect ice. Icing is then detected when the temperature is below zero degrees and the power output is lower than what could be expected, assuming that the deviation is caused by ice on the blades. Deviation from normal blade pitch angle can also be incorporated into this method. One of the best ways to detect icing is to use a web camera to monitor the turbine blade. It is of course complicated to use this information efficiently, since it requires manned surveillance and enough light to be able to distinguish ice. It is also important to consider that different types of ice give different effects on aerodynamics and imbalance for the wind turbine. Therefore, it is equally important to detect or model the type of ice as the total ice load [23].

HoloOptics

The HoloOptics ice sensors detect ice with an optical sensor, see figure 3.2. An IR-emitter send out light that is reflected by a probe and registered by a photo detector. The optical properties will change when there is an ice coating on the sensor, and according to the manufacturer ice is detected when 95 % of the probe is covered with ice, 50 μm should be enough for clear ice and 90 μm of other types of ice. The sensor is then heated as soon as ice is detected, which means that the intensity of the icing can be measured [3].

Figure 3.2: Holooptics ice detector [24]

IceMonitor

The IceMonitor measures the ice load on a standard cylinder according to the ISO-standard 12494, which means that ice is measured on a freely rotating 30 mm thick cylinder, 0.5 m long [25], see figure 3.3. The rotation of the cylinder is supposed to create a uniformly distributed ice layer. The weight of the accreted ice is measured by a load cell, and to keep the cylinder rotating electrical heating is applied to the bearings [3].

Figure 3.3: Icemonitor ice detector [3]

IGUS

IGUS monitors uses the blades natural frequency to monitor ice directly on the rotor blades. Ice is detected by a frequency shift, and according to the manufacturer it is possible to detect ice also when the turbine is not running [26].

Other systems

There are a number of other different ice detection systems on the market. Labkotec, developed in cooperation with the Finnish research centre VTT, uses ultrasonic signals to detect ice. It is designed to detect both in-cloud icing and freezing precipitation [27]. Yet another system is the Goodridge Ice Sensor, which detects ice using ultrasonic vibrations. When ice accretes, the resonance frequency will be lowered which then can be detected by the sensor [28].

3.2 Anti-icing and de-icing

Ice mitigation systems can be divided into two main strategies: anti-icing and de-icing. The strategy of anti-icing systems is to prevent ice from building up, whereas de-icing removes a built-up ice layer. Ice mitigation is important from a number of different perspectives. Firstly, ice on a wind turbine will cause increased loads and possible increased fatigue. Secondly, the loss of aerodynamic performance will cause lowered production. Finally, it is extremely important for wind turbine operators to be able to guarantee that the risk of ice throw is negligibly small, from a health and safety point of view.

Today, no universal solution for anti- and de-icing exists. The three main strategies of today is blade heaters, circulation of hot air inside the blade and ice-phobic coatings. The technique being the most favorable is dependent on a number of factors. Firstly, the icing climatology has to be assessed to be able to decide the gains associated with the ice mitigation system. Then, factors such as the control system, the type of blade, the ice detection system and the type of heating are equally important factors. Efficient ice detection, coupled to a fast control system and efficient heating, able to remove all ice before any risk of ice throw develops would be the ideal system. Preventing ice from building up, i.e. using an anti-icing system, should be considered as the best option keeping safety issues and increased noise levels in mind [23].

4 Modeling of icing climatology using meteorological models

4.1 Meteorological models

To be able to model icing climatology at a location, it is necessary to first have information other climate and weather conditions such as wind speed and direction, temperature and humidity. This can be done using meteorological models. The basic structure of such a model uses atmospheric physics laws and empirical relationships to predict conditions in three-dimensional grid boxes stacked vertically and horizontally. The models normally use multiple nested domains and by running the model from larger to smaller domains, each smaller domain can receive feedback and boundary conditions from the outer. This enables impact from large weather systems on regional conditions [29].

Atmospheric models use primitive equations, which are a set of non-linear differential equations. They consist of three main sets of equations [29]:

1. *Conservation of momentum*: a form of the Navier-Stokes equations that describe the hydrodynamical flow on the surface of a sphere, with the assumption that the vertical motion is negligible compared to the horizontal motion, and that the fluid layer depth is negligible compared to the radius of the sphere.
2. *Thermal energy equation*: To relate the temperature of the system to the heat sources and sinks.
3. *Continuity equation*: Conservation of mass.

The equations are used together with e.g. the ideal gas law. Meteorological models can be thermotropic, barotropic, hydrostatic or non-hydrostatic. The reason for the different types is different abilities to lengthen the time step and increase the computational speed [29]. They all use different approximations and simplifications.

1. The thermotropic model is based on the assumption that while the magnitude of the thermal wind may change, its direction will not [30].
2. The barotropic model assumes a barotropic atmosphere, which means that the geostrophic wind will be independent of height in respect of direction and speed. This in turn means that there will be no vertical wind shear. A barotropic model assumes that the atmosphere is in geostrophic balance, with a ideal geostrophic wind [30].
3. The hydrostatic model filters out acoustic waves from the vertical momentum equations which means that the vertical acceleration is assumed to be small. This kind of model is better suited for larger scale modeling and less suitable for smaller regions. Hydrostatic equilibrium refers to the condition where a volume of a fluid is at constant velocity or at rest, when compression due to gravity is balanced by a pressure-gradient force [29].
4. The non-hydrostatic model instead use the entire vertical momentum equations, and can be solved either elastically or inelastically. The former means that the model is fully compressible and solves the continuity equations completely. The equations are then valid for all scales and conditions [29].

4.1.1 Numerical weather prediction

The idea behind numerical weather prediction is to sample the state of a fluid, in this case the atmosphere, at a certain time and then use fluid dynamics and thermodynamics to estimate the state at a time step into the future. Due to the non-linearity of the equations incorporated in the meteorological models it is impossible to solve them analytically, hence the numerical approach. The time steps for global models are usually tens of minutes and for regional scale predictions usually one to four minutes [29].

Processes that are too small-scale to include in the model need to be parametrized. This means that small-scale, complex processes are replaced by a simplified process. The amount of solar radiation reaching the ground, as well as cloud formation, occur on a molecular level and thus need to be parametrized. The processes are represented by relating them to variables on a scale the model resolves. A problem with parametrization is that for higher resolution, simplifications that are statistically valid for larger scales become questionable. The models for numerical weather prediction can be either global or regional. Regional domains use global models to set boundary conditions. To better adapt the model results to local conditions, post-processing in the form of model output statistics, MOS, can be applied [29]. Three examples of common models are described in the sections below.

WRF

One of the numerical models widely used today is the Weather Research and Forecasting Model, WRF. WRF is a fully-compressible, non-hydrostatic mesoscale model with a hydrostatic option. Mesoscale model means that it is a high-resolution model for use on a regional scale. It was created through a cooperation including the National Center for Atmospheric Research (USA), the National Ocenanic and Atmospheric Administration (USA) as well as several other organizations and universities [31]. The model uses a terrain-following pressure vertical coordinate. It it also possible to choose different kinds of parametrization schemes for turbulence, clouds etcetera.

COAMPS

COAMPS (Coupled Ocean/Atmosphere Mesoscale Prediction System) is a non-hydrostatic three-dimensional mesoscale model developed by Naval Research Laboratory Marine Meteorology. It also includes a hydrostatic ocean model, which can be integrated with the atmospheric model. It includes predictive equations for pressure perturbation, temperature, turbulent kinetic energy as well as mixing ratios of clouds, rain, ice, graupel, snow and water vapour. It performs parametrizations for boundary layer processes, radiation and precipitation [32].

AROME

AROME (Applicaton Recherche Operationalisation Meso-Echelle) is the mesoscale version of the model ALADIN (Aire Limite Adaption Dynamique International), a French model developed from the global ECWMF IFS (European Centre for Medium-Range Weather Forecasts, Integrated Forecast System) model. Similar to WRF and COAMPS, it is a non-hydrostatic model. AROME is equipped with advanced microphysics scheme and prediction of rain, snow, graupel, cloud water and cloud ice [33].

4.2 Using the models to simulate icing

It is possible to model icing climatology at a certain location combining output from meteorological models with an ice accretion model. Meteorological models are able to predict the parameters needed to calculate the ice load, thus providing means to make predictions and estimates of the icing climate at interesting locations (see figure 4.1). The figure illustrates the procedure when using meteorological models in combination with the Makkon model to model the icing climatology. This has been made possible during the last few years and was earlier impossible due to the high resolution needed for the simulations [34]. To be able to predict and estimate the icing of a wind turbine blade, some simplifications are generally made. Firstly, up till today it is not possible to directly model the icing of the turbine blade. Therefore, the assumption is made that the ice load on the standard cylinder used in the Makkonen algorithm can be used. Also, it is assumed that the incubation time, i.e the time between the onset of meteorological icing and instrumental icing, is zero. Usually the modeling is performed for an unheated surface [9].

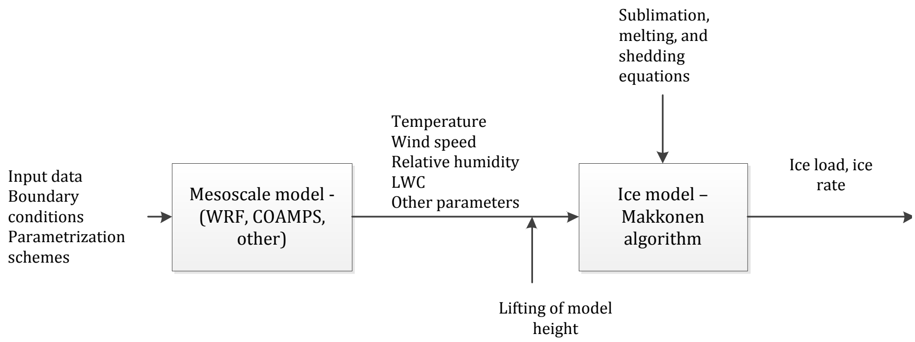
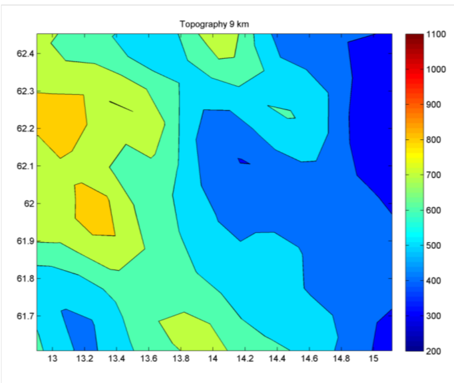
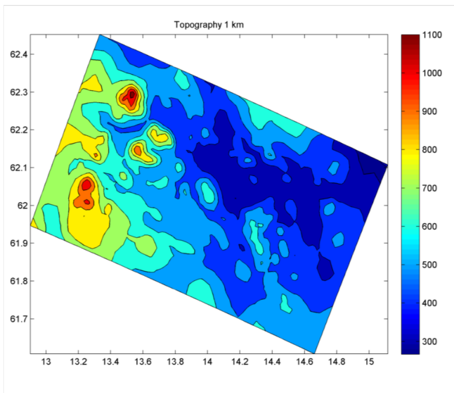


Figure 4.1: Methodology to model icing climatology using mesoscale models

Since the ice accretion model widely used today (see equation (2.1)) uses the droplet flux density as a parameter, two of the most important inputs are the liquid water content, LWC, and the droplet size distribution, normally MVD. These parameters also pose some of the the largest problems and uncertainties in the meteorological models. Only recently, enough sophisticated micro-physical parametrization schemes have been developed. The possibility to use higher resolution due to availability of more computational power has made it possible to predict these parameters sufficiently accurate [34]. Studies have shown that a high resolution is of utmost importance, since a general problem when using meteorological models to predict icing is the smoothing of the terrain due to low resolution. An example of the difference in terrain elevation when using 1km horizontal resolution and 9km horizontal resolutionis shown in figure 4.2. Since a high resolution leads to a computationally too expensive simulation, an underestimation of terrain height is almost inevitable. A lower terrain height will in many cases lead to an underestimation of LWC leading to an underestimation of ice load (see 4.2.1). Research on this matter has shown that it is possible to reduce the error caused by the smoothed terrain by scaling the model terrain height to match the real height [35]. Another issue with low resolution and the associative smoothed terrain is that it can lead to problems predicting LWC during periods with temperature inversions. This is due to the inversion layer suppressing turbulence and vertical mixing of humidity [34].



(a) 9km horizontal resolution [36]



(b) 1km horizontal resolution [36]

Figure 4.2: The difference in terrain elevation when using 1km horizontal resolution and 9km horizontal resolution

The cloud micro-physics can be resolved using different parametrization schemes. In a study by Nygaard et al. [34], three different schemes are compared and the results evaluated. Their conclusion is that the simplest scheme, EGCP01, which only predicts the total condensate and not explicitly cloud water content, is not able to predict the parameters determining icing conditions. The other two micro-physics schemes in the study, the Morrison and the Thompson scheme, are double-moment cloud microphysics schemes which means that they predict both the mass and the number of the advected quantities. The Thompson scheme predicts number mass concentration of cloud water, cloud ice, snow, rain and graupel, plus the number concentration of cloud ice and rain. The Morrison scheme predicts mass and number concentration of all the five parameters [34]. Their conclusion is that the Thompson scheme most accurately predicts the icing events, the most sophisticated scheme, the Morrison scheme, tended to overestimate the LWC, whereas the least sophisticated, EGCP01, instead underestimated it. The combination of the Thompson scheme and the highest resolution gave the best result [34].

The results from a number of different studies show that the meteorological models in combination with ice accretion models lack the ability to predict the maximum ice load. The load is often underestimated [37]. Although the models are generally sufficiently good at predicting the onset of icing events, since the icing load, the duration of the icing as well as the type of ice formed are important factors, the models used in previous studies need to be improved [14].

4.2.1 Adjusting model terrain to real terrain height

The difference between modeled terrain height and real terrain height will cause problems when using the model output to simulate icing [38]. The next step when modeling icing climatology is therefore to adjust the model terrain height. One way to counteract the underestimation of the terrain height is to perform lifting of the output parameters from the model to the correct, real terrain height. This can be done using different methodologies of varying accuracy and complexity. The basic principle is to sample the state of an air parcel at model terrain height and lift it to the accurate height letting temperature and pressure change with the change in altitude. This will cause the relative humidity in the air parcel to increase and when saturation vapour pressure is reached, water vapor will start to condensate. The result will be an increase of the liquid water content in the air if the real terrain height is above the condensation level, and a correction of the temperature and pressure to better reflect the real terrain height.

The analysis and lifting of the model data can be done by first finding the dew point temperature at the model terrain height, then calculating the height where the air parcel will be saturated and checking if it will be below the real terrain height. If that is the case, the lifting should continue above this level, up to the real terrain height, with the temperature decrease following taking into consideration the condensation of water vapor and latent heat release. The amount of condensed water can then be calculated, first calculating the difference between the saturated vapor pressure at each height step, and then using the ideal gas law to find the increase in mass water per mass unit air. The corresponding increase in liquid water content will give a better approximation of the real conditions compared to the modeled [38].

When a non-saturated air parcel is lifted, the temperature decrease can be assumed to follow the dry adiabatic lapse rate, which is the temperature decrease per height step due to the change in pressure. The dry adibatic lapse rate can be calculated according to equations (4.1) and (4.2), deriving the equation from the barometric law and the 1st law of thermodynamics.

$$\begin{aligned}
H &= E + PV \\
dH &= dE + d(PV) = dW + dQ + d(PV) \\
dW &= -PdV \\
dH &= dQ + VdP
\end{aligned} \tag{4.1}$$

where H is the entalphy, E is the internal energy, P is the pressure, V the volume, Q the heat added to the system and W the work performed on the system. Consider a thermodynamic cycle with an adiabatic expansion, an isothermal compression and finally isobaric heating, returning the system to the starting condition. For the adiabatic process, $dQ = 0$ and $dH = VdP$, for the isothermal process $dH = 0$ assuming an ideal gas and for the isobaric process $dH = -mC_p dT$,where T is the temperature and C_p the specific heat capacity. Because the sum of the entalphy changes will be zero, this means that $VdP = mC_pdT$. Using the barometric law and $m = \rho V$, the adiabatic lapse rate can be found [39].

$$
\begin{aligned}
VdP &= mC_pdT \\
\frac{dP}{dz} &= -\rho_a g \\
\Gamma = -\frac{dT}{dz} &= \frac{g}{C_p}
\end{aligned}
\tag{4.2}
$$

where z is the height, and Γ is the dry adiabatic lapse rate, 9.8 K/km.

When the air parcel reaches saturated conditions, the temperature decrease rate will instead follow the wet adiabatic lapse rate, which takes into account the latent heat release from the condensating water. The height where the relative humidity of the air parcel is 100 % is sometimes called lifted condensation level, LCL (see figure 4.3). The wet adiabatic lapse rate is between 2 and 7 K/km and because the water vapor content of the air parcel will change during the lifting above the condensation level, the wet adiabatic lapse rate should be calculated for each height step of the lifting when the air parcel is saturated.

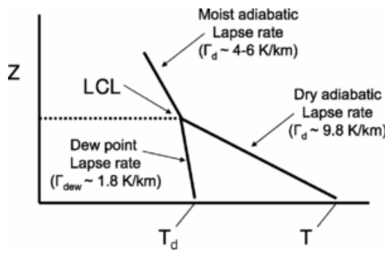


Figure 4.3: Dry adiabatic lapse rate, saturation level and moist adiabatic lapse rate

The condensation level can either be calculated numerically or by using thermodynamic diagrams making use of the relation between the LCL and the dew point. LCL cannot be calculated analytically since the change in relative humidity will depend on the pressure and the temperature and in turn the saturation pressure, which will change with the temperature and surrounding pressure [40]. This means that the saturation pressure need to be calculated in each height step during the lifting. The saturation pressure should be calculated according to equation (4.3), which is a special case of the Clausius Clapeyron equation (see for instance [41]). Moreover, it is important to take into consideration the difference between water vapor pressure over a water surface and over an ice surface.

$$
\frac{de_s}{dT} = \frac{L_v(T)e_s}{R_vT^2} \tag{4.3}
$$

where e_s is the saturation pressure, L_v the latent heat release from vaporization and R_v the gas constant.

Since the solution of the equation for the change of saturation pressure with temperature will be complicated in reality, a number of approximate and empirical equations exist for calculation of the saturation pressure over water and ice. An equation often used is the Magnus Teten equation (saturation pressure for water, see equation (4.4)). The equation can also be adapted for calculation of vapor pressure over ice [38].

$$
e_s = 6.1078e^{(17.269388(T-273.16)/(T-35.86)} \tag{4.4}
$$

An iterative process can be used to calculate the LCL, guessing an altitude and computing the relative humidity. There also exist approximate equations as well as empirical formulas to calculate the LCL. One of the simplest equations for approximating the LCL is the Etsy equation, derived by finding the temperature intersection between the dry and the wet adiabatic lapse rate [40]:

$$h_{LCL} = \frac{T - T_{dew}}{\Gamma_{dry} - \Gamma_{wet}} = 125(T - T_{dew}) \tag{4.5}$$

Lifting the model output variables to the real terrain height will only be correct in the above described way if the atmosphere is not stable. Since temperature inversions are common in Sweden, especially during the winter time (see chapter 1), checking the stability conditions before performing the lifting is of interest.

The simplest way of checking the stability conditions is by using the temperature change with height. If the temperature is increasing with height, conditions are stable and convection will be small or negligible. In fact, even if the temperature is constant or slightly decreasing with height the conditions can be considered stable since a lifted air parcel should be considered to change temperature following the adiabatic lapse rate. As long as the temperature decrease of the atmosphere is smaller than the adiabatic lapse rate, the conditions can be assumed stable [39]. A correct stability analysis would also take into consideration turbulence energy and vertical movements in the atmosphere, by using for instance the Richardson number (see for instance Salby [40]) [38].

It could be discussed whether the described height adjustment is physically correct and attains the goal of better reflecting the real conditions. On one hand, the lifting assumes adiabatic temperature decrease without heat exchange with the surroundings and without continuously checking the surrounding conditions, which arguably is physically incorrect. On the other hand, the assumption behind the implementation of the height adjustment is that the model does not capture the correct variations in the atmosphere, which means that this simple height adjustment still is a way of correcting the conditions. The aim is not to lift the parameters to the top of a real hill in the model, but to a hill not existing in the model. If the hill really existed in the model, then there's the question on whether the air would actually be lifted over the hill or whether it would go around it. Since this is not the case, the question arises if it is interesting to check the modeled atmospheric stability or if this will be incorrect [38]. The fact remains that for a low resolution model output, the pressure will be different than at the real site, and some sort of post-processing should definitely be performed. The most common way as of today is height-adjusting following the above described method [42], [43], [13].

4.3 Methodologies for normal year correction

For wind power developers, the crucial factor is how much a planned wind park will produce. Therefore, means to assess the long term icing climatology are important. The icing climatology at an interesting site will have effects on production, loads and whether investments in anti-icing technology are necessary. Long-term correction of wind speeds to calculate the long-term production is a normal part of the site assessment and there exist a number of techniques for doing this. The same is not true for assessment of long-term icing climatology. As well as for ice modeling, normal year correction of icing climatology is a developing field and there does not exist any standard methods. After post-processing the output from the meteorological models, normal year correction of the parameters should ideally be performed, either before or after the ice modeling.

4.3.1 Introduction to normal year correction

A normal year is a theoretical year within which a studied parameter varies according to a long term average. Normal year correction refers to calculating this variation using reliable data from real years and a long term reference. The aim is to find, for instance, the monthly mean or median wind speed or monthly mean temperature for a normal year in a long term perspective. For new wind power developments, it is of importance to know the mean, maximum and minimum average wind speeds that can be expected during the life time of the wind turbines [8]. In the general case, measurements are available from a limited time period, and this data is necessarily not representative for a longer time period. There exists a large number of models for normal year correction and the basis is usually a shorter, reliable source of data, such as measurements. Today, the most common way is to use some sort of wind energy index, such as the Swedish Wind Index, the Danish Wind Index or the Geostrophic Wind Index (for description, see for instance [44]). The different wind indices all use different methodologies to enable calculation of normal year power production from a wind farm. The normal year production can also be calculated by first calculating mean wind speeds and then relating this to an expected production for the site in question [44].

4.3.2 Normal year correction of icing climatology

Normal year correction of wind speed is a tested and approved way of estimating the long term climatology, making an assessment of normal year ice load, production losses or number of hours with active icing is less so. Ice accretion is related to atmospheric parameters in a highly non-linear way (see chapter 2.2), which means that the number of active ice hours, the ice loads and the corresponding production losses will vary to a large extent from year to year. Focusing on using long-term, low resolution meteorological model output and short-term, high resolution meteorological model output, some different methodologies can been motivated. None of the below suggested methodologies have been thoroughly tested and the theoretical reasoning deviates. All methodologies are developed by the author if not explicitly stated otherwise. The same is true regarding the assumptions and theoretical motivations.

Synoptic weather classes

Given the large variations of the modeled ice loads and active ice hours from year to year, one way to find normal years is to discard the atypical years before performing a normal year correction. Defining an extreme or atypical year can be done in several ways, and one way is to look at it in terms of synoptic weather systems. Synoptic scale weather systems are wind regimes and cyclonic systems studied on a large scale basis. There exist a large number of ways to distinguish between and classify synoptic weather systems. Synoptic weather classes classify weather systems in terms distinguishable patterns, such as high or low pressure zones, movement of weather systems and cyclonic or acyclonic circulation [45]. The occurrence and frequency of the classes can then be studied for a large number of winter seasons, and if atypical years are found these can be discarded or given less weight in the long-term assessment of the icing climatology (see Figure 4.4).

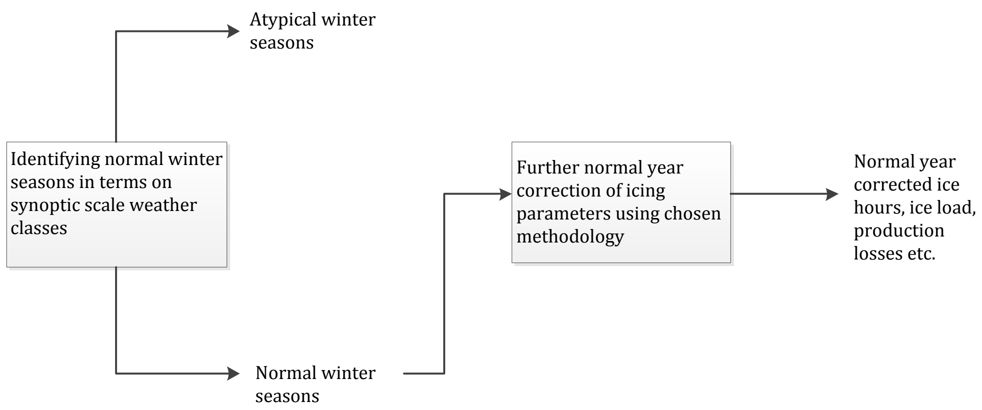


Figure 4.4: Using synoptic weather classes for normal year correction

The theoretical background to this methodology is that seasons with extreme icing could possibly be coupled to larger scale weather systems. Icing occurs during certain weather conditions and extreme icing seasons should be coupled to prevailing such conditions. If these conditions are coupled to synoptic weather systems, a classification of normal synoptic weather years will also lead to a classification of normal icing years [35]. After identifying atypical winter seasons, normal year ice loads, active ice hours or other interesting parameters can be calculated using further normal year correction methodologies.

Basic relation between high and low resolution ice parameters

A simple methodology to find the normal year ice load or active ice hours is to find a basic relation between high resolution and low resolution model ice parameters. The assumption made is that one season in the low resolution series will be related to the long term, low resolution reference series in the same way as one season from the high resolution, short term series would be to a long term, high resolution series (for schematic procedure, see figure 4.5). The high resolution, normal year could then be calculated according to equation (4.6), similar to the procedure used when wind indices are used for normal year correction of wind speed. The low resolution normal year could be defined as for instance monthly means calculated from all the modeled seasons. This is a simplified way of normal year correction of the ice parameters, and it gives disproportionate weight to the season used as basis [42].

$$normalyear_{high} = \frac{season_{high} normalyear_{low}}{season_{low}} \tag{4.6}$$

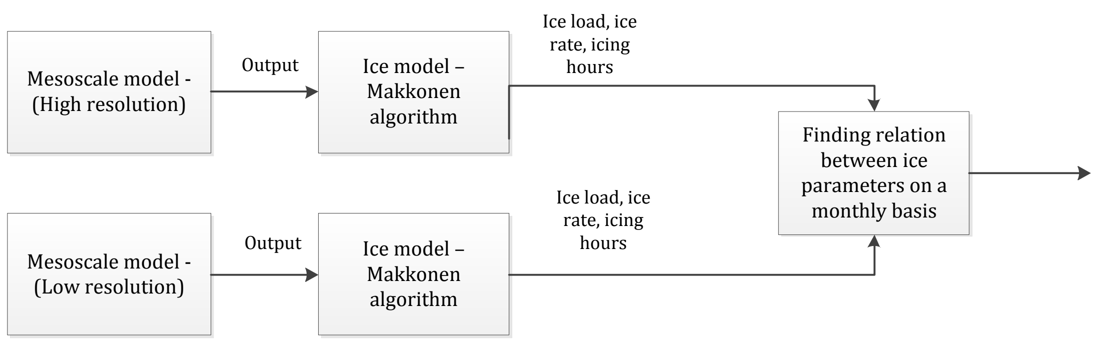


Figure 4.5: Relating high resolution model output to low resolution output

Linear regression adjustment

Whe performing a long term correction of wind speed using short term measurements and long term reference series, the long term time series is usually fitted to the measurements. This can be done by using some kind of linear relation between the two [23]. The reasoning behind this is the assumption that the short term measurements better reflect the real wind regime at the studied site, and by linearly adjusting the long term series to the short term, the long term climatology will better reflect the climatology. The same methodology and reasoning can be applied to other meteorological parameters, such as pressure, temperature and water vapour content. The method can be applied to the output parameters from the low resolution mesoscale model, assuming that the high resolution model output better reflect the real climatology. Height adjustment of the time series should also be performed in combination with the regression [46]. Figure 4.6 shows the method.

This methodology further assumes that a linear relationship between the low resolution and high resolution model output exists. Therefore, when choosing what parameters to linearly correct, this assumption has to be motivated. Due to the sensitivity and uncertainties in the prediction of liquid water content and other condensates, a linear regression of these parameters from the low resolution model output to the high will most probably give questionable results. Also, even though applying linear regression to the output parameters from the ice model would be a straight forward and simple way of correcting the long term reference series, the non-linear equations and uncertainties preceding the output means that the result will probably be unreliable.

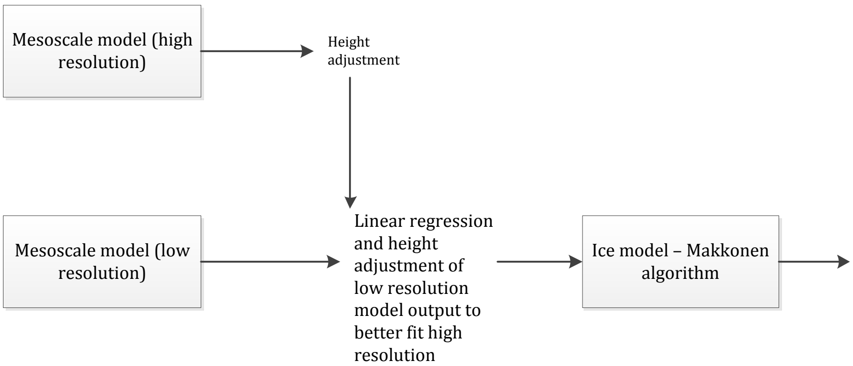


Figure 4.6: Normal year correction using linear regression

Iterative height adjustment of the low resolution ice parameters

The aim of the normal year correction of the icing climatology using long term low resolution simulations together with short term high resolution simulations is to adjust the long term reference to the short term model output. One way of doing this is linear regression, but fact remains that the statistical approach does not reflect the physics of the atmosphere. The height adjustment using lifting algorithms, on the other hand, aims to do just that. Therefore, one idea for adjusting the long term reference to the short term model output is to tune the height adjustment. The method is visualized in figure 4.7.

The assumption made is that the height adjustment reflects the physics of the real atmosphere, and that it is capable of adjusting the low resolution parameters to the high resolution. Adjusting to the real terrain height is in this methodology assumed to be of less importance than adjusting the parameters to the high resolution model output. The method has been tested by Company A (see section 5.3).

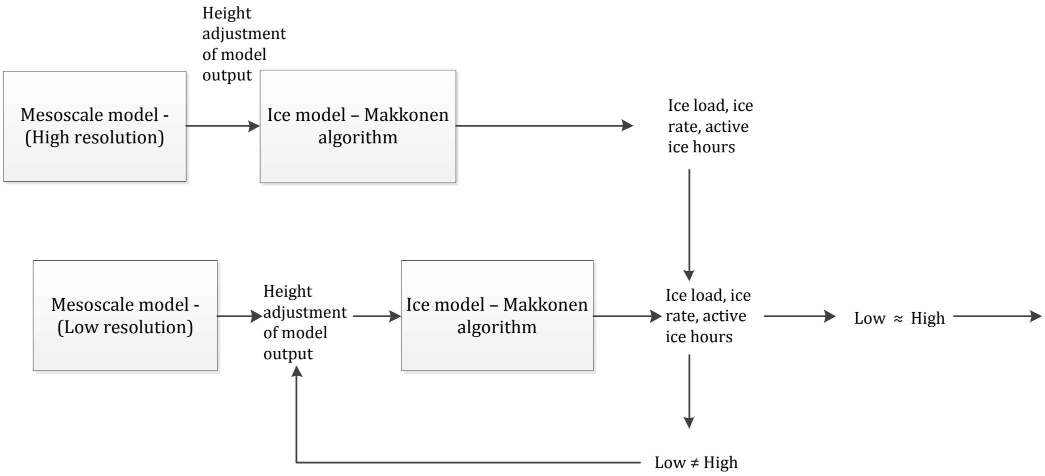


Figure 4.7: Normal year correction with iterative lifting

Other methods to find long term icing climatology

The methods for normal year correction of icing climatology so far described all use the high resolution simulation to adjust the long term low resolution output. Another possibility is to use measurements from different types of ice detectors to correct the low resolution time series. It is also interesting to use advanced statistical analysis to couple ice parameters to measured or modeled parameters. These methods are not within the scope of this thesis, see for instance Rindeskär [3] for a more thorough description.

5 Modeling icing climatology in northern Sweden

The increased interest in new wind power plants in northern Sweden has the consequence that an increased number of turbines will be situated in areas with cold and icing climate. This means that understanding the icing climatology will become increasingly important. Vattenfall Vindkraft AB has ordered state-of-the-art modeling of the icing climatology and production losses for a number cold climate sites from the companies Company B, Company C and Company A. The companies have had access to data from Vattenfall for the sites in question. The simulations have been evaluated for the sites Site A, Site B, Site D, Site C and two additional sites further south. The site most interesting for evaluation of the results is Site A, where a wind power plant is already built and has been operating during winter seasons.

5.1 Site A

Site A wind power plant is currently Vattenfall's largest onshore wind park. The park has 40 Vestas V90 wind turbines and a predicted yearly production of 240 GWh. The towers are 95 meters high, and the height up to the blade tip is 140 meters from ground level at the highest point. The highest point is 570 meters above sea level [47]. The site is subject to demanding icing conditions which have had large effects on the production. The turbines do not have any anti-icing or de-icing equipment and are being shut down by the control system in situations with severe icing. The control system do not have specific means to detect icing, but shuts down the turbines for reasons such as high vibrations [16].

Two types of ice detectors are installed on the turbines. Six of them have HoloOptics and one the IGUS-system. IceMonitor and HoloOptics are installed on the met mast. Estimations of icing losses have been made by comparing normal power curves to the power curves during the winter months, and calculating the losses. The production losses due to icing were estimated to 8.4 % during the studied winter [16].

5.2 Other sites

Vattenfall is investigating the possibilities to develop a wind power plant on the mountain Site B. The park will consist of up to 50 turbines and the installed power will be between 90 and 150 MW. An advantage with the site is that it is close to Site A, which means that the infrastructure is already well developed. Site B is a plateau, between 360 and 540 meters high with two higher peaks. As a part of the assessment, the icing climate at Site B is being investigated. The met mast in Site B is equipped with the icedetectors IceMonitor and HoloOptics [47], [8].

The possibilities to develop a wind power plant in Site D are also investigated. This park would have up to nine turbines. The site in question is located close to Site D. This area has been assessed by the Swedish Energy Agency and found to be of national interest for wind utilization, above all due to the strong winds and the area being uninhabited. Fortum and Skellefteå Kraft are planning to erect wind turbines in the area. The area is 400 to 750 meters over sea level [47].

Another site interesting for wind power development being subject to icing is Site C, in the same geographical area as Site A and Site B. The installed power would be between 70 and 120 MW, and up to 40 turbines [47]. Finally, Site E is also being assessed in terms of wind power development. It is at an elevation of 572 meters above sea level, meaning that even though it is further south than the other described sites, it may still be subject to icing conditions [8].

5.3 Company A

Company A has modeled icing climatology and the corresponding production losses at different sites on behalf of Vattenfall Vindkraft. They have performed simulations with high horizontal resolution (1-km) using the COAMPS-model for two seasons and with lower horizontal resolution (9-km) for 30 years (1981-2011) using the WRF-model [46]. The horizontal resolution refers to the size of the grid used in the meteorological model set-up. The sites in question are Site A, Site B, Site D and Site C.

The cloud processes in the WRF-modeling are calculated using the Thompson microphysics scheme, which has been shown to give the most accurate calculations of liquid water content (see 4.2). There are uncertainties in the distribution of moist air as well as in the choice of parametrization schemes for the boundary layer mixing processes [10]. The issue with smoothing of the terrain for simulations with low resolution has been accounted for by lifting the model terrain to the real terrain height [43]. For the icing model, they use the Makkonen algorithm to calculate icing on a standard cylinder (see 2.2). An icing event is defined as ice accumulation rate being >10 g/m/hour, which for the standard body equals a 0.5 mm thick layer of ice. The model takes into account the changed diameter of the iced object during an icing event. For the cloud droplet density they used a fixed number of 100 cm^{-1}. This represents rather large droplets and thus a larger α_1, which means higher frequency of icing and larger ice loads. Ice removal by melting is represented by an energy balance, where the energy available for melting equals the latent and sensible heat fluxes plus the net radiation term. The other terms in the energy balance are neglected.

The model used for the simulations and calculations has been improved during the last year, within a project funded by Energimyndigheten (Swedish Energy Agency). Within the project, production data from three Swedish wind farms has been made available together with icing measurements from eight sites. The availability of the data has made it possible to decrease the uncertainties and to develop a two parameter power curve, dependent on wind speed as well as ice load [43]. Production losses are estimated using the ice model output in combination with modeled wind speed and the two parameter power curve. They conclude that there are uncertainties in coupling the ice load to production losses, one of the reasons being that the power curve is based on data from only three sites. It is at this point not possible to say whether these sites are representative for the studied sites. Another uncertainty is the difficulty to translate the ice load on the standard cylinder to the ice load on the turbine blades. Operational data from wind power plants and results from wind tunnel experiments have been used to relate power loss to ice load. Company A has only calculated the production losses for their low resolution simulation.

Company A is counteracting the smoothing of the terrain by height adjusting the model output. They do not check stability conditions before implementing their lifting algorithm. Company A has further tested two methodologies for normal year correction of the icing climatology, the linear regression method and the iterative height adjustment method, for further description of the methods see chapter 4.3.

5.4 Company B

Company B Vindteknikk has modeled the icing climatology at different sites in northern Sweden. For their ice modeling they run a WRF-model with 1 km horizontal resolution and with 4 km horizontal resolution. The high resolution simulation is made for one year (covering the winters of 2009/2010 and 2010/2011), whereas the low resolution simulation is run for the time period 1/1-2000 to 27/12-2011. From the model output they calculate the icing climatology at the studied site. The lower resolution long term time series could possibly be used as a statistical basis to estimate the icing climatology in a longer perspective. Company B has performed icing climatology analyses for Site A, Site D and for two other sites further south. The most recent analysis is the one made for Site A [13].
The calculations are performed in a very similar way to Company A (see section 5.3) with active icing

defined as >10 g/m/hour and production losses related to the ice load [13]. Company B participated in the project funded by Energimyndigheten and therefore have access to the data and two parameter power curve (see section 5.3). Sublimation is included in the calculations by an energy balance between outgoing long wave radiation and latent heat release from the sublimation process and shedding is included as a constant fall-off factor [10].

At this point, Company B does not perform any normal year correction for the calculation of the icing climatology.

5.5 Company C

Company C has performed an icing climatology analysis with the mesoscale model AROME for three sites: Site A, Site D and Site E. For Site A, the calculations were performed for two different heights above ground level, 59 meters and 95 meters. For the two other sites the calculations were performed at 100 meters above ground level. The horizontal resolution used was 2.5 km. To perform an analysis of the icing climatology in a longer time perspective, 32 years (1979-2011) of ERA-Interim data were used. ERA-Interim is meteorological reanalysis data available from the ECWMF model, and has a resolution of approximately 80 km. The high resolution simulations with AROME were performed for two seasons, 2009/10 and 2010/11. The model terrain was adapted to the real terrain by lifting, similar to Company B's model including a stability check, and a constant cloud droplet number of 100 cm^{-1} is used [42].

Company C uses the Makkonen algorithm to calculate the ice load from the output of the meteorological model. Melting is modeled through an energy balance. Sublimation and shedding is modeled as a constant rate of 25 g/hr [42]. A difference from the analysis made by Company B and Company A (see section 5.3) is that Company C does not relate the ice load to production losses by using the two parameter power curve.

A normal year correction of the ice load is performed by assuming that the ice load calculated using AROME is related to the normal year ice load in the same way as the ERA-Interim ice load. The ice load is calculated for the years 1979-2010 using ERA-Interim data and the Makkonen algorithm. The result is given as monthly values of ice load. Normal year correction is then performed on the output by relating the monthly values for 2010 to the monthly mean values for the whole 32-year period [42]. The model is further described in section 4.3.

6 Method for data analysis

6.1 Time series

The data analysed is model data provided by Company B, Company A and Company C. Output from the respective meteorological model has been provided in processed as well as non-processed, raw data format by Company B and Company A, from the high resolution model as well as from the low resolution model. Company C has provided processed data from their high resolution simulation. A summary of the available data sets can found in table 6.1 and table 6.2. In the following sections, processed data refers to model output that has been height adjusted and in other ways post-processed by the respective company. Raw data refers to direct output from the mesoscale meteorological model used by the respective company. Lifted data refers to data that has been height adjusted by the author according to the methodology described in section 6.2. Normal year adjusted data or normal year parameter refers to data that has been adjusted using one of the methods described in section 6.5.

The data has been divided into winter seasons to enable seasonal analysis of the icing climatology. A winter season has been defined as 1st of October to 30th of April. The data has further been organized into months, to enable comparison of monthly values. The time series from all the companies include temperature, wind speed and direction, liquid water content and/or other condensates, pressure, water vapor content as well as a time vector. The processed time series include ice load and ice rate. Company B and Company A have provided time series of production with and without ice.

Table 6.1: High resolution time series

High resolution time series			
Company	Horizontal resolution	Time period	Sites
Company B	1 km	01.10.2009 - 30.04.2011	Site A
Company A	1 km	01.10.2009 - 30.04.2010 & 01.10.2010 - 30.04.2011	Site A, Site C, Site B, Site D
Company C	2.5 km	01.10.2009 - 01.05.2010 & 01.10.2010 - 01.05.2011	Site A, Site D, Site E

Table 6.2: Low resolution time series

Low resolution time series			
Company	Horizontal resolution	Time period	Sites
Company B	4 km	01.01.2000 - 27.12.2011	Site A
Company A	9 km	01.10.1981 - 30.04.2011	Site A, Site C, Site B
Company C	80 km	1979 - 2011	Site A, Site D, Site E (ERA-Interim)

The processed data provided by the companies has been analysed and compared, see section 7.1.

6.2 Lifting algorithms

To counteract the smoothing of the terrain in the model (see section 4.2.1), height-adjustment of the raw model output has been performed. Pressure, temperature, water vapour content and liquid water content has been adjusted following the changes with the lifting to a higher level. The algorithm follows the method described in section 4.2.1.

The saturation pressure was calculated using the Magnus-Teten formulation (equation (4.4)), combining vapour pressure over an ice surface with vapour pressure over a water surface when the temperature is far below zero degrees Celsius. For non-saturated conditions, a constant dry adiabatic lapse rate has been assumed. For saturated conditions a pseudo-adiabatic wet lapse rate was calculated for each time step, taking the latent heat release from condensing water into consideration.

The algorithm includes a possibility to perform a stability analysis using either absolute temperature or potential temperature. The potential temperature can be calculated as either normal potential temperature, virtual potential temperature or equivalent potential temperature (for definition see for example Salby [40]). The stability was calculated for each time step, and if the conditions were found stable, no height adjustment of temperature or liquid water content was performed. The pressure was adjusted to reflect the real terrain height. The stability analysis could only be performed when data from many model levels were available, as the temperature on different heights needed to be compared.

An alternative, basic lifting algorithm was also implemented based on finding the condenstaion level using the Etsy formula, equation (4.5). Constant lapse rates where used for both unsaturated and saturated conditions and neither dew point nor saturation pressure and temperature decrease was calculated in each time stepd, but instead only calculated ones for the entire height adjustment.

The height adjustment was performed on raw, non-processed data from the meteorological models, provided by Company B and Company A.

6.3 Ice model

The ice model used in the analysis is an implementation of the Makkonen formula for ice accumulation (equation (2.1)), including equations for melting and shedding. Melting is calculated using a heat balance found in for instance Harstveit [11], then calculating the total potential melting and adjusting it to the cylinder area and the existing ice layer. Sublimation is calculated using an algorithm developed by Ben Bernstein [14], estimating the sublimation rate from the relative humidity and the wind speed. The model is originally developed for aviation purposes. An empirical factor is included in the sublimation model.

The output from the ice model is ice mass in kg/m and ice accretion rate in kg/m/hour, where the unit m refers to meter of the standard cylinder, for which the Makkonen algorithm models ice accretion (see section 2.2). It is also possible to get other parameters, such as the efficiency factors or the cylinder diameter, as output. Input parameters are pressure, temperature, relative humidity and wind speed as time series, and initial diameter, cloud droplet density and time step as constants.

Ice modeling has been performed on all available data from Company B and Company A to enable a fair comparison between the data sets. That means that it has been performed on data processed by the companies, data processed using the above described height adjustment methods as well as on data adjusted using the normal year correction methods described in section 6.5 below. This has been done to eliminate differences between the output icing climatology caused by different ice models being used for the modeling.

6.4 Production losses

No modeling of production losses has been performed within this study. The modeled production losses available are only losses as modeled by Company B and Company A. No evaluation of normal year production losses with data adjusted according to the normal year correction methods described in this paper has therefore been possible.

6.5 Normal year correction

A number of different normal year correction methods have been developed by the author (see section 4.3) and performed on the datasets available. Since the focus of this thesis was using high and low resolution meteorological models to estimate the icing climatology, the aim of the normal year correction has been to adjust the low resolution ice parameters to the high resolution ice parameters. The methods have therefore been performed on datasets where both low and high resolution model output exist for the same site.

The result of the normal year correction methods has been evaluated on the basis of a few criteria. Firstly, the plausibility of the calculated ice parameters, that is, whether the ice loads and hours with active icing are feasible, close to the high resolution model values and comparable to measurements, the results delivered by the three companies and previous studies. Secondly, the sensitivity of the method. The sensitivity was tested by using different seasons from the high resolution model as basis for the normal year correction and by testing the method on data from different sites. A successful normal year correction method should give stable mean values of important variables, a reasonable variation in the results and it should give good results regardless of the studied site and data set. It should further not be sensitive to the length of the time series used as basis (see figure 6.1). The four criteria are thus: plausibility of the results, site dependency, sensitivity to data set used and sensitivity to the length of the time series used as reference.

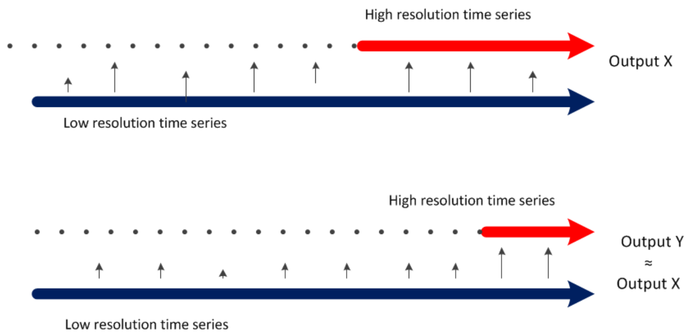


Figure 6.1: The result of the normal year correction method should not be sensitive to the length of the high resolution time series used.

6.5.1 Synoptic weather classes

To evaluate the possibility of finding atypical years in terms on synoptic weather classes (see section 4.3.2), an objective classification, objective GWL, was used (for description see James [48]. The frequency of the 31 possible weather classes during the winter seasons from 1979 to 2011 were determined, and a normal year in terms of weather classes was calculated as the mean frequency of each weather class. Each year between 1981 and 2011, the time period covered by the longest time series available to the author, was then evaluated in terms of deviation from the normal year of GWL-classes. If an extreme year in terms of deviation from the normal year could be distinguished, this year was considered an atypical year. The correlation between deviation from the normal year and interesting parameters was also determined.

6.5.2 Basic model

The normal year correction method described in section 4.3.2 was performed on the available data sets. The result was a calculated normal year ice load and normal year active ice hours. The result was not calculated with any higher resolution than monthly values. Sensitivity was tested by using different seasons as the basis for the correction.

6.5.3 Linear regression model

This method, described in section 4.3.2, was performed on all data sets where raw data was available in both high and low resolution. A simple linear correlation was found between the low resolution output and the high resolution output for wind speed, pressure, temperature and relative humidity. The regression for the wind speed was forced through origo to avoid the problem that the fitted wind speed would otherwise never be 0 m/s. The linearly adjusted parameters from the low resolution time series were then used as input to the ice model.

The method was tested in three different implementations. The first method was to first perform the regression and then the height adjustment on the data, regression - lifting. The low resolution raw data parameters were then linearly adjusted to the high resolution, raw data parameters and then lifted as if they were on the high resolution grid. The second way was to first perform the height adjustment and then the regression, lifting - regression. The third method was to apply linear regression to the output parameters from the ice model. The result was evaluated according to the criteria described in section 6.5, using monthly mean values as well as yearly means. The correlation between the parameters of the high resolution model and the low resolution model was evaluated after the regression.

6.5.4 Mean value model

This method is based on calculating mean values of all in-parameters to the ice model. The method was performed on height adjusted data and data that was first processed using the lifting - regression method or the regression - lifting method. Long term mean values were calculated from all available winter seasons. The result was evaluated according to the criteria in section 6.5. Long term mean values of liquid water content were not calculated due to the very large variation in this parameter.

6.5.5 Iterative adjustment model

The normal year correction method described in section 4.3.2 is based on iteratively adjusting the height up to which the lifting of variables from the raw data is performed. The aim is to find an adjusted height at which the output from icemodel for the low resolution data is as close as possible to the output from the high resolution model data. The method has been performed on raw data from Company A and Company B. First, the accumulated difference between the low and high resolution ice load, using height adjusted data, was calculated. If it was higher than 10 %, an adjusted height adjustment was performed. The height up to which the raw data parameters was lifted was found by starting at a height fifty meters below the real terrain height. This means that in the initial step, the parameters were only lifted to a height corresponding to fifty meters below the real terrain height. The adjusted parameters were then used as input to the ice model and the output was compared to the high resolution ice parameters. The iterative adjusting of the lifting height, in steps of two meters, and following ice modeling was performed until the accumulated difference between the high resolution and the low resolution output was less than 10 %. The threshold difference of 10 % was chosen because it was found to be possible to achieve with the chosen methodology.

Data from the two seasons represented in both the high and the low resolution model were used in the analysis, and the comparison was based on ice loads from the respective season, comparing ice loads from 2009/2010 from the high and low resolution modeling and analogously for the winter 2010/2011. The adjusted lifting height was found for separate winters, which means that it is not neccesarily the same for both seasons. After finding the adjusted heights for both seasons they were thereafter averaged to find a height up to which the whole time series was lifted.

This method could also be used to find an adjusted lifting height at which other parameters than the ice load come closer to the high resolution output than when lifting to the real terrain height. This was not evaluated in this study, but using active ice hours instead of ice loads would possibly give interesting results.

6.6 Production losses and comparison with measurements

Ice measurements and production analysis have been performed for Site A. The production analysis was performed by Jan-Åke Dahlberg at Vattenfall Vindkraft and measurement data was delivered by Peter Krohn at Vattenfall R&D. The result was analysed and evaluated by Benjamin Martinez at Vattenfall R&D. In the production analysis, icing was detected as a deviation from the normal power curve when the temperature was below 0°C. The production losses were calculated analogously. The theoretical production losses if the turbines were forced to shut down when the deviation from the normal power curve was above a certain threshold (50, 150 and 250 kW) was also evaluated. The analysis has been performed for the winter season 2010/2011 and the result has been made available for this study. The result has been compared to production losses modeled by Company B and Company A.

7 Key results and discussion

In this chapter the key results are presented and discussed. Summary, final discussion and conclusions are found in chapter 8.

Since only high resolution, processed data was provided by Company C, no normal year correction has been performed on the data from this source. For this reason, no effort has been put into evaluating this data set. Due to Site A being the only site with modeled values from all companies, focus has been put on results from this site. If not stated explicitly, all results presented are from Site A, at 95-100 meters above ground level and 550 meters above sea level, for the winter season 2010/2011. The results are of course available for all modeled seasons, but for simplicity only one season is presented here.

7.1 Model output and measurements

The key results from the analysis of the time series provided by Company B, Company A and Company C are presented and compared to key numbers from the analysis of production data and ice measurements performed Benjamin Martinez at Vattenfall R&D [49]. The results presented in this section are output from the mesoscale models and ice models used by Company B, Company A and Company C, from the production losses analysis and from the ice measurement analysis. Only a short presentation of key parameters are presented, due to the focus of the study being the possibilities for normal year correction of the icing climatology. The section aims to visualize the similarities and differerences in the different model outputs as well as the measured parameters.

7.1.1 Ice parameters

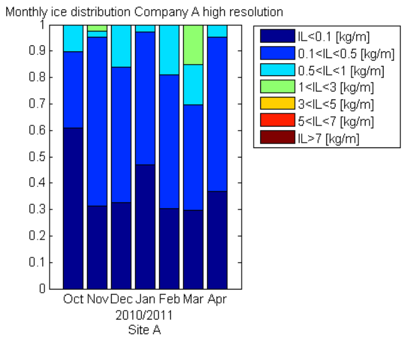
The modeled and measured mean and max ice load at Site A season 2010/2011 are shown in table 7.1. The measured ice loads are results from an IceMonitor placed at 58 meters height above ground level and 570 meters above sea level in Site A, the met mast position. The modeled ice loads are results from the simulations by Company B, Company A and Company C, at a height 95-100 m above ground level and 550 meters above sea level. The result shows that all the models predict mean and max ice load of the same order of magnitude, but the measured ice loads are significantly higher.

The ice load distribution per month is shown in figure 7.1. The ice load distribution is shown as modeled by Company B and Company A in their high resolution models and as measured values, for the season 2010/2011 in Site A. Company A and Company B model similar ice load distributions, although Company B models the highest frequency of high ice loads in January whereas Company A models the peak in March. The measured values show overall higher ice loads than do the models, the highest frequency of high ice loads measured in November and December. The difference in ice loads between measured and modeled values is an indication of the difficulties related to both measuring and modeling ice. The result could be seen as an indication that the models fail to simulate the real ice loads. Due to the high uncertainties related to ice measurements, this conculsion should not be drawn without further investigation and analysis, which is out of the scope of this study.

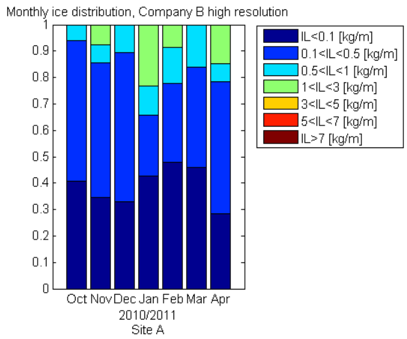
A brief analysis of the time series for ice load show that there are differences in the modeled ice loads for individual ice events, but that the onset of the events most of the time are modeled at approximately the same time by all the models. An example of an ice event is shown in figure 7.2.

Table 7.1: Modeled and measured ice load season 2010/2011

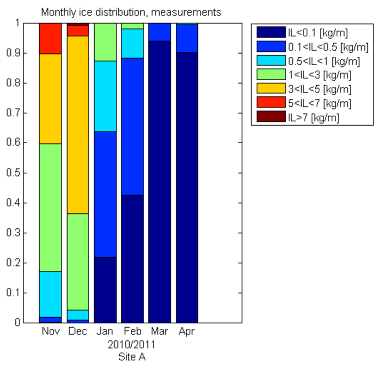
Modeled and measured ice load 2010/2011		
	Mean ice load (kg/m)	Max ice load (kg/m)
Company B high resolution	0.32	2.00
Company B low resolution	0.27	1.42
Company A high resolution	0.26	1.38
Company A processed low resolution	0.38	1.43
Company C	0.22	1.25
Measured [49]	1.42	7.75



(a) Monthly ice load distribution Company A, high resolution. Site A.



(b) Monthly ice load distribution Company B, high resolution. Site A.



(c) Monthly measured ice load distribution [49]. Site A.

Figure 7.1: Monthly ice load distribution, modeled compared to measurements. Site A.

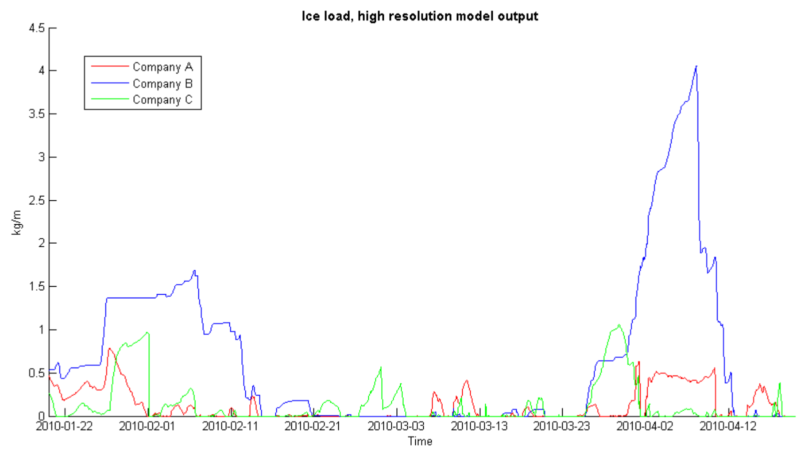


Figure 7.2: Ice load, time series for January to April 2010. High resolution model output from Company B, Company C and Company A. Site A.

The low resolution monthly mean active ice hours as modeled by Company B and Company A are shown in figure 7.3. The low resolution model was chosen for this visualization, the reason being that Company B and Company A have run their low resolution model for eleven and thirty seasons respectively, the low resolution mean values thus being less effected by extreme seasons. A drawback using the low resolution model output is that it should be considered as having a lower quality, and also that Company B and Company A use different resolution and different post-processing tools for their low resolution model runs. Keeping in mind that Company B is using the WRF-model for their high resolution simulation whereas Company A is using the COAMPS-model, the comparison between the low resolution model outputs is still considered to be of interest. As can be seen in figure 7.3, Company A models the highest number of active ice hours in April and Company B in November. The large difference in monthly modeled active ice hours is interesting and an indication of a difference in the implementation of the ice model by Company A and Company B. One possible explanation to part of the effect could be a sensitivity of the model, as implemented by Company A, when the temperature is close to zero (for further discussion, see section 7.3).

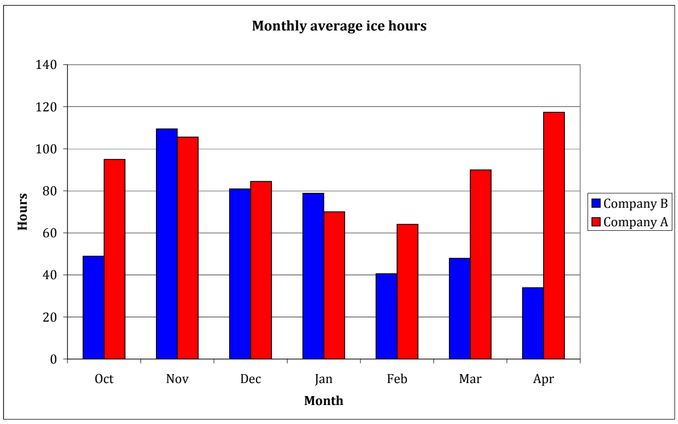


Figure 7.3: Mean number of active ice hours from low resolution model output, Company B and Company A. Site A.

In figure 7.4 the active ice hours per season are shown, as modeled by Company B and Company A in their low resolution simulations for Site A. Both companies model high numbers of active ice hours during the seasons 2000/2001, 2003/2004, 2004/2005 and 2009/2010. Both companies model low numbers of active ice hours during 2005/2006 and 2010/2011. Company A is consistently modeling a higher number of active ice hours than is Company B.

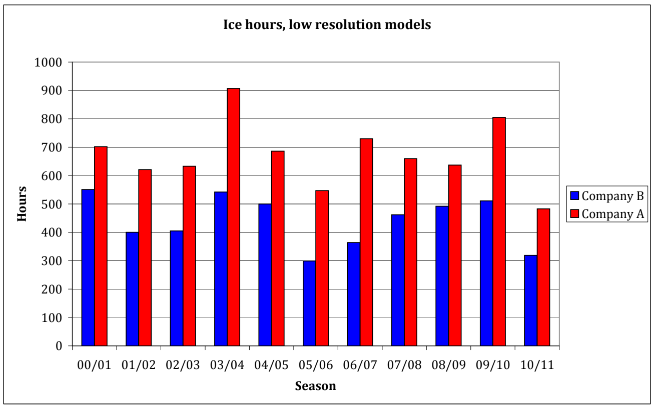


Figure 7.4: Active ice hours per season from low resolution model output, Company B and Company A. Site A.

7.1.2 Production losses

The modeled and measured production losses for the season 2010/2011 are shown in table 7.2. The measured production losses are production losses for the whole park, whereas the modeled production losses from Company A and Company B are extracted values from 550 m above sea level and 100 m above ground. The highest production losses are modeled by Company B in their high resolution model, the lowest by Company A. The measured production losses are higher than the modeled, 8.4 % compared to Company B's high resolution modeled losses of 5.6 %. Keeping in mind that the modeled values are production losses only at one specific position, the results are not directly comparable in terms of absolute numbers, although a comparison of the orders of magnitude can be made. The production losses for the seasons 2000/2001 to 2010/2011 as modeled by Company B and Company A in their low resolution model run are shown in figure 7.5. The low resolution model output was chosen to enable a visualization of the longer term modeled production loss estimates and a comparison between Company B and Company A, since production losses were not modeled for Company A's high resolution simulation. Only production losses modeled by the companies are available, since no modeling of the production losses was performed within this study. The measured production losses are aerodynamic losses, meaning that periods when the turbines are not operating are not included. Company B consistently models higher production losses than Company A.

Table 7.2: Modeled and measured production loss due to ice accumulation season 2010/2011

Modeled and measured production losses 2010/2011	
	Production losses
Company B high resolution	5.6 %
Company B low resolution	4.7 %
Company A low resolution	3.6 %
Measured	8.4 %

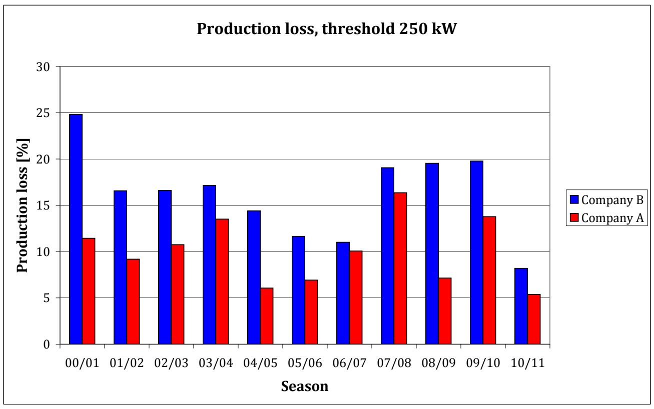


Figure 7.5: Production losses per season from low resolution model output, Company B and Company A. Site A.

Figure 7.6 shows measured and modeled production losses per month during the winter season 2010/2011. As can be seen in figure 7.6, the highest production losses are measured in February. The highest modeled losses are found in December and January. High production losses are modeled in March, where almost no production losses are measured.

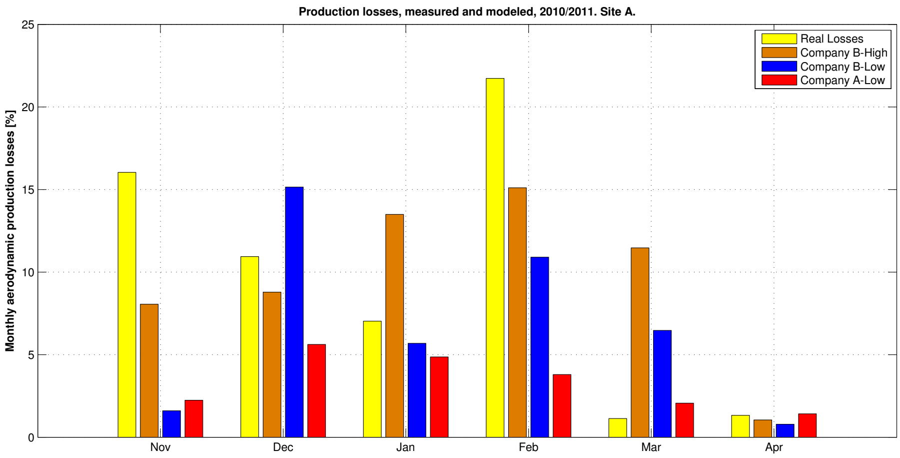
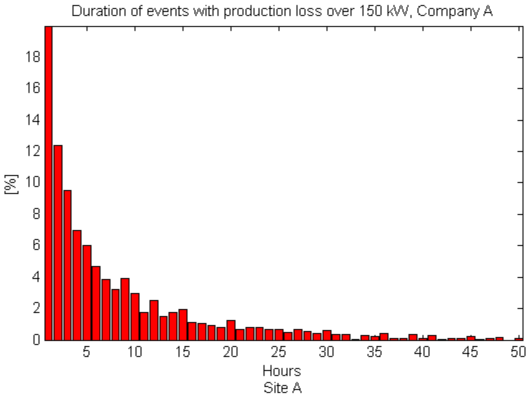
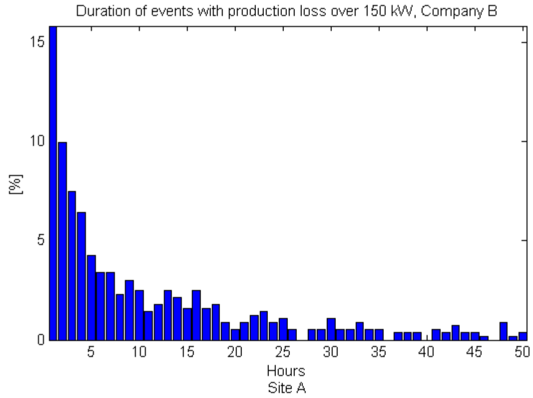


Figure 7.6: Production losses per month, modeled by Company B and Company A as well as measured at Site A 2010/2011 [49].

It is also of interest to estimate the length of individual production loss events. In figure 7.7 the duration of the modeled production loss events are shown. The y-axis is the percentage of the total number of events and the x-axis is the duration in hours. Most modeled production loss events lasted for less than ten hours, the normal duration being one hour. Company B models 15 % and Company A 20 % events of one hour duration. The values are derived from the low resolution model output, meaning thirty winter seasons of data from Company A and eleven seasons from Company B. During thirty and eleven modeled seasons respectively, some production loss events with losses above 150 kW will last for over forty hours. This means that the model predicts events with severe icing of the turbines lasting over forty hours. The percentage of the production losses occuring during ice events of different length are visualized in figure 7.8.

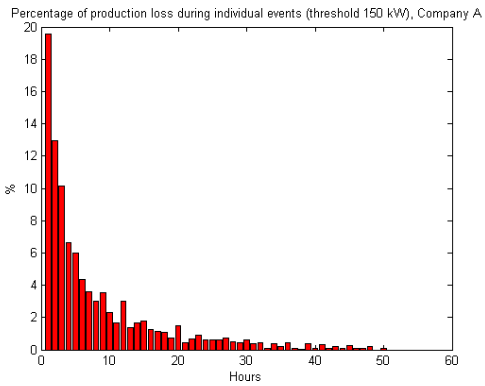


(a) Distribution of duration of events with production loss over 150 kW Company A, high resolution. Site A.

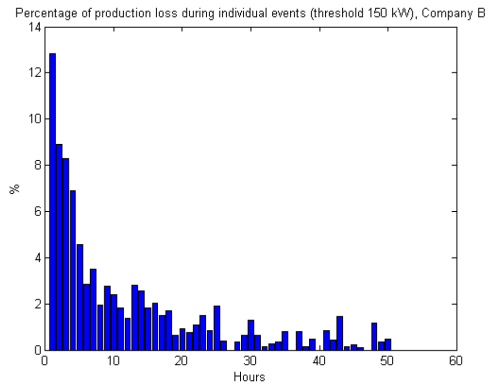


(b) Distribution of duration of events with production loss over 150 kW Company B, low resolution. Site A.

Figure 7.7: Distribution of duration of events with production loss over 150 kW. Site A



(a) Percentage of production (over 150 kW) loss per event, Company A. Site A.



(b) Percentage of production (over 150 kW) loss per event Company B, low resolution. Site A.

Figure 7.8: Percentage production loss (over 150 kW) during events of different length. Site A

Ice accumulation of wind turbines is not only related to aerodynamic production losses, but also to risks of ice throw. One possibility to avoid these risks is to shut down the turbines when the production losses are above a certain threshold, when the losses are due to icing. In figure 7.9 the aerodynamic ice losses and the health and safety ice losses are compared. The health and safety losses are here defined as the production losses if the turbines are forced to shut down when the production loss is above 150 kW, due to safety hazards such as ice throw. It is clear from the figure that the losses will increase considerably if the turbines are shut down when the production loss exceeds 150 kW. The increase is shown in table 7.3.

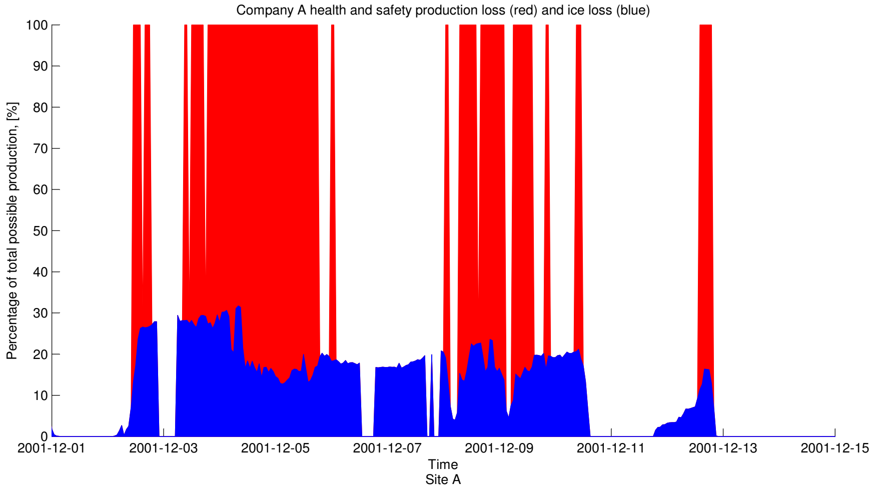


Figure 7.9: Aerodynamic ice losses versus health and safety ice losses. The difference in production loss when the turbines are allowed to continue operating with ice on the blades and when they are forced to shut down when the production loss is above 150 kW. Company A, low resolution. Site A.

Table 7.3: The production losses when using 50 kW, 150 kW and 250 kW as thresholds for turbine shut-down

Modeled health and safety production losses 2010/2011				
Company	Aerodynamic ice losses	250 kW	150 kW	50 kW
Company B high resolution	5.6 %	21.3 %	24.1 %	31.1 %
Company B low resolution	4.7 %	8.2 %	11.1 %	20.2 %
Company A	2.9 %	5.4 %	8.8 %	18.8 %
Measured	8.4 %	14.4 %	18.3 %	32.3 %

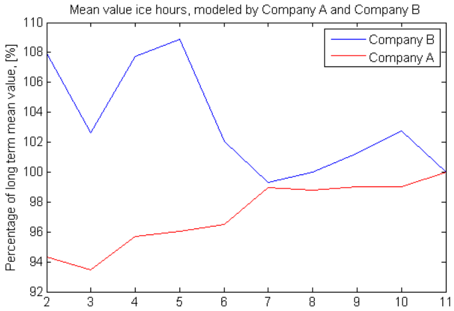
A limitation of using thresholds in kW to visualize the aerodynamic losses due to ice, is that when the wind speed is low, the production loss will not reach the threshold even though a large percentage of the production is lost. As modeled by Company B and Company A, the production loss is dependent on the wind speed and the ice load. Using thresholds in terms of loss in percentage of total production would possibly give a better estimate of the ice losses. The resulting production losses when using thresholds in percentage are shown in table 7.4. Even though there are some differences comparing to the production losses when using kW as thresholds, the resulting production losses when using percentage as thresholds show the same pattern. What type of threshold to use should be decided based on what the aim of the visualization is.

Table 7.4: The production losses when using 5 %, 15 % and 25 % as thresholds for turbine shut-down

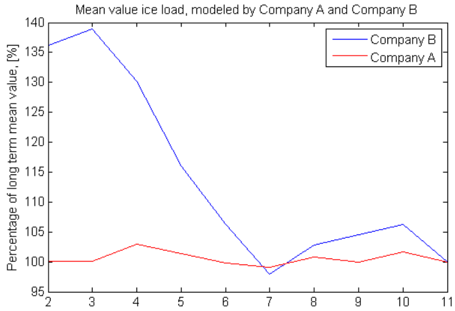
Modeled health and safety production losses 2010/2011				
Company	Aerodynamic ice losses	25 %	15 %	5 %
Company B low resolution	4.7 %	6.8 %	11.2 %	22.4 %
Company A	2.9 %	5.5 %	9.9 %	22.7 %

7.1.3 Effect of the length of the time series

One of the differences between the time series provided by Company B and by Company A is that the time series from Company A is nineteen years longer. The length of the time series will have an effect on calculated long term mean values, and the effect is visualized in figure 7.10. The result shows the smoothing effect on the mean value of having a thirty year time series compared to an eleven year time series. A thirty year time series will to a higher extent reflect the long term averages of ice load and ice hours.



(a) Ice hours mean value dependency on length of time series. Site A.



(b) Ice load mean value dependency on length of time series. Site A.

Figure 7.10: Mean value dependency on length of time series. The percentage of the long term mean value of ice loads and ice hours, shown as a function of the number of the eleven most recent seasons used. Site A.

It is not impossible that the most recent eleven year period was an extreme period in terms of icing conditions or production losses. The effect of the length of the time series on the mean values are shown in table 7.5 and 7.6. In table 7.5, the mean values for Company B's eleven years time series, along with mean values for Company A's most recent modeled winter seasons and the mean values for Company A's whole 30 years time series. In table 7.6, the difference between Company B and Company A mean values are shown, both the difference between Company B's eleven years series and Company A's last eleven years, as well as between Company B's eleven years and Company A's thirty and between Company A's eleven years and Company A's thirty. The data presented is data processed by the companies. The result shows a clear difference between the eleven year mean values and the thirty year mean value, the largest difference between the eleven year production losses and the thirty year produciton losses. This means that there is a clear effect of having an eleven year time series compared to a thirty year, which in turn means that eleven year mean values should be given a higher uncertainty.

Table 7.5: The effect of the length of the time series on the mean values of active ice hours, ice load and production losses

Effect of the length of the time series			
Parameter	Mean value Company B 11 years	Mean value Company A 11 years	Mean value Company A 30 years
Ice load	0.27 kg/m	0.39 kg/m	0.38 kg/m
Active ice hours	441 hours	730 hours	626 hours
Production losses	11.2 %	3.5 %	4.9 %

Table 7.6: The effect of the length of the time series on the mean values, the deviation in percentage

Effect of the length of the time series			
Parameter	Diff. Company B11 and Company A11	Diff. Company B11 and Company A30	Diff. Company A11 and Company A30
Ice load	31 %	29 %	2.6 %
Active ice hours	39 %	29 %	17 %
Production losses	220 %	128 %	29 %

7.2 Height adjustment algorithms

The results of the height adjustments are shown in figure 7.11 and 7.12. The results show that the algorithm is capable of better adjusting the low resolution model output to the high resolution output, meaning a closer resemblance to the state at real terrain height. The figures show the effect on raw data from the WRF-model run by Company B, but the same result was achieved processing Company A raw data. As discussed in section 4.2.1, it can be argued that the height adjustment following this methodology is physically incorrect. The analysis of result shows that when the height difference between the model and the real terrain is large, the modeled change in liquid water content can be very large during some periods. It could be discussed whether the modeled amount of LWC is possible or whether a transfer to precipitation would occur [38]. A limit of the possible amount LWC has not been set in this study.

The stability check implemented and evaluated in the study showed that the model predicted stable conditions during about 60 % of the time during the winter season when potential temperature was used for the stability check. For the final evaluation of the results, no stability check was performed, due to two reasons. Firstly, the neccessary data sets were not available from all sites and modelers. Secondly, the question of how to treat cases with stable conditions was not enough investigated. One way is to neglect the height adjustment when the conditions were stable, but it is difficult to argue whether this is the correct way. The question arises whether the stability conditions predicted by the model is of interest when the height adjustment does the assumption that the modeled conditions are not a correct reflection of the real conditions.

The basic lifting algorithm (see section 4.3.2) was not used in the data analysis, since the result showed that it gave a difference in liquid water content that was unplausibly high, and since it was not considered to be physically correct.

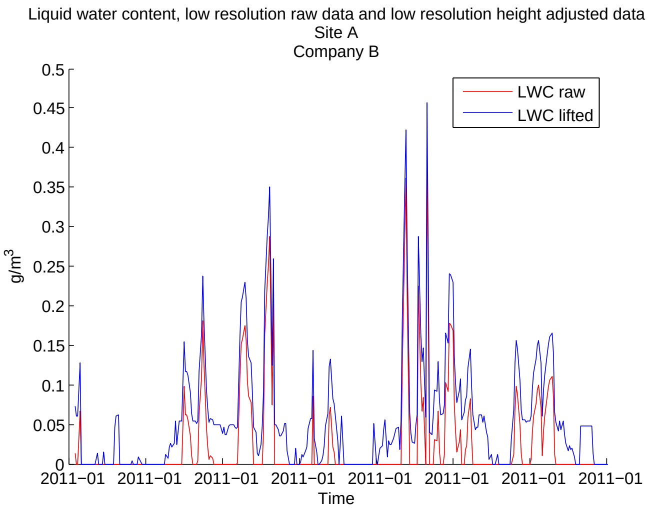
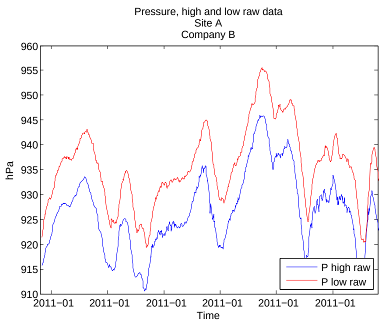
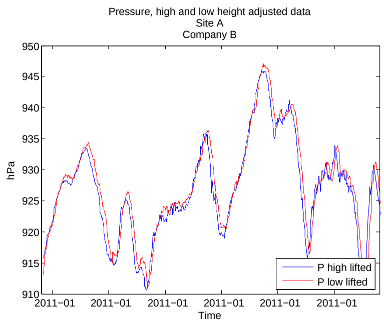


Figure 7.11: Effect of height adjustment on liquid water content, Company B. Site A.



(a) Difference between high and low resolution modeled pressure, Company B raw, non-processed data. Site A.



(b) Difference between high and low resolution modeled pressure, Company B height adjusted data. Site A.

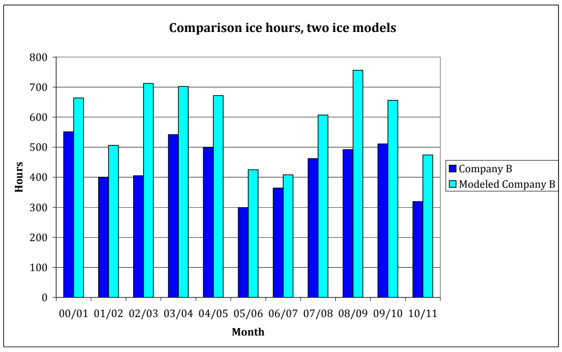
Figure 7.12: Effect of height adjustment on pressure. Site A

7.3 Ice model

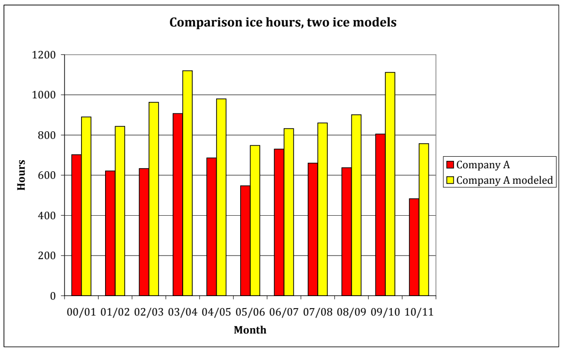
The ice model used in this study is an implementation of the Makkonen algortihm. The implementation has been shown to be rather sensitive to small changes of the input parameters and to give high ice loads and a high number of active ice hours. To enable a fair comparison with measured ice loads and production losses, the ice model should be improved, but this was not possible within the scope of this study. The workaround this problem has been to only compare ice loads and active ice hours as modeled by Company B, Company A and Company C with measured ice load and production, since the ice models developed by the companies have been tested and evaluated. A comparison of the ice models developed by Company B and Company A with the ice model used in this study showed that the ice model used here gave higher ice loads and more ice hours but that the variation was similar. This means that the ice model is concluded to be stable although predicting more ice (see figure 7.13). For the analysis of the normal year correction methods, all data analysed has been run through the same ice model, thus eliminating the uncertainty of comparing results from different models. The results have been compared in terms of relative numbers instead of kilograms ice and number of active ice hours.

As discussed, the Makkonen algorithm has some limitations, the most important being that it models ice accretion on a cylinder and not on a wind turbine. For further discussion of the limitations see chapter 2.2.4. A problem with the implementation of the model is its sensitivity when the temperature is close to 0°C. The model does not predict any ice accretion when the temperature is above 0°C, which means that it is sensitive to small changes in the modeled temperature. The sensitivity is apparent when evaluating the monthly variations of ice hours. The model gives a high number of active ice hours during the later parts of the winter seasons, especially in April when the temperature frequently fluctuates around 0°C. Since temperatures around 0°C are often accompanied by high humidity, this leads to the model predicting a high ice accumulation rate. This problem does not only occur in the ice model as it is implemented in this study, but has also been addressed by Company A [38]. The result is most probably not a reflection of the real icing climatology, and a good solution to solve this problem has not been found in this study. A suggestion by Baltscheffsky [38] was to test the behaviour of the model if the threshold temperature for ice growth was instead set to -1°C. This was not thoroughly tested in this study, but the sensitivity of the model to small temperature changes around 0°C is a problem that should be adressed in future studies.

To summarize, the ice model used in this study shows a high sensitivity to the input parameters, something that is apparent when evaluating the resulting ice loads and ice hours. The ice loads modeled using different data sets, or post-processed by the companies, should therefore *not* be compared in terms of absolute numbers, nor should the active ice hours, even though they show a lower sensitivity. The ice model should be tuned, for example by comparing to measurements, and improved, before such comparisons are made.



(a) Active ice hours modeled by Company B and by ice model used in this study. Site A.



(b) Active ice hours modeled by Company B and by ice model used in this study. Site A.

Figure 7.13: Comparison of the output from the ice models used by Company B and Company A and the ice model used in this study.

7.4 Normal year correction

In this section, the implemented normal year correction methods are evaluated and compared according to the criteria stated in section 6.5. Due to the sensitivity of the ice model used in the study and the uncertainty regarding the modeled ice loads versus the real icing climatology, the focus has been on evaluating the possibilities to find a normal year correction method that is insensitive to site and length of high resolution basis as well as giving ice loads and active ice hours in line with the high resolution model for the respective seasons. The focus has not been on finding long term mean ice loads and active ice hours and will therefore not be the final result.

To enable an evaluation of the ability of the normal year correction methods to give an icing climatology better reflecting reality, the percental deviation of the low resolution ice parameters from the high resolution model output, before correction is performed, is presented in table 7.7. The values presented are ice parameters from the height adjusted, high resolution model and from the height adjusted, low resolution model. The deviation presented is the difference in percentage from the high resolution model output for the respective season.

Table 7.7: Comparison high and low resolution ice parameters mean values, before normal year correction

Low resolution height adjusted ice parameters deviation from high resolution height adjusted ice parameters			
Company	Parameter	Deviation from high resolution model output 2009/2010	Deviation from high resolution model output 2010/2011
Company B data	Ice load	135.9 %	110.1 %
	Active ice hours	46.2 %	-42.8 %
Company A data	Ice load	-77.5 %	-80.1 %
	Active ice hours	-62.9 %	-57.3 %

7.4.1 GWL-classes

The normal year correction method based on evaluating atypical years in terms of GWL-classes was performed on the data sets. The result of the first evaluation showed that the deviation from the normal year frequency of the GWL-classes is above 10 % for all the studied winter seasons between 1979 and 2011 (figure 7.14). This means that none of the studied winter seasons were found to be a normal year in terms of GWL-classes. One of the reasons for this is probably the large number of GWL-classes, 31 individual classes. During a studied winter season, the probability will thus be high that at least some of the classes show a pattern deviating from the normal winter.

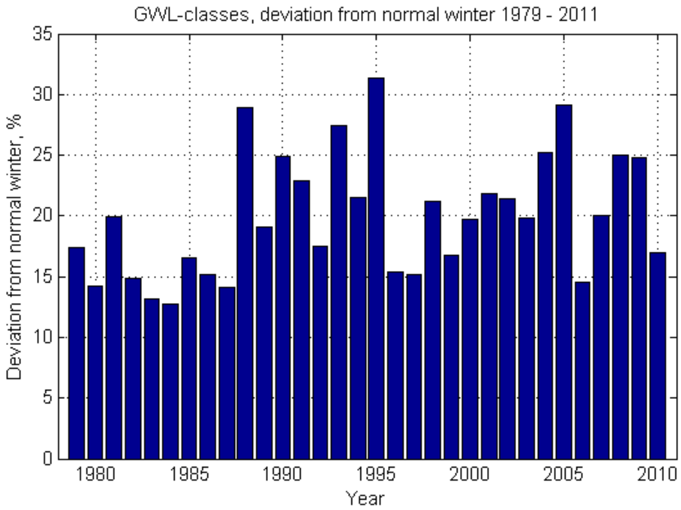


Figure 7.14: GWL-classes. Deviation in percentage from a normal year in terms of GWL-classes, calculated as mean frequency of the respective class during a 32-year period.

Although all the studied winter seasons deviate from the normal winter in terms of GWL-classes, it is clear from figure 7.14 that a number of seasons deviate significantly more. The correlation between the deviation from the normal year GWL and interesting parameters was therefore evaluated. The r-square for deviation from normal year GWL and number of active ice hours was found to be 0.05 and for the mean temperature and the deviation from normal year GWL it was approximately 0.03, the correlation being approxmately the same for all studied data sets. A higher correlation could not be found for other tested parameters. This means that in this study, no correlation between the temperature, the active ice hours and the deviation from normal year GWL was found.

Even though a correlation between the GWL-classes and the icing climatology was not found in this brief evaluation, the possibility still exists that it would be possible to find a relation between ice parameters and synoptic weather classes. The weather classes used in this study are centered around central Europe, and using a classification focusing on northern parts of Scandinavia would be more interesting. Also, it would probably be more feasible to find a correlation between one or two weather classes and icing climatology than to look at all classes. Icing climatology is highly dependent on wind direction, and studying correlation between prevailing wind direction and icing climatology could also be interesting. This was out of the scope of this study.

7.4.2 Basic method

The basic method is based on finding a simple relationship between the high resolution and the low resolution model output. Based on the assumption that a studied season from the high resolution model output is related to a high resolution normal year in the same way as the low resolution seasons and normal year, this method gives high weight to the season chosen as basis (see table 7.8). Since the result shows the method to be very sensitive to the season used as basis and since it is not theoretically motivated to perform the normal year correction following this method, no further analysis was performed in this study.

Table 7.8: Result of the normal year correction basic method. Site A

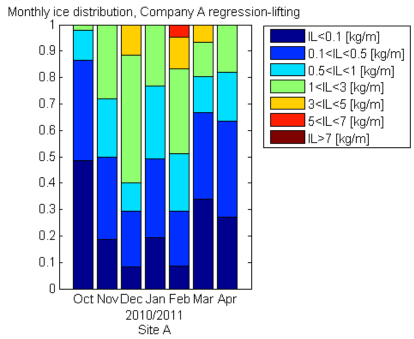
Result of normal year correction, basic indices method				
Company	Parameter	Mean values	Difference from high resolution value	Deviation when using other season as correction basis
Company B data	Ice load	0.035 kg/m	-30%	163.1 %
	Active ice hours	643 hours	49.2 %	-33 %
Company A data	Ice load	0.783 kg/m	150.2 %	118.1 %
	Active ice hours	1126 hours	43.4 %	-25 %

7.4.3 Linear regression methods

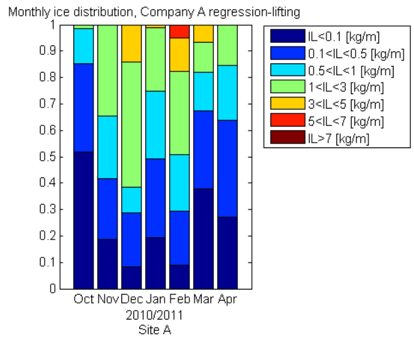
The regression methods are based on using linear regression at different steps in the post-processing of raw model data, to adjust the low resolution model output to the high resolution model output. The regression has been performed in three different ways, applying it to raw data, to height adjusted data and to calculated ice parameters.

Regression - lifting

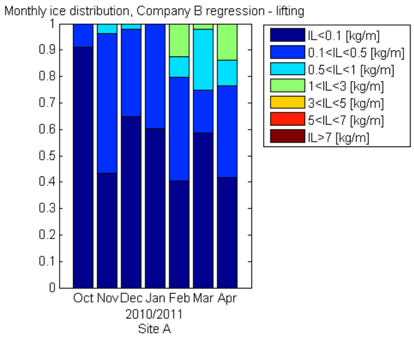
The regression-lifting method is based on first applying linear regression to the low resolution data set and then using height adjustment to adjust the model terrain height to the real terrain height, using the height difference from the high resolution model. The results are shown in figure 7.15 and in the tables 7.9 and 7.10. The figure shows the normal year monthly ice load distribution from Company A and Company B model data when using the regression-lifting method. The top two subfigures show Company A monthly ice load distribution and the bottom two Company B monthly ice load distribution. The two right subfigures show the ice load distribution when only one season, 2009/2010, was used as basis for the correction. The changes in ice load distribution and mean yearly ice load and active ice hours (see table 7.9) are very small when using only one season as basis for the correction instead of two, meaning that the method is robust and not very sensitive to the length of the time series used as correction basis. Comparing the result in table 7.10 to the figures in table 7.7, the conclusion can be drawn that the method manages to give mean ice loads closer to the high resolution modeled ice loads, but that the deviation from the high resolution output for the active ice hours is significantly lower. Again, the ice loads modeled using different data sets should not be compared, neither to each other nor to the ice loads modeled by the companies.



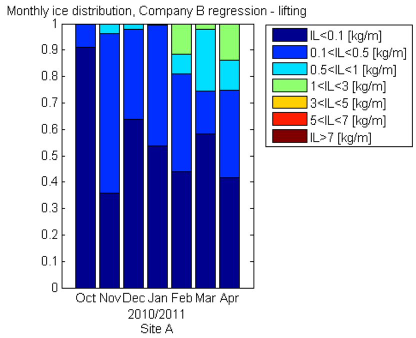
(a) Monthly ice load distribution Company A data, regression-lifting two seasons. Site A.



(b) Monthly ice load distribution Company A, regression-lifting, basis season 2009/2010. Site A.



(c) Monthly ice load distribution for Company B data, regression-lifting, basis two seasons. Site A.



(d) Monthly ice load distribution Company B data, regression-lifting, basis season 2009/2010. Site A.

Figure 7.15: Monthly ice load distribution after normal year correction with regression-lifting method. Site A

Table 7.9: Result of the regression-lifting normal year correction, effect of length of correction basis

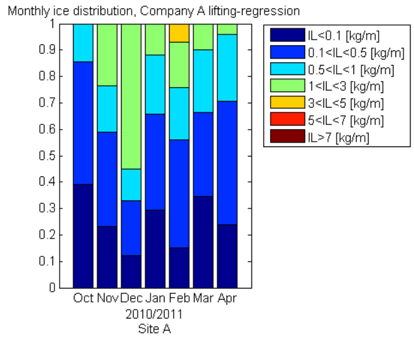
Result of regression-lifting normal year correction for Site A				
Company	Parameter	Mean values	Deviation using only 2009/2010 as correction basis	Deviation using only 2010/2011 as correction basis
Company B data	Ice load	0.03 kg/m	-7.5 %	9.7 %
	Active ice hours	367 hours	-1.6 %	1.6 %
Company A data	Ice load	0.59 kg/m	1.49 %	-0.26 %
	Active ice hours	533 hours	1.29 %	-0.13 %

Table 7.10: Result of regression-lifting normal year correction, compared to high resolution model output for the seasons 2009/2010 and 2010/2011. Site A

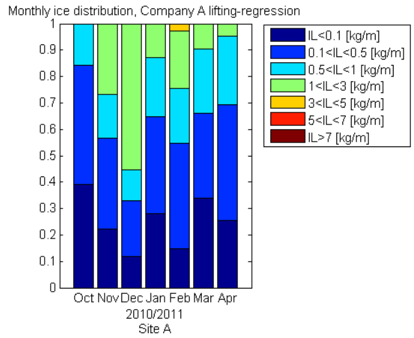
Result of regression-lifting normal year correction for Site A			
Company	Parameter	Deviation from high resolution 2009/2010	Deviation from high resolution 2010/2011
Company B data	Ice load	-49.0 %	-56.6 %
	Active ice hours	20.0 %	24.6 %
Company A data	Ice load	-10.4 %	9.5 %
	Active ice hours	0.73 %	-10.39 %

Lifting - regression

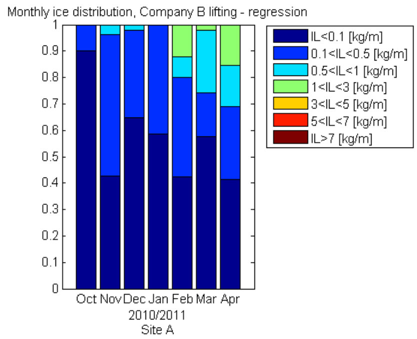
The lifting-regression method applies linear regression to the height adjusted parameters from the low resolution model to the high resolution model. The result is shown in figure 7.16 as well as in the tables 7.11 and 7.12, with same setup as for the visualization of the result from the regression-lifting method. Similar to the result of the regression-lifting method, the normal year monthly ice distribution does not change significantly when using only 2009/2010 as correction basis. The yearly mean values of ice load and active ice hours are also not sensitive to using a shorter time period as correction basis. The result further shows that the method is capable of better adjusting the number of active ice hours for the seasons 2009/2010 and 2010/2011 to the high resolution modeled active ice hours. For this specific data set, the method is capable of adjusting the yearly mean ice load from the Company A data to the high resolution output, but not for the Company B data.



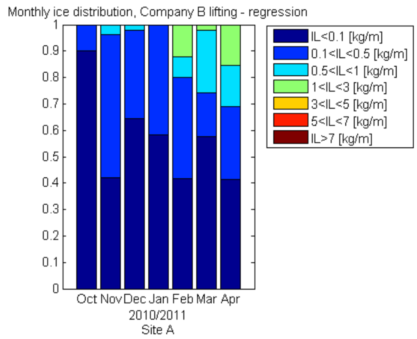
(a) Monthly ice load distribution Company A data, lifting-regression two seasons. Site A.



(b) Monthly ice load distribution Company A data, lifting-regression basis season 2010/2009. Site A.



(c) Monthly ice load distribution for Company B data, lifting-regression, basis two seasons. Site A.



(d) Monthly ice load distribution for Company B data, lifting-regression basis season 2010/2009. Site A.

Figure 7.16: Monthly ice load distribution after normal year correction with the lifting-regression method. Site A

Table 7.11: Result of the lifting-regression normal year correction, effect of length of correction basis

Result of lifting-regression normal year correction for Site A				
Company	Parameter	Mean values	Deviation using only 2009/2010 as correction basis	Deviation using only 2010/2011 as correction basis
Company B data	Ice load	0.13 kg/m	-1.25 %	1.35 %
	Active ice hours	522 hours	-0.69 %	1.00 %
Company A data	Ice load	0.59 kg/m	-2.67 %	2.47 %
	Active ice hours	640 hours	-2.9 %	2.41 %

Table 7.12: Result of lifting-regression normal year correction, compared to high resolution model output for the seasons 2009/2010 and 2010/2011. Site A

Result of lifting-regression normal year correction for Site A			
Company	Parameter	Deviation from high resolution 2009/2010	Deviation from high resolution 2010/2011
Company B data	Ice load	84.9 %	83.3 %
	Active ice hours	0.56 %	19.6 %
Company A data	Ice load	-7.28 %	22.5 %
	Active ice hours	13.2 %	5.7 %

Regression of ice parameters

Here, linear regression has been performed on the output ice load and active ice hours from the low resolution and high resolution ice models, relating the low resolution active ice hours and ice load to the high resolution active ice hours and ice load. Figure 7.17 shows the monthly ice load distribution for Company A data and the monthly ice load distribution when using only one season, 2009/2010, as basis. The difference when using only one season as correction basis is a little larger than for the other two regression methods, regression-lifting and lifting-regression. This is not surprising, since the regression here is performed directly on the ice parameters, thus giving a larger weight to the differences between the two seasons in terms of ice loads and ice hours.The improvement is higher for the Company B data. The differences in the mesoscale model outputs may be small, but accumulating during the post-processing the difference in output can still be large, and using linear regression to ice parameters is maybe not enough to counteract the difference. The method applying linear regression to ice parameters require high quality post-processing in the steps before the regression, and to achieve good results, more seasons of high resolution series and low resolution long term reference series with as high resolution as possible should be used.

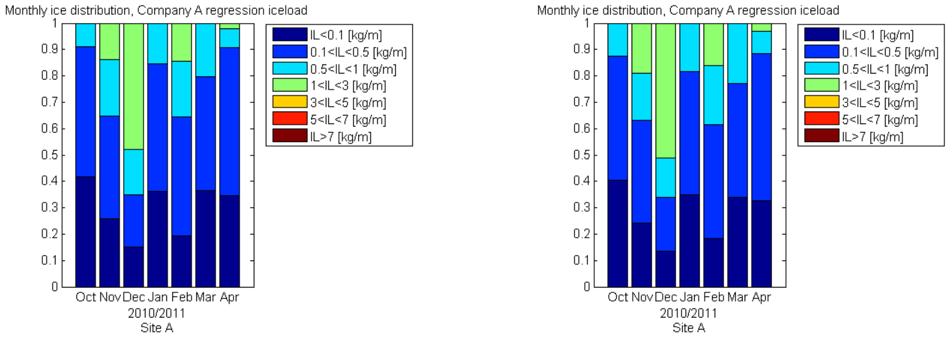


Figure 7.17: Monthly ice load distribution after normal year correction with regression of ice parameters, Company A data. The left figure with two seasons as basis, the right with only the season 2009/2010. Site A.

Table 7.13: Result of the ice parameter regression normal year correction, effect of length of correction basis

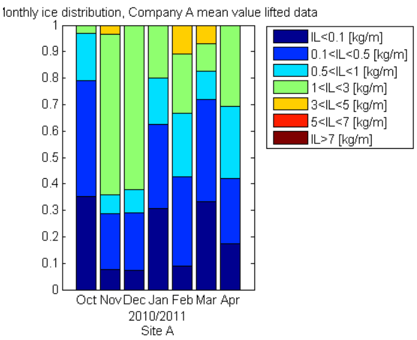
Result of ice parameter regression normal year correction for Site A				
Company	Parameter	Mean values	Deviation using only 2009/2010 as correction basis	Deviation using only 2010/2011 as correction basis
Company B data	Ice load	0.07 kg/m	1.39 %	-1.61 %
	Active ice hours	374 hours	4.92 %	-18.52%
Company A data	Ice load	0.37 kg/m	-7.58 %	23.41 %
	Active ice hours	546 hours	-2.37 %	2.88 %

Table 7.14: Result of ice parameter regression normal year correction, compared to high resolution model output for the seasons 2009/2010 and 2010/2011. Site A.

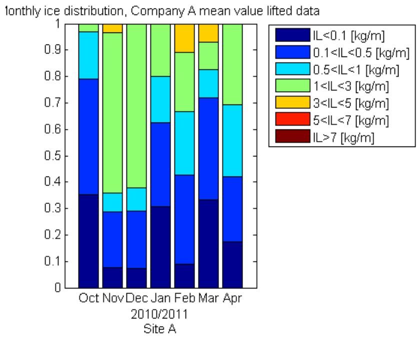
Result of ice parameter regression normal year correction for Site A			
Company	Parameter	Deviation from high resolution 2009/2010	Deviation from high resolution 2010/2011
Company B data	Ice load	9.7 %	-2.3 %
	Active ice hours	-29.7 %	-19.3 %
Company A data	Ice load	-47.3 %	-17.5 %
	Active ice hours	-8.9 %	-8.3 %

7.4.4 Mean value methods

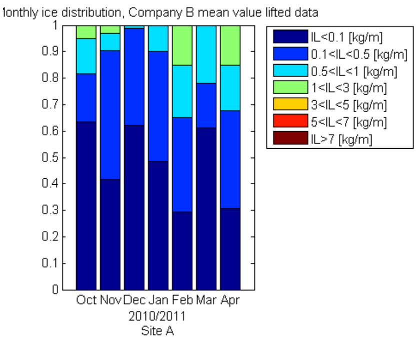
The mean value normal year correction method is based on finding time series with mean values from all the available low resolution, height adjusted time series, before using them as input to the ice model. The first evaluation was performed on Company A model data, and the result showed that the method was not able to adjust the low resolution ice parameters to the high resolution (see table 7.15). The result is clear and similar numbers were found when evaluating Company B's data set. The reason for this result is that using mean values will smoothen the time series, not giving a reasonable variation of the parameters such as temperature and wind speed. Using the mean value time series as input to the ice model will not give a realistic icing climatology as output. The lack of natural variation in for instance temperature will give unrealistic ice loads and numbers of activeice hours. The dependency of the method using a shorter time series as basis will be very small, due to the effect being smoothed by the averaged values, and the normal year monthly ice distribution will not changed to a traceable extent (see figure 7.18). A more extensive evaluation of the method was not performed.



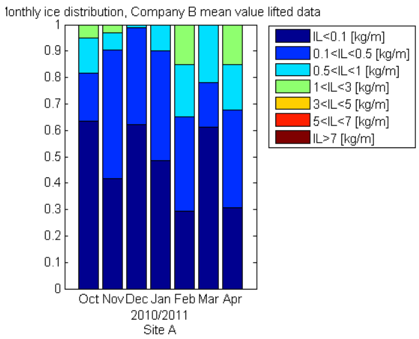
(a) Monthly ice load distribution Company A, mean value on lifted data, basis two seasons. Site A.



(b) Monthly ice load distribution Company A, mean value on lifted data basis season 2009/2010. Site A.



(c) Monthly ice load distribution Company B, mean value on lifted data, basis two seasons. Site A.



(d) Monthly ice load distribution Company B, mean value on lifted data basis season 2009/2010. Site A.

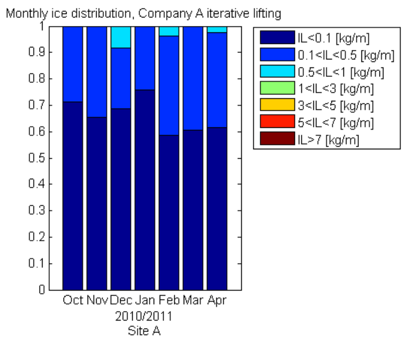
Figure 7.18: Monthly ice load distribution after normal year correction with the mean value method on height adjusted data. Site A.

Table 7.15: Result of mean value normal year correction compared to high resolution model output for the seasons 2009/2010 and 2010/2011. Site A.

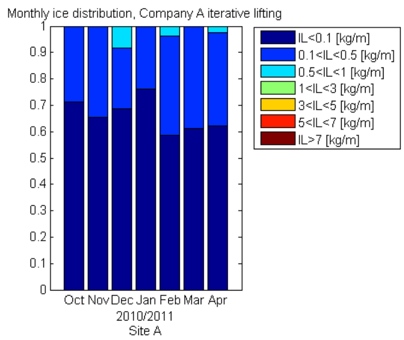
Result of mean value normal year correction for Site A			
Company	Parameter	Deviation from high resolution 2009/2010	Deviation from high resolution 2010/2011
Company A data	Ice load	1303.8 %	456.7 %
	Active ice hours	240.2 %	301.9 %

7.4.5 Iterative adjustment method

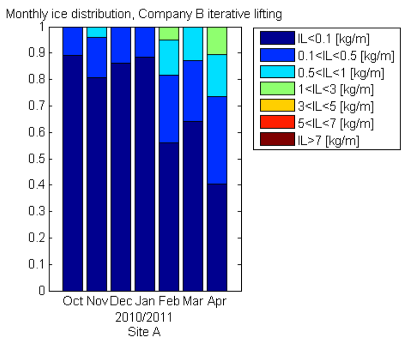
The results of the normal year correction method using iterative height adjustment to adjust the low resolution output to the high resolution, show that the improvement was highly dependent on the possibility of finding a common lifting height for both seasons studied. If a common lifting height could not be found, the normal year ice loads and ice hours would not be more simliar to those of the high resolution model than before post-processing (see table 7.16). For the data sets used in this study, a common lifting height was found for the Company B data but not for the Company A data. Since this method is based on a somewhat different reasoning than the regression methods, not making use of any statistical tools, the result was difficult to evaluate in the same manner. The dependency of using shorter or longer time series as basis for the correction will be zero if a common lifting height is found.



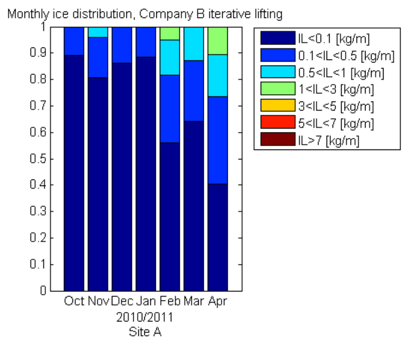
(a) Monthly ice load distribution Company A, iterative height adjustment method two seasons. Site A.



(b) Monthly ice load distribution Company A, iterative height adjustment method basis 2009/2010. Site A.



(c) Monthly ice load distribution Company B, iterative height adjustment method two seasons. Site A.



(d) Monthly ice load distribution Company B, iterative height adjustment method two seasons. Site A.

Figure 7.19: Monthly ice load distribution after normal year correction with iterative height adjustment method. Site A

The iterative normal year correction method was implemented comparing the output ice loads in this study. After evaluating the results from all the other normal year correction methods, a conclusion to be drawn is that it would probably have been wiser to use active ice hours as basis for the correction. The method as it is implemented here does not show very good results, even though the result of the comparison to high resolution data is better for the Company B data than for the Company A data. The reason for this could be the smaller difference in horizontal resolution for the Company B high and low resolution simulations. As previously stated, the height adjustment is less accurate when the height difference is large (see section 7.2 and 4.2.1). The height difference to the real terrain height being smaller for higher horizontal resolution, this could be the reason. Also, the height adjustment being able to adjust the low resolution model output to the high resolution could possibly be dependent on using the same model for the simulations, which was not the case for the Company A simulations in this study.

Table 7.16: Result of iterative height adjustment normal year correction method compared to high resolution model output for the seasons 2009/2010 and 2010/2011. Site A

Result of iterative height adjustment normal year correction for Site A			
Company	Parameter	Deviation from high resolution 2009/2010	Deviation from high resolution 2010/2011
Company B data	Ice load	-14.49 %	-15.40 %
	Active ice hours	-14.3 %	-4.69%
Company A data	Ice load	-89.52 %	-88.41 %
	Active ice hours	41.00 %	63.98 %

7.4.6 Summary of the results of the normal year correction

All the normal year correction methods developed in this study have been evaluated using the following the criteria: sensitivity to length of time series used as correction basis, ability to adjust the low resolution model output to high resolution model output for the respective season and plausibility of the results. Also, a criteria has been that it should further not be sensitive to the site or data set analysed. The evaluation of the methods showed that in most cases the ice load was a sensitive parameter to use for normal year correction, whereas the active ice hours were not. Therefore, and since active ice hours have been shown to be highly correlated to production losses (see section 3), in the final evaluation of the results, active ice hours were used. The evaluation of the different methods showed that the regression methods applying linear regression to the low resolution parameters before the ice model had the lowest sensitivity to length of time series used and gave the most feasible results. This was true for all data sets and all sites. The lifting-regression method as well as the regression-lifting method both showed low sensitivity to the length of time series, a change of the mean values of about 1 % when using only one season as basis for the correction. The modeled active ice hours showed a difference of only 2.5 - 5.2 % from the high resolution model. A summary of the results of all the methods is found in figure 7.20.

Table 7.17: The results of the evaluation of the different normal year correction methodologies, the methods giving the smallest difference from the high resolution modeled ice parameters and the methods being least sensitive to length of time series used as basis. For all available sites.

Summary of the results of the normal year correction			
Company	Site	Smallest deviation from high resolution active ice hours	Lowest sensitivity
Company B	Site A	Lifting-regression, 2.43 %	Lifting-regression, 1.72 %
Company A	Site A	Regression-lifting, 5.21 %	Regression-lifting, 1.41 %
	Site B	Regression-lifting 3.82 %	Regression-lifting, 1.31 %
	Site C	Lifting-regression 3.09 %	Lifting-regression, 0.40 %

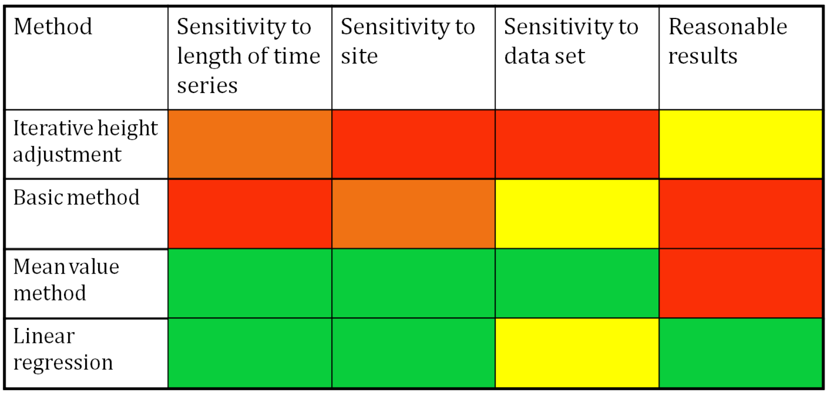


Figure 7.20: Summary of the results of the normal year correction methods, in terms of the four criteria used. Green means that the method fulfils the criteria, red that it fails to do so.

The normal year active ice hours using the three different regression methods are calculated by taking the mean of all modeled years, which means thirty winter seasons of Company A data and eleven seasons of Company B data. The modeled long term icing climatology can thus be visualized as the deviation from the normal year active ice hours. The deviation in percent for season 2000/2001 to 2010/2011 is shown in figure 7.21 for Company A and in figure 7.22 for Company B. The result shows that even though the exact same deviation is not modeled, the variation is similar. According to the result, season 2003/2004 had 20-50 % more ice hours than a normal year, and 2005/2006 had 15-35 % less. Using the Company B data, 2007/2008 is modeled as a normal year in terms of active ice hours, whereas using the Company A data it is modeled as a year with 10-15 % more active ice hours than a normal year. The most recent season, 2010/2011, is modeled as having 10-25 % less ice hours than the normal year. Assessing the reasons for the differences between the two data sets, two main aspects have to be kept in mind. Firstly, the long term reference from Company A is thirty years long, meaning that the normal year is calculated from thirty years values. The long term reference from Company B is only eleven seasons, thus introducing a larger uncertainty into the calculation of the normal year active ice hours. Secondly, the low resolution simulation made by Company B has a higher horizontal resolution, meaning that the height adjustment is less uncertain for this data set. The differences in the modeled normal year ice hours could depend on these two differences.

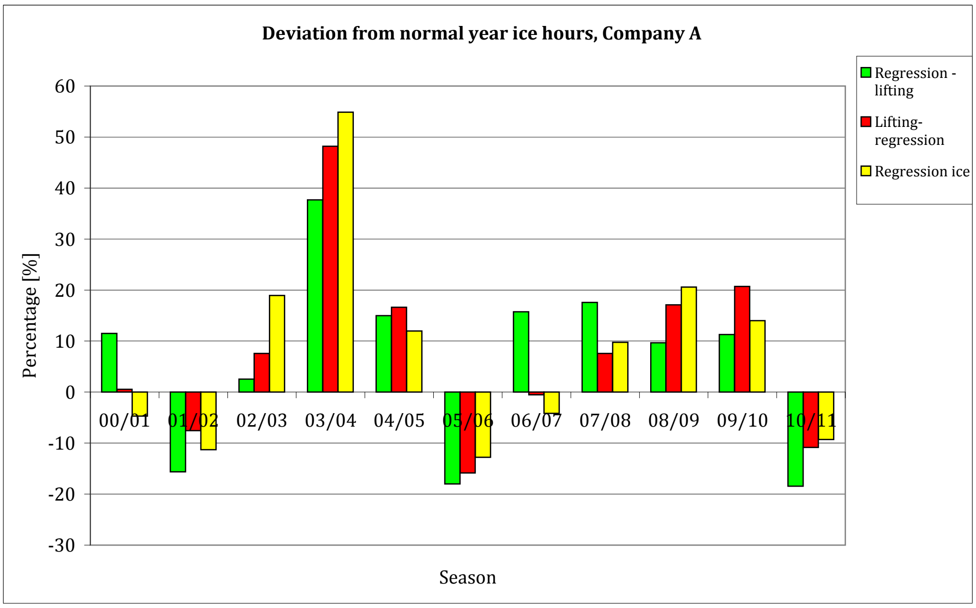


Figure 7.21: Active ice hours, the deviation from the normal year active ice hours in percent, Company A. The regression normal year correction methods. Site A.

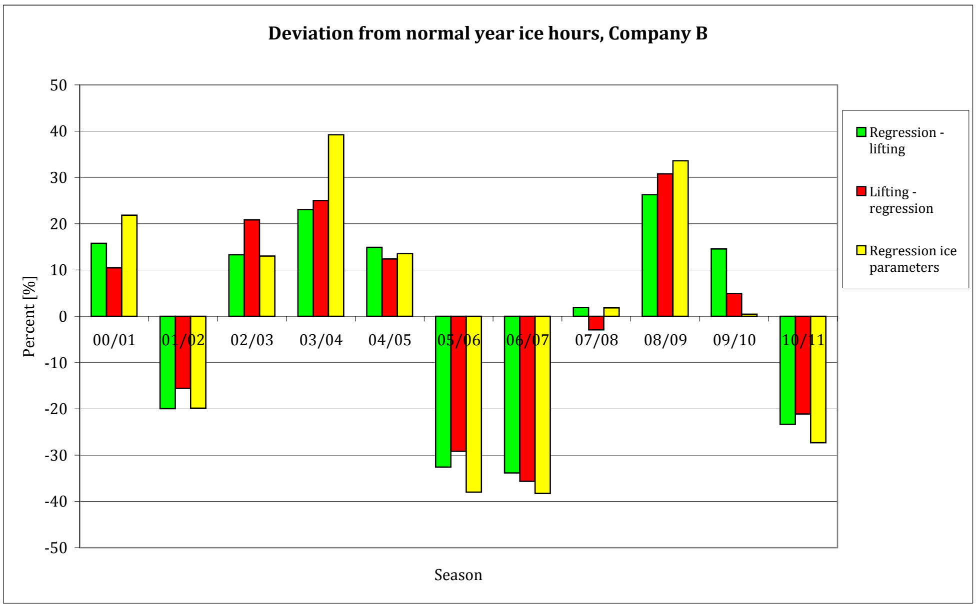


Figure 7.22: Active ice hours, the deviation from the normal year active ice hours in percent, Company B. The regression normal year correction methods. Site A.

8 Conclusions and summarizing discussion

Ice modeling for wind turbine applications is a developing field and as such, many obstacles remain before a reliable and affordable way to estimate icing climatology is developed. The main focus of this thesis has been to evaluate the possibilities to estimate the icing climatology using state-of-the-art meteorological mesoscale models and ice models. In this concluding section of the report, conclusions are found along with suggestions for future work.

8.1 Time series

The time series used for evaluation of the long term icing climatology in this study were results from mesoscale meteorological models of different types and with different horizontal resolution. The icing climatology was modeled at sites in northern Sweden by Company C, Company A and Company B using different methods for post-processing the data. A comparison between the modeled ice parameters showed both similarities and differences. All companies modeled mean and max ice loads of the same order of magnitude and the onset of the icing events were most of the time captured by all modelers. The same was not true regarding neither the duration of the icing events nor the maximum ice load during individual icing events. Evaluation of the monthly mean ice loads and active ice hours visualized some differences in the ice models used by Company B and Company A, Company A modeling the highest number of active ice hours in April whereas Company B modeling a peak in November. It was further apparent that Company B and Company A model the production losses differently, Company B modeling higher production losses even though Company A modeled a higher number of active ice hours.

Further comparing the modeled values to measured ice loads and production losses showed large differences and few similarities. Unfortunately, since ice detection and measuring is a highly uncertain matter, comparing ice loads from the models and the measurements does not give very reliable indications of the quality of the model output. Comparing modeled production losses to measured also pose some problems, determining when stand-still should be defined as due to ice accumulation. Modeling production losses caused by ice accumulation is a new technique that will hopefully be improved in the near future.

Two main problems are identified when evaluating and analyzing the time series. Firstly, even though the output from the meteorological model does not differ very much, apart from effects of horizontal resolution, the different post-processing methods performed by the companies lead to differences in the final result. Secondly, the lack of reliable, long term measurements complicates the evaluation of the results. The companies have used different resolution for their simulations as well as modeled between eleven and thirty years of icing climatlogy. Company B using higher horizontal resolution but modeling a shorter time period, it is not straightforward to draw a conclusion regarding which modeler doing the most simulations. A combination of Company B's resolution and Company A's length of simulation should have been the best option. Also, using the same mesoscale model for all simulations is of high importance, something that was not done in the case of Company A for the simulations evaluated here.

8.2 Height adjustment

The height adjustment algorithm used in this study was able to adjust the low resolution model output to better reflect the conditions at real terrain height. However, it was sensitive when the height difference between model terrain and real terrain was large, giving very high levels of LWC during certain conditions. Since the time series provided by Company B were the result of a simulation with higher horizontal resolution and corresponding smaller height difference, the mentioned effect was smaller for this data set than for Company A's. To decrease this effect, improving the height adjustment algorithms should be a part of further improving the assessment of the icing climatology. The possibilities to evaluate the stability conditions and different methods to treat cases with stable conditions need to be evaluated more thorough before including it into the model. Also, evaluation of the effects of limiting the possible liquid water content should be performed.

To better reflect the real icing climatology of a wind farm, a horizontal adjustment to the position of each individual turbine position should be included. The icing conditions within a wind farm will depend on the individual turbine height and the flow conditions surrounding it. Therefore, horizontally and vertically adjusting the parameters to reflect the conditions at each turbine should improve the reliability of ice and production loss calculations.

8.3 Ice modeling

The ice model used in this study was shown to be rather sensitive to small changes of the input parameters. To enable a better evaluation of the icing climatology, the height adjustment algorithm and the normal year correction methods, the ice model should be improved. The differences in the output from the ice model when evaluating different data sets is partly due to the sensitivity to LWC and small temperature changes. To eliminate the differences caused by the ice model it should be tested, improved and possibly tuned to measurements and production data.

However, the ice accretion algorithm used today need to be replaced by a way to more accurately model ice accretion on wind turbines, and more reliable means to measure real ice accretion and ice loads need to be developed, to enable better evaluation and verification of modeled icing climatology. A robust way to model ice accretion on wind turbines is most likely not possible within the coming few years. Without reliable ways to model ice accretion on wind turbines, the existing ice models should be improved, including better equations for shedding and melting. Also, changing the focus from modeling ice accretion on a cylinder to instead evaluating the icing potential, neglecting the changing diameter of the modeled cylinder, should be tested and evaluated.

8.4 Normal year correction

The different normal year correction methods implemented in this study were evaluated based on the criteria that the method should not be sensitive to the length of time series used as basis or the site studied, and give reasonable values of active ice hours and ice loads. The evaluation showed that the linear regression methods, regression-lifting and lifting-regression, gave good results. The methods were not very sensitive to whether one or two seasons were used as basis for the correction; they gave good results for all studied sites and for both Company B and Company A model data. The evaluation further showed active ice hours to be a more reliable parameter to use for the normal year correction, showing lower sensitivity than the ice load and giving values closer to the high resolution model output.

The basic method did not show good results, nor did the mean value method, and the iterative height adjustment method was sensitive to the time series used as basis. The iterative height adjustment method should be further improved, using active ice hours instead of ice loads as correction basis and further improving the lifting algorithm, before discarding the possibilities of using this method. The normal year correction methods should be evaluated using longer high resolution time series and as high resolution as possible for the long term, low resolution time series. The time series should further be output from the same mesoscale meteorological model and consistent data from more sites should be used.

8.5 Conclusions and recommendations

The analysis of the time series and the evaluation of the different normal year correction methods show that assessment of icing climatology is an uncertain matter. Small changes in the height adjustment algorithm and the ice model give significant changes in the output ice parameters. Also, it was apparent that even though Company B and Company A have had access to the same production data, their model for calculation of production losses differed significantly. Company A has been using different model for their low resolution and high resolutions simulations, something that is not recommended and cause problems when evaluating the normal year correction methods. Company A will in the future use the WRF-model for all their simulations, which is recommended.

It is recommended that future assessments of icing climatology use height adjustment as well as horizontal adjustment to adapt the model output to the real conditions. It is further recommended that as high horizontal resolution as possible is used, and that the low resolution reference series covers as long time period as possible. For long term icing climatology assessment, the linear-regression methods are promising.

The conclusion to be drawn from the normal year correction of icing climatology in this study, is that the yearly variation of icing severity should be expected to be large. During a thirty year time period, a wind power plant will experience few normal years in terms of active ice hours, and winters with 40 % more active ice hours than a normal year as well as winters with 40 % less. Wind power developers will have to face the challenges of varying icing climatology, and find ways to assess it, for the industry to be able to take advantage of the wind resources of northern Scandinavia.

8.5.1 Future work

The goal of this thesis has been to analyze modeled icing climatology and to develop and evaluate methods for normal year correction of icing climatology. For further studies, firstly, it is of importance to improve and develop the ice model, by improving the physical model and by tuning it to measurements and production data. It would also be of interest to look into other possibilities to model ice, such as a statistical approach combined with measurements. The normal year correction methods could be further improved and evaluated using more data sets and improved post-processing tools. To improve the evaluation, high resolution data from the WRF-model should be provided by Company A. Data from the most recent season, 2011/2012, should also be analysed, both in terms of modeled values and in terms of measurements. It would further be of interest to develop methods to model production losses using the output from the ice model, something that could be realized using production data from site A. Finally, means to better analyze measured ice loads and production losses and compare to modeled values should be developed.

9 Bibliography

[1] The European Wind Energy Association, 2012. Retrieved 2012-02-10 from `http://www.ewea.org`.

[2] Göran Ronsten. Presentation, WinterWind Conference, Skellefteå, 2012.

[3] Erik Rindeskär. Modelling of icing of wind farms in cold climate - A comparison between measured and modelled data for reproducing and predicting ice accretion. Master's thesis, Uppsala University, Department of geosciences,, Uppsala, Sweden, 2010.

[4] Öyvind Bjyrkedal. Company B, Personal Communication, 2012-02-13.

[5] Lasse Makkonen. Models for the growth of rime, glaze, icicles and wet snow on structures. *Phil. Trans Royal Society London vol 358*, page 2913, 2000.

[6] Marcus Walsh. Accretion and Removal of Wind Turbine Icing in Polar Conditions. Master's thesis, Aalto University, School of Engineering and Architecture, Department of Applied Mechanics, Espoo, Finland, 2010.

[7] Lasse Makkonen. Modeling of ice accretion on wires. *Journal of Applied Meteorology and Climatology vol 23*, page 929, 1984.

[8] Daniel Gustafsson. Vattenfall Vindkraft, Personal communication, 2012-02-17.

[9] René Cattin. Icing of Wind Turbines- Vindforsk projects, a survey of the development and research needs - Elforsk report 12:13, DRAFT. WinterWind, Skellefteå, Sweden, 2012.

[10] Öyvind Bjyrkedal. Site A - Icing analysis and production loss estimates, Report: KVT/OB/2012/R006. Company B, client: Vattenfall Vindkraft, 2012.

[11] Knut Harstveit. Using Routine Meteorological Data from Airfields to produce a Map of Ice Risk Zones in Norway. The Tenth International Workshop on Atmospheric Icing of Structures, IWAIS, 2002. `http//www.vtt.fi/virtual/arcticwind/publications.htm`.

[12] Lasse Makkonen and J.R Stallabrass. The effect of roughness on the rate of ice accretion on a cylinder. *Annals of Glaciology vol 6*, pages 142–145, 1985.

[13] Öyvind Bjyrkedal. Site D - Icing analysis and production loss estimates. Company B, client: Vattenfall Vindkraft, 2011.

[14] Måns Håkansson. Analysis of simulations, observations and production data - A subproject within the Icing Issue Program (IIP). Technical report, Vattenfall Vindkraft, October 2011.

[15] Petteri Antikainen and Sami Peuranen. Ice Loads, Case study. Conference proceedings, BOREAS, Levi, Finland, 2000.

[16] Jan-Åke Dahlberg and Sven-Erik Thor. Analysis of the production in Site A - A subproject within the Icing Issue Program (IIP). Technical report, Vattenfall Vindkraft, June 2011.

[17] Matthew C. Homola, Mohammad S. Virk, Per J. Nicklasson, and Per A. Sundsbo. Performance losses due to ice accretion for a 5 MW wind turbine. Technical report, Department of Technology, Narvik University College, March 2011.

[18] Matthew C. Homola, Tomas Wallenius, Lasse Makkonen, Per J. Nicklasson, and Per A. Sundsbo. The relationship between chord length and rime icing on wind turbines. Technical report, Department of Computer Science, Electrical Engineering and Space Technology, Narvik University College, October 2009.

[19] T. Laakso, I. Baring-Gould, M. Durstewitz, R. Horbaty, A. Lacroix, E. Peltola, G. Ronsten, L. Tallhaug, and T. Wallenius. State-of-the-art of wind energy in cold climates. Technical report, VTT, October 2010.

[20] Matthew C. Homola, Per J. Nicklasson, and Per A. Sundsbo. Ice Sensors for Wind Turbines. *Cold regions science and technology vol 46*, pages 125–131, 2006.

[21] Matthew C. Homola, Per J. Nicklasson, and Göran Ronsten. Modelling of ice induced power losses and comparison with observations. 13th International Conference on Atmosperic Icing of Structures, Andermatt, Switzerland, 2009.

[22] Olivier Parent and Adrian Ilinca. Anti-icing and de-icing techniques for wind turbines: Critical review. *Cold regions science and technology vol 65*, 2010.

[23] Jan Åke Dahlberg. Vattenfall Vindkraft, Personal communication, 2012.

[24] HoloOptics. Retrieved from `http://www.holooptics.net` 2012-05-05, 2012.

[25] Swedish Standards Institute. Atmospheric Icing of Structures, SS-ISO 12494. Technical report, December 2001.

[26] Technische und Innovative Systeme IGUS. Retrieved 2012-02-16 from `http://www.igus-its.de/downloads/vortragdewek-its-06-1120.pdf`, 2012.

[27] Labkotec Oy. Retrieved 2012-02-16 from `http://www.labkotec.fi/se/produkter/isdetektor_for_vindkraft/`, 2012.

[28] Goodrich SIS. Retrieved 2012-02-16 from `http://www.goodrich.com/Goodrich/Businesses/Sensors-and-Integrated-Systems/Products/Ice-Detection-and-Ice-Protection-Systems/Ice-Detection-Systems`, 2012.

[29] Roger A. Pielke. *Mesoscale Meteorological Modeling*. Academic Press, 2 edition, 2002.

[30] John M. Wallace and Peter V. Hobbs. *Atmospheric Science: An Introductory Survey*. Academic Press, 1977.

[31] WRF. The Weather Research and Forecast Model, 2012. Retrieved 2012-01-19 from `http://www.wrf.com`.

[32] Travis A. Smith, Timothy J. Campbell, Richard A. Allard, and Suzanne N. Carroll. User's Guide for the Coupled Ocean/Atmospheric Mesoscale Prediction System (COAMPS) Version 5.0. Technical report, Naval Research Laboratory, March 2010.

[33] Centre National de Recherches Météorologiques, 2012. Retrieved 2012-02-09 from `http://www.cnrm.meteo.fr/arome/`.

[34] Bjorn Egil Kringlebotn Nygaard, Jon Egill Kristjansson, and Lasse Makkonen. Prediction of In-Cloud Icing Conditions at Ground Level Using the WRF Model. *Journal of Applied Meteorology and Climatology*, 50:2445–2459, 2011.

[35] Petra Thorsson. Modelling of atmospheric icing - An introductiory essay. Technical report, Uppsala University, December 2011.

[36] Hans Bergström. Uppsala University, Presentation Winterwind Conference, Skellefteå, 2012-02-07.

[37] Roger Oechslin. Wind power forecasting considering icing. Master's thesis, University of Innsbruck, Innsbruck, Austria, 2011.

[38] Magnus Baltscheffsky. Company A, Personal Communication, 2012-04-01.

[39] Daniel J. Jacob. *Introduction to Atmospheric Chemistry.* Princeton University Press, 1999.

[40] Murry L. Salby. *Fundamentals of atmospheric physics.* Academic Press, 1996.

[41] Gerald R. North and Tatiana L. Erukhimova. *Atmospheric Thermodynamics.* Cambridge University Press, 2009.

[42] Magnus Asp and Esbjörn Olsson. Nedisningsanalys för Vattenfall Vindkraft AB. Company C, client: Vattenfall Vindkraft, 2012.

[43] Stefan Söderberg. Nedisningsstudie : högupplöst modellering av tidsserier för Site B, Site C och Site A - under perioden 20090501 till 20110430. Company A, Uppsala, 2011.

[44] Martin Högström. Wind climate estimates - validation of modelled wind climate and normal year correction. Master's thesis, Lund Uuniversity, Department of Geosciences, Lund, Sweden, 2007.

[45] Working group I IPCC. Climate Change 2001: The Scientific basis. Retrieved from `http://www.grida.no/publications/other/ipcc_tar/` 2012-05-05, 2001.

[46] Stefan Söderberg. Company A, Presentation, 2012-02-15, 2012.

[47] Vattenfall AB. Retrieved 2012-02-16 from `http://www.vattenfall.se/sv/` (in Swedish), 2012.

[48] P.M James. An objective classification method for Hess and Brezowsky Grosswetterlagen over Europe. *Theoretical and Applied Climatology Vol 88,*.

[49] Benjamin Martinez. Vattenfall R&D, Personal Communication, 2012-05-15.