UiT The Arctic University of Norway

Faculty of Science and Technology

Department of Technology and Safety

Risk and Resilience Assessment of Wind Farms' Performance in Cold Climate Regions

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By

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A thesis submitted in fulfillment of the requirements for the degree of

Doctor of Philosophy (Ph.D.)

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*“And it is He (**Allah**) who sends the winds as good tidings before His mercy”*

Quran (25:48)

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Abstract

Wind energy conversion systems, such as wind farms, are growing in numbers and capacity all over the globe. The onshore wind energy generation sector witnessed an increase of approximately 144 TWh during 2020, with onshore wind farms capacity addition of 108 GW, which is twice as much as the added capacity during 2019 (IEA, 2021). This staggering increase in capacity imposes higher need for improved methodologies and expertise, in measuring and improving the performance of wind farms.

Cold climate regions are known to have an appealing potential for attracting wind farms installation and investments. However, the weather conditions in cold climate regions impose risks and challenges to the operation and maintenance of wind turbines, and to the workers at wind farms. Another challenge prevails in the lack of data and expertise related to wind energy projects in cold climate regions, due to the fact that wind farms installations are relatively new in these regions. Furthermore, cold climate regions are more sensitive to climate changes than other parts of the globe, which increases concerns about the environmental impact of increased investments in wind farms in those regions.

The risks and challenges discussed in this thesis can be classified in different ways, some risks are induced by weather conditions that affect the operation and performance of wind turbines, such as the reliability, availability, and maintainability of wind turbines, and there are the risks that are induced by the wind farms that will affect the societal, the economic, and the environmental status of the surroundings of wind farms.

This thesis introduces applicable methodologies that can be used to measure performance-related aspects of wind farms in cold climate regions, on different levels, and operating under different scenarios. Moreover, in a performance-related context, a methodology for measuring the resilience of wind farms facing disruptive events is introduced, and lastly, the different risks related to the operation of wind farms in cold climate regions are identified and analyzed through a methodology that allows for proper ranking of risks to prioritize the measures that can be used to mitigate those risks.

Keywords: wind farm; wind turbine; cold climate regions; Arctic region; overall performance index; resilience assessment; risk assessment; operation and maintenance.

Abbreviations

WF	Wind farm
WT	Wind turbine
CCR	Cold climate region
MW	Megawatt
kW	kilowatt
OPI	Overall performance index
MCDM	Multi-criteria decision-making
WSM	Weighted sum method
IEC	International electrotechnical commission
ISO	International organization for standardization
NOK	Norwegian krone
BN	Bayesian network
LCOE	Levelized cost of energy
CAPEX	Capital expenditures
OPEX	Operational expenditures
CA	Communication availability
CMS	Condition monitoring system
SCADA	Supervisory Control and Data Acquisition

Notations

$R(t)$	Reliability
$F(t)$	Probability of failure
p	Probability of an event
λ	Number of events over a specific period, the mean value of the Poisson distribution
t	Fixed time interval
k, x	Number of events the Poisson distribution finds the probability of
ρ	Restoration
R	Reliability conditional probability
M	Maintainability conditional probability
S	Supportability conditional probability
O	Organizational resilience conditional probability
d	Throwing distance
D	Rotor blade diameter
H	Hub height
v	Wind speed
W_i	Relative weight of performance indicator
S_i	Score of performance indicator
NoisyOrDist	Noisy or distribution function
NoisyAndDist	Noisy and distribution function
X_n	Variables in a joint probability distribution
$\mu_A(x)$	Membership function
X	Universal set containing all values of the inputs to the fuzzy logic process
A	Fuzzy set
(a, b, c)	The three points denoting the triangular fuzzy membership function

List of appended papers

Paper 1

Mustafa, A. M., A. Barabadi, T. Markeset and M. Naseri (2021), An overall performance index for wind farms: a case study in Norway Arctic region, International Journal of System Assurance Engineering and Management.

Paper 2

Mustafa, A. M. and A. Barabadi (2021), Resilience Assessment of Wind Farms in the Arctic with the Application of Bayesian Networks, Energies, **14**(15): 4439.

Paper 3

Albara M. Mustafa, Abbas Barabadi. Criteria-Based Fuzzy Logic Risk Analysis of Wind Farms Operation in Cold Climate Regions. Energies. 2022; **15** (4):1335.

Paper 4

Mustafa, A. M., A. Barabadi and T. Markeset (2019), Risk assessment of wind farm development in ice proven area, *Proceedings of the 25 th International Conference on Port and Ocean Engineering under Arctic Conditions (POAC)*, June 9-13, 2019, Delft, The Netherlands

Paper 5

Mustafa, A., T. Markeset and A. Barabadi (2020), Wind Turbine Failures Review and Gearbox Condition Monitoring, *ESREL*, Milano, Italy.

Paper 6

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Chapter 1

1 Introduction

1.1 Wind energy in cold climate regions

Wind energy applications are flourishing in cold climate regions (CCRs). CCRs are recognized as regions that experience a minimum hourly temperature at or below -20°C for at least 9 days per year when measurements are taken for a long term such as 10 years or more of measurement (Lehtomäki et al., 2018). Moreover, the long-term average temperature of the location should be below 0°C (Lehtomäki et al., 2018). According to the Global Wind Energy Council, the annual rate of increase of wind energy capacity in CCRs exceeded 20% compared to before 2010 (GWEC, 2011). According to the Wind Power Monthly market update (Lehtomäki, 2016), around 100 Gigawatt (GW) of wind energy were installed in CCRs by the end of 2015. The same report anticipated that the increase in the installed capacity of wind energy in CCRs would reach 12 GW per year. This significant increase in this sector's investments should be accompanied by extensive research, to cope with the challenges and risks that might be faced.

Most of the challenges and risks that face wind energy applications installed in CCRs are due to the harsh weather conditions in CCRs. These risks and challenges affect the performance of wind farms (WFs), and their resilience, which is defined as the ability of a technological system to restore its capacity to perform at an acceptable level, when encountering disruptive events (Firesmith, 2019). The majority of current studies concerning the performance of WFs in CCRs focus on the effects of icing on the structural behavior of WTs (Alsabagh et al., 2013), the resulting power losses due to harsh weather conditions (Kilpatrick et al., 2020), the currently used anti/de-icing technologies (Wei et al., 2020) (Dai et al., 2012) (Parent and Ilinca, 2011), and risks caused by ice fall, ice throw, and thrown blade parts (Bredesen and Refsum, 2015) (Rastayesh et al., 2019). What characterizes these studies is that they mostly focus on the technical part of the performance of WFs, at the expense of other performance aspects that concern primarily the risks and challenges caused by the operation of WFs, which might affect the surrounding environment, community, and economy, characterized by the sustainability performance.

Similarly, risks related to WFs in CCRs can be classified into risks caused by harsh weather conditions, such as ice accretion on the blades of WTs, snow accumulation on roads of WFs, and extremely cold temperatures that affect the dexterity of laborers at WFs, and risks caused by the WFs that affect their surrounding environment, community, and economy, such as the impact of WFs on wildlife, the noise and visual annoyance to nearby residents, and their economic situation. The analyses of these risks can provide a holistic view of the different risks that are important for decision-making by designers of WFs, stakeholders, and the community.

Additionally, the performance of WFs under disruptive events, which could be caused by unpredictable extreme weather conditions taking place in CCRs, can be an interesting topic, expressed by the resilience of WFs, which is not researched enough in the literature. There is a lack of a sufficiently comprehensive framework for the resilience of WFs in CCRs, that discusses resilience from different aspects, which can be an addition to researches such as (Skobiei et al., 2021), where the resilience of offshore WFs is discussed in the light of one factor, which is the redundancy of operating vessels to support the maintenance activities. Considering several different factors, affecting and shaping the resilience of WFs in CCRs, can provide a more comprehensive framework for measuring resilience, and a demonstration of the interactions between such factors. This can be attained by utilizing the concept of conditional probability as an example, and by using the Bayesian Networks to create different operating scenarios.

The current thesis proposes a hierarchical structure for the performance of WFs, consisting of the technical performance, which can be measured by certain indicators such as the reliability of the wind turbines (WTs), their capacity, and availability. The other part the of performance structure is the sustainability performance, which is concerned with the impacts WFs have on the surrounding environment, community, and economy. Furthermore, the thesis proposes methodologies to calculate the performance of WFs in CCRs, by calculating an overall performance index (OPI). Moreover, the thesis introduces a methodology to measure the resilience of WFs in CCRs under various operating scenarios using the Bayesian networks and analyzes the related risks to WFs in CCRs with the application of Fuzzy logic tools.

1.2 Problem definition

WFs in cold CCRs are subject to several risks that affect their performance. The data and information on the performance and the associated risks to WFs in CCRs might be lacking and insufficient, due to the fact that wind energy applications in such regions are relatively new. For example, in 2010, the total installed wind energy capacity in Sweden was 2,163 MW, of which only 124 MW was located in cold climate regions. Norway, in the same year, had a total installed wind energy capacity of 436 MW, with only 48 MW installed in cold climate regions (Battisti, 2015). Today, the total wind energy capacity installed in the northern part of Norway, in the counties of Nordland, Troms, and Finnmark, has reached 473 MW, which is nearly 10 times the capacity installed 10 years ago in the same region, the Arctic region. It can be said that the Arctic region and most cold climate regions are among the largest “non-standard” markets in wind energy today (Lehtomäki et al. 2018).

The newness of the wind energy market in CCRs entails less expertise in the operational conditions that are experienced by WFs, less available data on the operation and maintenance of WTs under severe weather conditions, leading to less comprehensive risk analysis of potential risks, and minimal research on the resilience of WFs in case of unexpected disruptive events taking place.

In order to proceed with a comprehensive assessment of the performance of WFs in the light of potential risks, this study suggests a number of methodologies that can be applied to calculate the overall performance of WFs, identify and analyze the potential risks to and from WFs in CCRs, and calculate the resilience of WFs under various operating scenarios, induced by the weather conditions encountered in the CCRs.

1.3 Purpose and objectives

The purpose of this research is to propose methodologies that can be applied to enhance the performance of WFs in CCRs, and identify the potential risks and challenges that can emerge specifically in CCRs, and affect the performance of WFs, by attaining the following objectives:

1. Developing an index for WFs operating in CCRs that calculates the overall performance of WFs, by combining the technical aspects and the sustainability aspects of WFs.
2. Identifying the most prominent risks related to WFs in CCRs and proposing a methodology to analyze those risks.
3. Assessing the resilience of WFs in CCRs, which can be done by developing a methodology, that calculates the resilience under various scenarios that differ in severity.

1.4 Research questions

In order to fulfill the above-mentioned purpose, three research questions have been formulated in order to help with identifying the key purposes of the research as follows:

Q1. What are the performance aspects that determine the overall performance of WFs operating in CCRs and how can they be measured?

Q2. What are the risks and challenges related to WFs in CCRs during their operation and maintenance and how to analyze them?

Q3. How to measure the resilience of WFs in CCRs under different operating scenarios, including disruptive operating conditions?

These three research questions have been investigated throughout the 6 papers included in this research. The papers attempt to study and discuss the different aspects mentioned in the research questions. Table 1 shows which of the research papers covered and answered which of the research questions.

Table 1: Papers covering research questions

	Paper 1	**Paper 2**	**Paper 3**	**Paper 4**	**Paper 5**	**Paper 6**
Q1	✓	✓		✓	✓	✓
Q2	✓	✓	✓	✓	✓	
Q3	✓	✓	✓	✓	✓	

1.5 Scope and limitations

The scope of this research covers the assessment of risks and resilience of the performance of WFs located in CCRs. The research focused on the Arctic region of Norway as a part of the CCRs. The data analyzed in the papers were gathered from WFs located in the Arctic region of Norway. However, the methodologies applied in this research are applicable to WFs located in CCRs or in other non-CCRs.

Regarding the performance of WFs in CCRs, the research is limited to qualitatively calculating an overall performance index for WFs, by measuring two categories of performance indicators: the technical performance indicators, and the sustainability performance indicators. The research calculated and compared the overall performance index of a WF located in a CCR to another that is located outside a CCR.

Regarding the resilience of WFs, the research is limited to certain factors contributing to shaping the resilience of wind farms in CCRs. Those factors are the reliability of WTs, the maintainability of the WTs, the supportability of the WF, and the organizational resilience of the WF. Moreover, the research calculates the resilience of WFs as a percentage and was limited to three main operating scenarios, which are the non-cold climate operating conditions scenario, the cold climate operating conditions scenario, and the black swan operating conditions scenario.

Regarding the analysis of risks to WFs, the research is limited to analyzing 6 types of risks, which are i) the increased stoppage rate of WTs due to harsh weather conditions, ii) ice throw from wind turbines, iii) cold stress to workers at wind farms, iv) limited accessibility to wind farms due to snow cover on roads, v) environmental risks caused by the wind farms, and vi) the social opposition risk to installing WFs in CCRs. The research aimed at ranking these 6 risks, depending on their probability of occurrence and severity of consequences, and making a comparison in terms of the ranking of these risks between a WF located in a CCR and a WF located outside this region.

1.6 Data gathering

In order to achieve the goals and objectives of this study, data from two WFs in the Arctic region of Norway were collected throughout this study. Two non-disclosure agreements had to be signed with the two companies owning the two WFs. The gathered WFs data consisted of alarm logs which indicated errors and potential failures the WTs experienced, in addition to the time they were detected and their duration, ice detection events on the blades of the WTs, and the duration of each corresponding stoppage caused by ice accretion, the unavailability of communication events between the WTs and the supervisory system, power production-related conditions such as wind speed, nacelle position, rotor and generator speeds, amount of power produced by each WT, as well as maintenance reports of WTs, which showed the type of failure, the replaced parts, the maintenance activity duration, and the number of personnel carried out the maintenance activities.

In addition, data were collected from experts in the wind energy field, analyzed, and used to make up for the lack of data in certain areas. For example, in Paper 1 experts were asked to assess the relative weight of each performance indicator qualitatively, by giving each indicator a value between (1 and 10), depending on the importance of the indicator to the overall performance of the WF. In Paper 3, experts provided values (from 0 to 10) for the probabilities, consequences, and risk levels in order to plot the membership functions, which were used later in the fuzzy logic process to rank the risks identified in the paper.

1.7 Thesis structure

Chapter 2 presents the background upon which the thesis is built, which encompasses the hierarchical structure of the overall performance of WFs, the resilience of WFs in CCRs, and the identification of WFs-related risks in CCRs. Chapter 3 introduces the research methodologies used to calculate the overall performance index of WFs in CCRs, their resilience under three distinct operating scenarios, and the analysis of six identified risks. The discussion and results of the application of the proposed methodologies, using WFs in the Arctic region of Norway as case studies, are illustrated in Chapter 4. Finally, the conclusions are given in Chapter 5.

1.8 Description of publications

Paper 1

Mustafa, A. M., A. Barabadi, T. Markeset and M. Naseri (2021), An overall performance index for wind farms: a case study in Norway Arctic region, International Journal of System Assurance Engineering and Management.

My contribution is developing the methodology used in the paper, communicating with WFs and collecting performance data from one WF, communicating with experts and collecting their answers, analyzing the data, and writing the paper. Masoud Naseri helped me with the calculation made in the paper. Abbas Barabadi and Tore Markeset reviewed the paper and provided comments to improve it.

In Paper 1, we developed a methodology to measure the performance of WFs, by designing a set of performance indicators, that represent the technical and sustainability performance aspects of WFs. Experts in wind energy field provided their assessments regarding the relative weight of each performance indicator. Furthermore, A set of criteria was defined for each performance indicator, and by using the weighted sum method, which is one of the famous methods for multiple-criteria decision making (MCDM), the overall performance index was calculated. This methodology was applied to a WF in the Arctic region of Norway. The resulting overall performance index was 61.3%, which indicated that the WF performance could be described as good. Furthermore, the same methodology was applied to a WF located in a non-cold climate region. Due to the fact that the sustainability performance of this WF was lower than the cold-climate WF, the resulting overall performance index was calculated to be nearly 60%.

Paper 2

Mustafa, A. M. and A. Barabadi (2021), Resilience Assessment of Wind Farms in the Arctic with the Application of Bayesian Networks, Energies, **14**(15): 4439.

My contribution is developing the methodology used in the paper, collecting the data of a WF in the Arctic region of Norway, developing and mapping the Bayesian network, running the network, analyzing the data, and writing the paper. Abbas Barabadi reviewed the paper and provided comments to improve it.

In Paper 2, we developed a methodology, using Bayesian networks, to calculate the resilience of WFs as a percentage, while operating under cold climate conditions, and subjected to disruptive events. Three scenarios were defined, and the corresponding resulting resilience was calculated for each scenario. The first scenario implies that the WF operates under non-cold climate conditions, in which the calculated resilience of the WF was the highest. The second scenario is when the WF is operating under cold climate conditions, in which the WF shows a slight degradation in the calculated resilience. The third and final scenario is a black swan scenario, during this scenario the resilience of the WF is significantly reduced due to the severe characteristics of the operating conditions of this scenario.

Paper 3

Albara M. Mustafa, Abbas Barabadi. Criteria-Based Fuzzy Logic Risk Analysis of Wind Farms Operation in Cold Climate Regions. Energies. 2022; **15** (4):1335.

My contribution is developing the methodology of the paper, collecting the data of a WF, collecting and analyzing responses from experts, developing the membership functions and fuzzy logic inference using MATLAB fuzzy logic toolbox, running the model, and writing the paper. Abbas Barabadi reviewed the paper and provided comments to improve it.

In Paper 3 we reviewed the most prominent risks that WFs in cold climate regions are subjected to. In total, 6 risks were identified and analyzed. Experts were communicated to provide their subjective values of probabilities, consequences, and output risk levels (low, medium, high, etc.) for each risk. Afterwards, a set of rules were defined for the different combinations of probabilities and consequences during the fuzzy inference step. A WF in the Arctic region of Norway was selected as a case study, the fuzzy logic toolbox in MATLAB calculated the resulting risk level of all the identified risks for the selected WF, which led eventually to ranking them according to the resulting risks levels. In addition, a WF in a non-cold-climate region was selected to demonstrate the effects of the Arctic operating conditions on the ranking of risks.

Paper 4

Mustafa, A. M., A. Barabadi and T. Markeset (2019), Risk assessment of wind farm development in ice proven area, *Proceedings of the 25 th International Conference on Port and Ocean Engineering under Arctic Conditions (POAC)*, June 9-13, 2019, Delft, The Netherlands

My contribution is reviewing the different types of ice and snow that can accrete on WTs, and the different effects and risks such accretion may represent, during operation and maintenance activities. Moreover, I developed a cross-tabular assessment table that ranks the different types of ice and snow according to the potential risk they may represent to the different parts of onshore and offshore WTs. Abbas Barabadi and Tore Markeset reviewed the paper and provided comments to improve it.

In Paper 4 we outlined the different types of icing that may affect the performance and availability of onshore and offshore WFs located in CCRs. The main types of ice included in the paper are i) Atmospheric icing, ii) Super-structure Icing, and iii) Sea ice. The paper describes the process of formation of each type of ice, and which components in WTs are prone to each ice type. Furthermore, the paper discusses the effects of icing on WTs and WFs in terms of i) mechanical equipment performance, ii) operation and maintenance crew performance, iii) accessibility to WFs and iv) public safety risks. Lastly, the paper proposes a cross-tabular assessment to assess the impacts of icing on the safety of WTs and WFs in CCRs. The conclusion of the paper is that glaze ice and freezing rain and snow induce the highest impact on the structure of WTs. Moreover, operation and maintenance crew performance is highly affected by glaze ice, as it causes slipping, tripping, and falling risks.

Paper 5

Mustafa, A., T. Markeset and A. Barabadi (2020), Wind Turbine Failures Review and Gearbox Condition Monitoring, *ESREL*, Milano, Italy,

My contribution is reviewing the research done on the measured failure rates of the components of WTs, and the resulting downtime of those failures, in order to determine the most critical component to the availability of WTs. Moreover, I reviewed the commonly used condition monitoring systems (CMS), and Supervisory Control and Data Acquisition (SCADA) systems, to track the health conditions of the different components of WTs. The paper concludes, as other research with a similar aim, that the most critical component to the availability of WTs is the gearbox. Based on that, I reviewed the causes of gearbox failures and the used CM systems to monitor its health condition. Abbas Barabadi and Tore Markeset reviewed the paper and provided comments to improve it.

Paper 5 reviews the critical failures WTs usually experience during their operation by determining the failure rates of components and the resulting downtime from each failure. In addition, the paper provides a brief review of the current CMS and the SCADA systems utilized to monitor the condition and performance of WTs. The paper goes further into Investigating the causes of gearbox failure, which was determined to be the most critical type of failure to WTs, based on the review, and reviews the current CM methods used to monitor the health condition of the gearbox.

Paper 6

Mustafa, A. M., T. Markeset and A. Barabadi (2020), Downtime Cost Estimation: A Wind Farm in the Arctic Case Study, *Esrel 2020*, Italy,

My contribution is reviewing the contributing costs to the levelized cost of energy (LCOE) from WFs, the risk factors affecting the values of LCOE, selecting a WF in the Arctic region of Norway as a case study, calculating the downtime cost by making use of the LCOE of the WF, caused by the failure of a gearbox in a WT. Abbas Barabadi and Tore Markeset reviewed the paper and provided comments to improve it.

Paper 6 proposes a method to calculate the monetary cost of downtime resulting from a failure in a WT or a WF. The main contributing factors to the LCOE of WFs are the capital expenditures (CAPEX) and the operational expenditures (OPEX). The paper explains the details of each of these contributing factors and how to combine them in an equation to calculate the LCOE. Furthermore, the paper outlines the risk factors that might affect the values of the variables in the LCOE equation. In addition, a WF in the Arctic region of Norway was selected to calculate the monetary losses resulting from the downtime caused by the failure of a gearbox in one of the WTs.

1.9 Research strategy and design

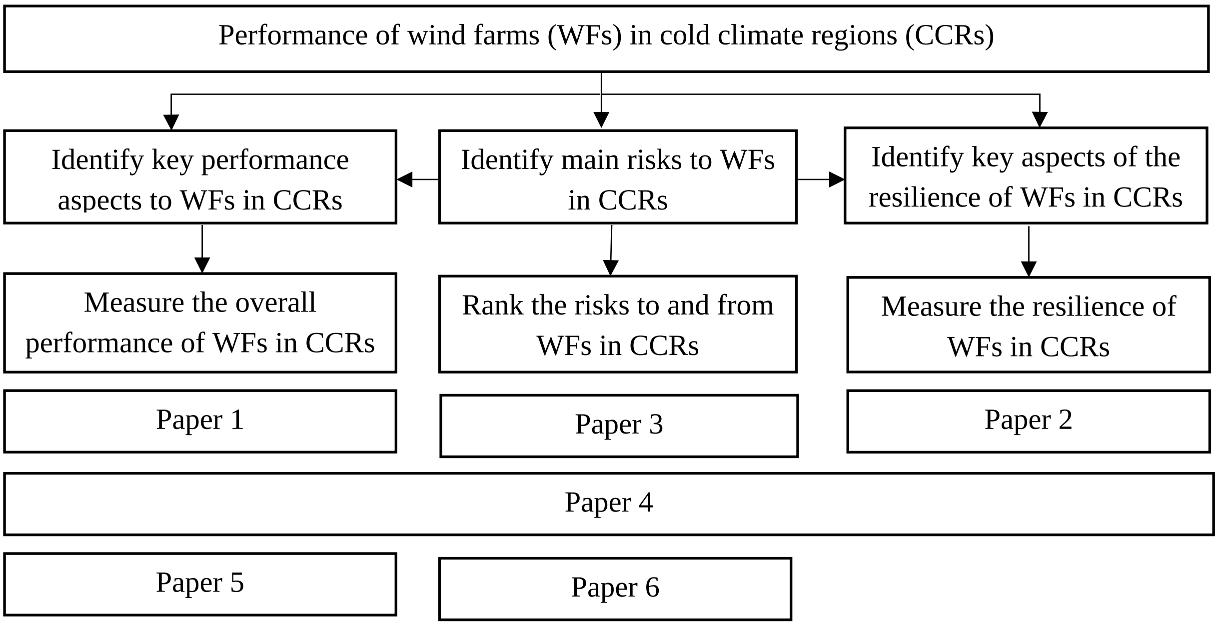

Figure 1. Research process and strategy for this study

In this research certain aspects related to the performance of WFs, operating in CCRs were covered in six published papers. Figure 1 describes the overall process followed in this research and connects each of the six papers to the process. The process is divided into 3 main activities. The first activity is to identify the key performance indicators of WFs in CCRs and to calculate the overall performance of WFs by developing an overall performance index, presented mainly in paper 1. The second main activity is to identify the main risks affecting the performance of WFs in CCRs, as well as the main risks WFs induce on their surroundings in CCRs, which were covered and ranked in paper 3. Lastly, the third main activity is to identify the main aspects contributing to the resilience of WFs in CCRs, and to develop a methodology that measures the resilience of WFs when operating under different operational conditions in CCRs, which were covered in Paper 2.

It should be noted that identifying the key risks to WFs in CCRs, in the second main activity of this process, helps with the identification of the most affected WFs performance indicators by the operational conditions in CCRs, described in the first main activity. Moreover, it helps with the identification of the main contributing aspects to the resilience of WFs in CCRs, presented in the third main activity. Therefore, the second main activity in this process can be described as a central activity to the whole research process.

Papers 4, 5, and 6 discussed partially the aspects related to the three main activities. Therefore, the discussions in the following sections of this thesis are mainly focusing on papers 1, 2, and 3 that cover the three main activities extensively.

Chapter 2

2 Background

2.1 Overall Performance of wind farms in cold climate regions

WFs located in CCRs are subjected to a plethora of challenges. Most of these challenges emerge from the harsh weather conditions such as very low temperatures, ice accretion on the blades of the WTs, and snow accumulation on roads of the WFs, which can hinder the accessibility to the WTs in case they needed maintenance (Lehtomäki et al., 2018). Such challenges affect the technical performance of the WF, which is related to the amount of power produced by the WF (Koo et al., 2018), and can be described and measured by certain indicators, which were developed in this thesis, and described in Figure 2, where the technical performance is constituted by the quality, availability, and capacity performance indicators. In addition, the availability performance indicator can be furtherly sub-categorized into three sub-performance indicators, which are the reliability, maintainability, and supportability performance indicators.

On the other hand, the operation of WFs impacts the surroundings. The impacts can be measured by the sustainability performance of the WF. The social and safety, environmental, and the economic performance indicators represent the three pillars of sustainability performance indicator of a technological system (Diaz-Balteiro et al., 2017).

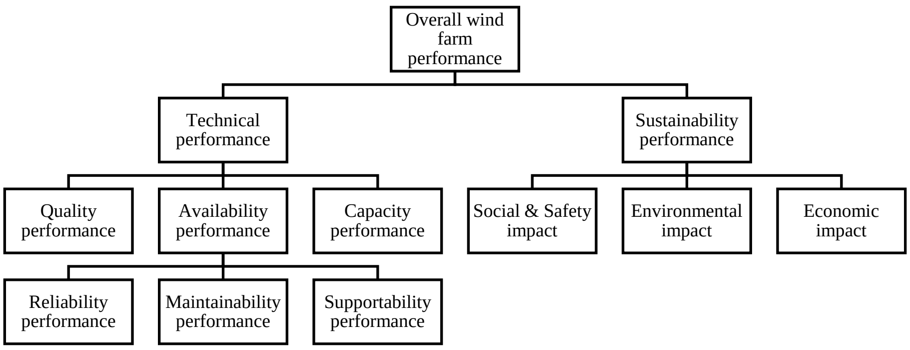

Figure 2. The overall performance model for wind farms

2.1.1 Technical performance

Technical performance is mainly related to the technical functions of WFs, in terms of the amount of electricity generated (Koo et al., 2018), and how they are affected under cold climate conditions. Technical performance refers to the importance of the quality of the power produced by the WFs, as well as their capacity and availability performances, which can be described in terms of the reliability, maintainability, and supportability of the WFs (IEC, 2015).

2.1.1.1 Quality performance

The quality performance of WFs reflects the design and manufacturing quality of WTs and the WF layout. It also implies maintaining stability between generated and demanded power (Arulampalam et al., 2006). Unstable weather conditions, commonly occurring in CCRs, can cause fluctuations in power production due to significant variations in wind speed. Other hazards, such as ice accretion on the blades of WTs (Alsabagh et al., 2013) and limited accessibility to WFs due to snow accumulation on the roads (Lehtomäki et al., 2018), will also limit maintenance activities and reduce the quality of power production.

2.1.1.2 Capacity performance

The capacity performance of a WT can be defined as its ability to deliver power according to the design capacity, or according to current demands, in a fixed period with given production resources (Barabady et al. 2010, Shahidul et al. 2013). In light of this definition, the capacity of a WF should reflect the highest sustainable rate of power produced that can be achieved, given the specifications of the WF, the current resources, weather conditions, and maintenance strategies. Capacity can duly affect the efficiency and effectiveness of the operation of a WF (Isaza et al. 2015).

WFs in CCRs are challenged by severe weather conditions, such as ice accretion, snow accumulation, and low temperatures, which can lead to a reduction in wind farm capacity. In addition, the selection of a suitable maintenance strategy plays an important role in attaining the maximum capacity of a WF. Considering these factors, the capacity performance of WFs is expected to be degraded under CCR weather conditions.

2.1.1.3 Availability performance

Availability is defined as “the ability of a functional unit to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided” (ISO/IEC-2382, 2015). According to the International Electrotechnical Commission (IEC), the availability performance depends upon the combined characteristics of the reliability and maintainability of the item and the maintenance support performance (IEC, 2015), which will be discussed in light of CCR operational conditions.

i) Reliability performance: reliability is defined as “the ability of a component or a system to perform its required functions without failure during a specified time interval, under given conditions”(IEC, 2015). The main aim of system or equipment reliability is to prevent or mitigate the failures that lead to downtimes and reduced power production from WFs.

The rate of failure of WT components may increase under severe weather conditions. Ice and snow may accumulate on the blades of WTs. Snow infiltration inside the nacelle and extreme temperatures may lead to condensation in the electronics and, consequently, can lead to electrical failure (Laakso et al. 2003). For the aforementioned reasons, the blades, control system, and electrical system are responsible for the highest failure rates (Pérez et al., 2013).

Poor component quality of, for example, the variable pitch system, the frequency conversion system, the electrical system, the control system, the gearbox, the generator, and the yaw system can lead to WT breakdown incidents, particularly under harsh weather conditions such as those found in CCRs (Zhang et al., 2013). Moreover, very low temperatures can change the properties of materials and fluids; for example, steel can become more brittle, and lubricants and hydraulic fluids’ viscosity increases (Barabadi and Markeset, 2011).

ii) Maintainability performance: Maintainability is defined as "the ability of an item to be retained in or restored to a state to perform as required, under given conditions of use and maintenance" (IEC, 2015). The maintainability of WTs in CCRs depends to a large extent on the accessibility to the wind farm/turbine to carry out the required maintenance and inspections. Snow accumulation on the roads of onshore WFs hinders the accessibility to the WTs and calls for snow-removal strategies, or the use of specially equipped vehicles, which will increase the cost of energy (Lehtomäki et al., 2018). Lower temperatures may affect the performance of several materials, such as iron and steel, polymers, and plastics, used in maintenance tools, which experience embitterment at cold temperatures (Markeset et al., 2015). Moreover, maintainability needs to consider human ergonomics, logistics management, design layout, and the level of experience and training of the maintenance personnel (Balindres et al., 2016). Figure 3 shows an example of the harsh weather conditions maintenance crews experience at Fakken WF, which may hinder proper maintenance activities.

Figure 3. Unclear visibility at Fakken WF due to snowy weather conditions (Mæhlum, 2013)

iii) Supportability performance: Supportability is defined as the "ability of an item to be supported to sustain the required availability with a defined operational profile and given logistic and maintenance resources" (IEC, 2015). The supportability of a WF is essentially connected to its maintainability performance, as supportability contributes to fast and frequent maintenance through timely repair/replacement of failed parts in order to maintain the availability of the WF (Kratz 2003). Based on that, numerous factors contribute to the supportability level achieved by WFs. These include logistics considerations of spare parts, personnel, procedures, test equipment, and integrated tools (Smith and Knezevic 1996).

The availability and the location of spare parts have a great impact on the supportability of a product/system (Markeset and Kumar 2005). Spare parts storage at WFs with large-scale WTs is normally limited to small-size spare parts, as it might not be feasible to store large components, such as blades and gearboxes, due to size and capital investment. However, it is the failure of the large-scale components that decreases the availability of WTs significantly and results in the longest downtime, such as the case of the gearbox, which is responsible for almost 56% of the total downtime resulting from failures of WT's main components (Artigao et al., 2018). Therefore, WF operators tend to order large-scale components from the suppliers once a propagation of failure is observed. In the Arctic region, as an example of a CCR, the remote geographical location from suppliers, the cold and harsh climate, and the insufficient and inconvenient infrastructure can affect the effectiveness, and efficiency of the logistics of required supportability services, and the delivery of supplies (Gao and Markeset 2007, Barabadi 2012). In addition, supportability was confirmed, during interviewing experts, to be one of the main challenges to WFs located in remote locations in CCRs.

2.1.2 Sustainability performance

Sustainability science focuses on the management of the relationship between the environment and humans (Afgan et al., 1998), by understanding the interactions between nature and society, meaning that the sustainability goals of a system are achieved through a scientific assessment of the current and the potential future conditions for the Earth System (Omer, 2008).

Sustainability in power production systems implies increasing energy production continuously, using minimum material and energy, as well as non-hazardous materials, cleaning the waste materials resulting from that production in natural ways, decreasing the risks related to human health as far as possible, and using raw materials, including environmental resources, in an efficient way, which in turn results in minimum life-cycle costs (Hallstedt et al. 2010).

The sustainability of WFs located in CCRs should comply with the principles of sustainability, which aim at preserving the ecosystem’s integrity and promoting human health while meeting the demands of the customer and society (Mayyas et al., 2012). Moreover, sustainability implies that WFs should be designed for disassembly, remanufacturing, and recycling, and should be highly recyclable at the end of their life. The conceptual priority in sustainability performance is mainly sustaining society and not explicitly the environment and the economy (Musango and Brent, 2011). Based on this, the sustainability performance indicators of WFs in CCRs are assessed by the following three impacts categories:

- Environmental impacts
- Social impacts
- Economic impacts

2.1.2.1 Environmental impacts of WFs in CCRs

Certain CCRs such as the Arctic are known for their unspoiled nature and wilderness. There are plentiful resources of different fish species, planktonic organisms, and bird habitats, which also make the area vulnerable found in some CCRs. Moreover, it is estimated that the Arctic region might contain 13% of the world’s undiscovered oil and 30% of its undiscovered gas (Gautier et al., 2009). Pollution resulting from energy production from fossil fuels may have serious consequences for the sensitive environment found in CCRs, especially in the Arctic region. WFs, on the other hand, generate electricity carbon-free with no long-term waste, and no cooling water (Pasqualetti, 2011), and are environmentally benign in several ways. However, their environmental performance needs to be assessed.

Anti-/de-icing chemicals, particularly glycol compounds, such as ethylene, propylene, and alkaline, may be used to de-ice wind-turbine blades, which may create human safety and health problems, cause environmental harm, represent a threat to surface and groundwater, damage roads and vehicles and may not be cost-effective (Back et al., 1999) and (Dai et al., 2012). In addition, WTs might be one of the reasons for bird mortality. However, research studies stated that, compared to fossil fuels, wind energy killed 20 times fewer birds, and the number of birds killed by WTs may be negligible compared to some other human activities (Sovacool, 2009). In addition, in the Arctic, as a CCR, WFs might be installed on important winter grazing areas for reindeer, which might lead to changes in reindeers' density in the region, which might be noticed as well during the construction phase of WFs.

2.1.2.2 Social and safety impact of WFs in CCRs

WFs also have impacts on the surrounding community and its safety. For example, the noise emitted by WTs during their construction and operation, and the visual annoyance that might increase the opposition from the surrounding community to installing WTs in certain areas. Moreover, ice thrown from operating WTs might be a major concern in CCRs, as pieces of thrown ice might hit the surroundings, including people, cars, animals, and other facilities. However, this issue might be sometimes exaggerated, as WFs in CCRs are normally located in remote locations, and the severity of icing differs from one WF to another and does not even take place in some WFs, depending on the surrounding geographical and environmental conditions. This was proved during the author's visits to WFs and by discussing this issue with operators of WFs in northern Norway.

In another context, it can be claimed that governments are violating the rights of indigenous communities by approving wind energy projects in certain areas, causing cultural destruction. Constructing wind farms on Sámi lands in northern Scandinavia, for example, may be considered unethical and overtly political, simply because it might appear as a systematic dispossession of their lands and a lack of recognition of their rights (Lawrence and Moritz, 2019).

2.1.2.3 Economic impact of WFs in CCRs

Wind energy projects create job opportunities for local communities throughout the wind farm's lifetime, especially the planning and construction phases since wind energy investments are known to be capital-intensive, with capital costs representing nearly 80% of the total costs of a wind energy project over its lifetime and measured in €/kW (Blanco, 2009). In addition, wind energy promotes the stability of electricity prices in a country, by diversifying the sources of energy. However, most wind energy projects are subsidized by governments due to the high capital and operational expenditures (CAPEX & OPEX) of such projects. Still, technological advances contribute to decreasing these costs, and will eventually lead to a more effective utilization rate of WTs, which is reflected by the percentage of time the WT is operational during the 8760 h (365 × 24) of the year. Thereafter, wind energy projects can yield positive returns on investments. Without even financial support from governments. Moreover, as the prices of fossil fuel-based energy become more expensive, wind energy becomes more competitive.

2.2 Resilience of wind farms in cold climate regions

The resilience of technological systems is defined as the extent to which the system can maintain a certain level of performance when encountered by disruptions (Firesmith, 2019). WFs in CCRs, as an example of a technological system, are prone to disruptions caused mainly by the harsh weather conditions that affect the resilience of WFs. Such weather conditions create uncertainties about the performance of WFs and how resilient WFs can be in the face of disruptions.

Engineering resilience can be defined mathematically as the sum of reliability and restoration, as per Equation 1 (Youn et al., 2011). Restoration is defined as "the event at which the 'up' state is re-established after failure" (IEC, 2015). According to (Rød et al., 2016) restoration depends on several factors, which are (i) the system failure event (i.e. the reliability of the system), (ii) the maintainability of disrupted components, (iii) the supportability of maintenance activities, and (iv) the organizational resilience of the WF.

$$\text{Resilience } (\Psi) = \text{Reliability (R)} + \text{Restoration } (\rho) \qquad (1)$$

By considering the uncertainties the weather conditions in CCRs may cause to the factors of restoration, a probabilistic approach can be designed to calculate the resilience, which was expressed in Equation 1, as a probabilistic value (between 0 and 1). Therefore, restoration can be expressed as the conditional probability of the previously mentioned four factors, as in Equation 2.

$$\text{Restoration } (\rho) = (1\text{-R}) \times \text{M} \times \text{S} \times \text{O} \qquad (2)$$

Where R, M, S, and O are the conditional probabilities of reliability, maintainability, supportability, and organizational resilience respectively. The values of these four variables are conditional, based on the weather conditions WFs experience in CCRs. Therefore, these four factors in addition to restoration and resilience are categorized as probabilistic output variables, with values depending on certain probabilistic input variables, as shown in Figure 4.

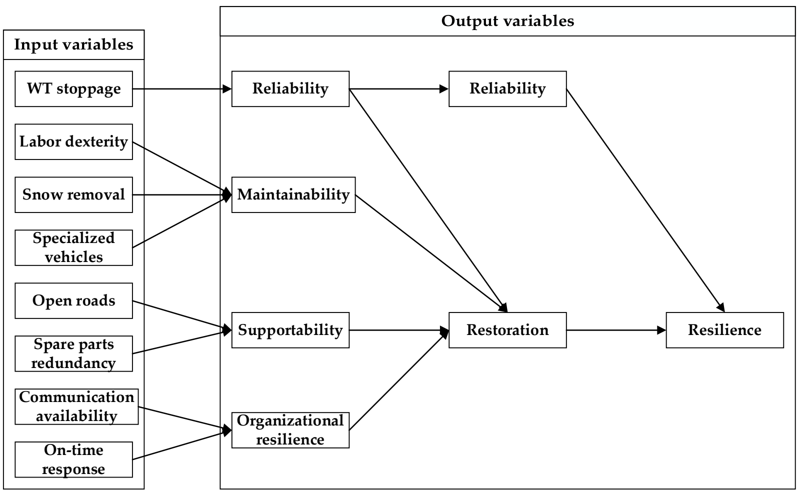

Figure 4. Input and output variables of the resilience of WFs (Mustafa and Barabadi, 2021)

1. Reliability (R(t)) can be probabilistically expressed as the inverse of the probability of failure (Rausand et al., 2020), as in Equation 3:

$$R(t) = 1- F(t) \tag{3}$$

Where F(t) is the probability at which the WTs stop operating due to hazards, caused by the harsh weather conditions in CCRs, or due to component degradation. For simplicity, Poisson distribution is used to represent the probability of the WT stoppage events, as shown in Equation 4 (2007):

$$p(k;(0,t), \lambda) = \frac{(\lambda t)^k}{k!} e^{-\lambda t} \tag{4}$$

Where k is the number of stoppage events of WTs the Poisson distribution finds the probability of, over a fixed period (0, t). λ is the number of WT stoppage events over a specific period, and it represents the mean value of the Poisson distribution.

2. Maintainability. It reflects how easily the system can be maintained, or how quickly the component or the system can be restored to a state, where it can perform at an acceptable capacity (IEC, 2015). The maintainability of WFs in this paper is dependent on two factors, which are the labor dexterity when carrying out the maintenance activities, and the accessibility to the WF, which are both affected by the weather conditions in CCRs.

3. Supportability. The supportability activities are tightly connected to the maintainability of WFs. Supportability to WFs in CCRs are mainly concerned with the on-site availability and the provision of WT spare parts, and maintenance tools that will help the service team to restore the performance of the WF and its availability, during and after disruptive events. Therefore, as shown in Figure 4, supportability is dependent on the redundancy of spare parts, and the accessibility to public roads to deliver the needed parts and tools from suppliers to the WF site.

4. Organizational resilience. The resilience of a WF as an organization implies the capacity of the operational team to prepare for disruptive events, respond, and adapt to them, whether these disruptive events take place gradually or as sudden (BS-65000, 2014). Therefore, the probabilistic approach to measuring the organizational resilience of WFs in CCRs depends on:

   - *Communication availability (CA),* which encompasses the communication between the operational team and the WF through monitoring systems. Incidents that lead to loss of data gathered from WTs, through SCADA systems and condition monitoring systems, render the communication with the WF unavailable. A Poisson distribution is used to estimate the probability of loss of connection events (x), taking place over a specific period (0, t), with considering an average number of loss-of-connection incidents (λ). Hence, the probability of connection availability can be represented as per Equation 5 (Zio, 2007):

$$CA = 1-p(x;(0,t), \lambda) =1- \frac{(\lambda t)^x}{x!} e^{-\lambda t} \tag{5}$$

   - *On-time response to events*. It represents how successful the response of the WF operator to the disruptive events the WF encounters, which can be also assessed by the percentage of times the operator takes action to respond to the disruptive event, which can be described as an on-time response. For example, if 85% or more of the disruptive events are responded to by the WF operator within the first hour of their occurrence, then the WF operator can be described as resilient, and the on-time response variable can be considered 100% successful (Hosseini and Barker, 2016).

2.3 Wind farms-related risks in cold climate regions

Paper 3 differentiates between risks caused by the harsh weather conditions in CCRs that affect the technical performance of WFs, and risks caused by the WFs, which affect the surroundings of the WFs such as the environment and the nearby community. Based on that, six types of risks are analyzed, which are as follows:

2.3.1 Risks caused by weather conditions that affect the performance of WFs

The following risks affect the technical performance of WFs in terms of their reliability, maintainability, and supportability performances described earlier in Fig. 1, which in turn affect the availability performance of WFs and their power production. These risks are as follows:

1. *Increased WT stoppages due to harsh weather conditions (WT stoppage)*. This risk encompasses the stoppages WTs experience that is caused by the harsh weather conditions, which affect the WTs and lead to increasing their stoppage rate in different ways. The physical properties of materials are affected by low temperatures in CCRs. For example, the gearbox lubricating oil viscosity differs with variation in temperatures, when the temperatures are very low, the viscosity of lubricating oil increases, and flows more slowly, creating more friction and thus negatively impacting the efficiency of the gearbox by overheating it and higher fatigue charges (Laakso et al., 2005).
   In addition, the ice accretion on the blades of the WTs leads to increased load on the structure of the WT, and imbalanced and unsafe operation, leading to shutting down the WT to avoid major losses such as losing the WT. As a consequence of that, the power production from the WT will be lost until the accreted ice melts down and the operation of the WT is restored (Andersen et al., 2011). Figure 5 illustrates the different types of ice that accrete on different parts of both onshore and offshore WTs. These ice types are furtherly explained and discussed in Paper 4.

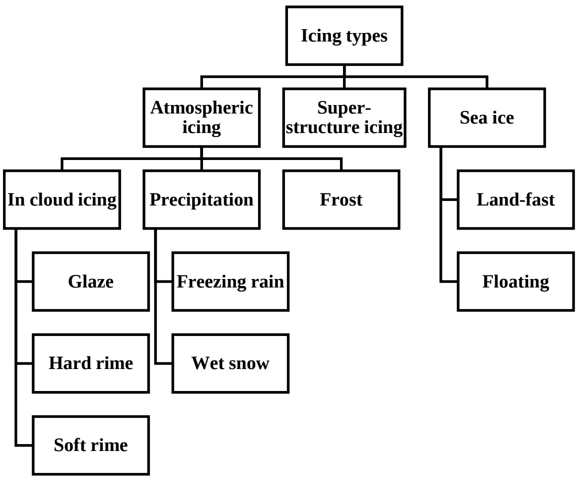

Figure 5. Ice types affecting onshore and offshore wind turbines (Mustafa et al., 2019)

The two most common types of ice that accrete on the blades of onshore WTs are rime ice and glaze ice. Rime ice forms when supercooled water droplets freeze immediately upon impacting the surface of the WT blade, while glaze ice forms when the liquid water freezes shortly after impacting the surface of the blade (Bravo Jimenez, 2018). Glaze ice accretion forms near the freezing point (0 ^{o}C) and has strong adhesion to the surface, it is transparent and has a higher density than rime ice. On the other hand, rime ice has lower adhesion to the surface and has a white or opaque color, and can be easily removed compared to glaze ice (Xue and Khawaja, 2016).

2. *Cold stress to workers (Cold stress).* Cold temperatures cause cold stress to crew workers and limit their dexterity (Wærø et al., 2018). Serious cold-related illnesses and injuries, caused by trench foot, frostbite, and hypothermia, may occur in case of extremely cold temperatures, in addition to permanent tissue damage, and death that may result as a consequence of major cold-related injuries (Mustafa and Barabadi, 2022).
   High wind speeds and cold temperatures are the two main factors contributing to cold stress for workers (Osczevski and Bluestein, 2005). Wind Chill Temperature (WCT) is a measure that determines the likelihood that workers are subjected to the risk of frostbite, which can be calculated using Eqn. 6, where V is the wind speed (km/h) 10 m above the surface and T is the air temperature (°C) (Osczevski and Bluestein, 2005):

$$WTC[°C] = 13.12 + 0.621T - 11.37V^{0.16} + 0.3965TV^{0.16} \qquad (6)$$

   Table 2 has been generated using Eqn. 6. The table is used to determine whether the workers at WFs in CCRs are subjected to the risk of frostbite or not, where the shaded region indicates an increased risk of frostbite (Osczevski and Bluestein, 2005).

Table 2: Wind Chill Temperature (WCT) chart (Mustafa and Barabadi, 2022)

		Air Temperature (°C)												
		10	**5**	**0**	**-5**	**-10**	**-15**	**-20**	**-25**	**-30**	**-35**	**-40**	**-45**	**-50**
Wind Speed (km/h)	**10**	9	3	-3	-9	-15	-21	-27	-33	-39	-45	-51	-57	-63
	15	8	2	-4	-11	-17	-23	-29	-35	-41	-48	-54	-60	-66
	20	7	1	-5	-12	-18	-24	-31	-37	-43	-49	-56	-62	-68
	25	7	1	-6	-12	-19	-25	-32	-38	-45	-51	-57	-64	-70
	30	7	0	-7	-13	-19	-26	-33	-39	-46	-52	-59	-65	-72
	35	6	0	-7	-14	-20	-27	-33	-40	-47	-53	-60	-66	-73
	40	6	-1	-7	-14	-21	-27	-34	-41	-48	-54	-61	-68	-74
	45	6	-1	-8	-15	-21	-28	-35	-42	-48	-55	-62	-69	-75
	50	6	-1	-8	-15	-22	-29	-35	-42	-49	-56	-63	-70	-76
	55	5	-2	-9	-15	-22	-29	-36	-43	-50	-57	-63	-70	-77
	60	5	-2	-9	-16	-23	-30	-37	-43	-50	-57	-64	-71	-78
	70	5	-2	-9	-16	-23	-30	-37	-44	-51	-59	-66	-73	-80
	80	4	-3	-10	-17	-24	-31	-38	-45	-52	-60	-67	-74	-81

3. *Limited accessibility to wind farms due to snow cover on the roads*. This risk is primarily related to the maintenance of WTs, as accumulated snow on the roads of a WF might

hinder the accessibility to the defected WTs and delay the maintenance activity. Furthermore, the WF will need to implement certain measures to overcome this challenge, either by using specially equipped vehicles such as snowmobiles and snow cats or by clearing off the snow on the roads, which can be costly (Lehtomäki et al., 2018). However, this issue is mostly encountered in case the maintenance strategy followed by the WF is a corrective maintenance strategy. Normally, WTs are monitored by condition monitoring systems (CMS), which will generate updated data about the health of the components of the WTs and will warn the WF operator, in case of unusual signals received from the measuring sensors. More details about CMSs are discussed in Paper 5 (Mustafa et al., 2020), where the condition monitoring of the gearbox is focused on.

2.3.2 Risks caused by WFs that impact their surroundings.

The following risks can be categorized as risks affecting the sustainability of WFs in CCRs, these risks focus on the impact of WFs on their surroundings, mainly the surrounding environment and community. These risks are described as follows:

1. *Risk of ice throw from WTs*. When the accreted ice on the blades of operational WTs starts melting, accompanied by the centrifugal force of the rotating blades, ice will detach and be thrown away in pieces far from the WT, which might hit humans, animals, and damage nearby structures. In addition, the melting ice on the blades of idle WTs will fall, presenting a danger to workers who happen to be close to the WT. In both cases, the distance to which the detached ice pieces might reach can be calculated using Equations (6&7) (Seifert et al., 2003):

$$d = 1.5\ (D+H), \text{ for operational WTs} \tag{6}$$

$$d = v\,\frac{D/2+H}{15}, \text{ for idle WTs} \tag{7}$$

   Where d is the throwing distance, D is the rotor blade diameter, H is the hub height, and v is the wind speed.

2. *Environmental risks*. There are different impacts WTs have on the environment. For example, there have been debates over WTs being responsible for the killing of birds and bats (Pavokovic and Mandusik, 2006). However, studies show that other human activities are responsible for the killing of birds and other species as high as 20 times more than WTs, such as the extraction and burning of fossil fuels activities (Sovacool, 2009). In addition, during the construction phase of WFs, surface or underground water might get polluted (Lu et al., 2019). In addition, pollution to water and the environment might take place in case chemical anti/de-icing compounds were used to prevent or remove the accreted ice off the blades. Moreover, lubricating oil may potentially leak from the gearbox, causing more pollution to the environment. Furthermore, WTs might impact the grazing activities of animals such as reindeers in the Arctic region, as reindeers might stop using the area where the WF is located, which might require extra efforts to make the reindeers use the WF area again for grazing (Eilertsen, 2006).

3. *Societal opposition to WFs*. The local community residing nearby WFs might be affected or annoyed by the visual appearance of WTs and the noise they generate. The presence of WFs in some countries or regions might prevent the local community from

effectively utilizing the surrounding lands, which can negatively affect its economy (Kucukali, 2016). Such risks, in addition to the risk of ice throw, might elevate the societal opposition to installing WFs. However, these issues could be less of a challenge to WFs in CCRs, as WFs are usually installed in remote areas far from the local communities.

Chapter 3

3 Research methodologies

In this chapter, I present the methodologies that were used to answer the research questions proposed in this thesis. This chapter is divided into three sections, each section answers one of the research questions. The first section presents the methodology followed to calculate the overall performance index (OPI) of WFs, which utilized a multi-criteria decision-making (MCDM) method considering two types of performance indicators i.e., the technical performance and the sustainability performance, with input data from experts concerning the relative weights of each performance indicator. The second section presents the use of Bayesian networks (BN) to calculate the resilience of WFs, under three distinctive operating scenarios, the designed BN calculates the resilience as a percentage value under disruptive and non-disruptive operating conditions, which were demonstrated in the three scenarios. The methodology explained in the third section illustrates the use of fuzzy logic and experts' judgements to analyze 6 risks related to the operation of WFs in CCRs.

3.1 Calculating the overall performance index of wind farms (Paper 1)

In this paper, I proposed a methodology for calculating the overall performance of WFs, by developing an index, called an OPI, which covers the technical performance and the sustainability performance, in order to present an overall image of WFs performance. The methodology was furtherly applied to a WF in northern Norway and showed that the selected WF had a good overall performance when calculated against a predefined qualitative scale of performances. The methodology, shown in Figure 6 depends mainly on collecting estimated values from experts for the relative weights of the technical and sustainability performance indicators. The relative weights of performance indicators describe their importance on a scale (from 1 to 10) to the overall performance of WFs, where 1 indicates the lowest importance and 10 indicates the highest importance.

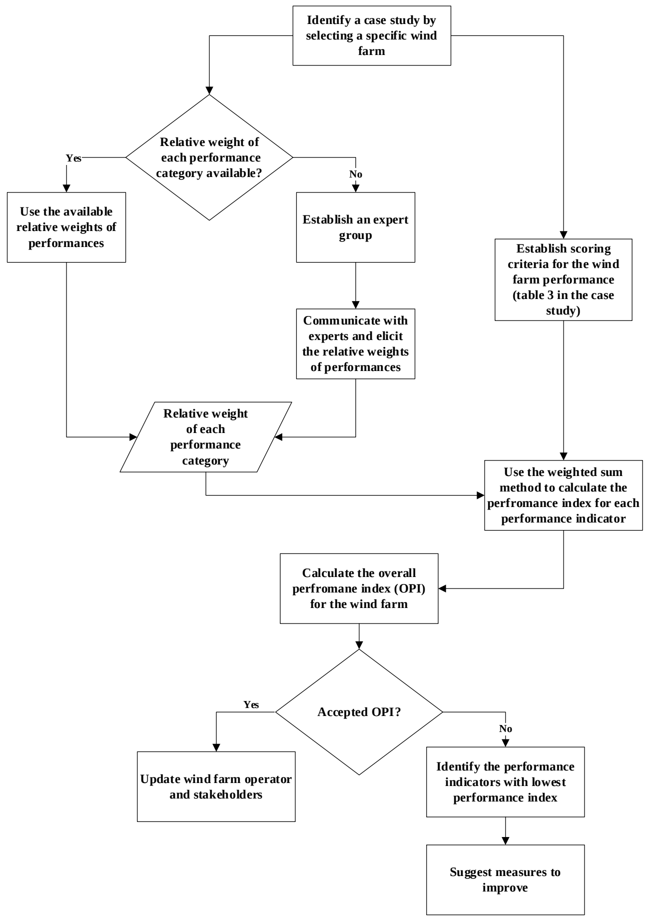

Figure 6. Overall performance index calculation methodology

The second main part of the followed methodology is establishing scoring criteria for each performance indicator. The established criteria rank each performance indicator from 1 to 4, based on how the WF performs technically and sustainably. For example, if a specific WF had a capacity factor between (10% - 20%), this indicates a lower performance of the WF, and therefore, the WF has a capacity performance score of 1. On the other hand, if the capacity factor of a WF was equal to or over 40%, then the WF has a capacity score of 4. The scoring criteria are demonstrated in Table 2 in Paper 1.

Thirdly, the weighted sum method (WSM) is used to combine the relative weights and the performance scoring of the performance indicators to calculate the OPI. The WSM is one of the most used methods in MCDM (Triantaphyllou, 2000). The WSM states mathematically, as per Equation 8, that the OPI is equal to the sum of products of the performance relative weights (W_i) and performance scores (S_i).

$$OPI = \sum_{i=1}^{n} w_i \times S_i \quad (8)$$

Equation 1 calculates the OPI as a percentage, where Table 2 can be used to qualitatively express the overall performance of the selected WF. Calculating the OPI will help stakeholders and operators of WFs to determine whether the overall performance of a specific WFs is acceptable or not. In addition, the proposed methodology allows for determining which performance indicators need improvements to increase the OPI value.

Another advantage is that by this methodology different WFs can be compared to each other in terms of which WF has better or the best overall performance.

Table 3. A qualitative scale for expressing the OPI

OPI	**Scale**
0-25%	Bad performance
26-50%	Average performance
51-75%	Good performance
76-100%	Excellent performance

3.2 Calculating the resilience of wind farms methodology (Paper 2)

In this paper, I modeled a Bayesian network (BN) and used it to calculate the resilience of WFs in CCRs. In addition, I defined three operating scenarios, during which WFs are subject to disruptive and non-disruptive operating conditions. These operating scenarios are i) non-cold climate conditions (baseline scenario), ii) cold climate conditions, and iii) Black swan cold climate conditions. The modeled BN calculates the resilience as a percentage value, and allows for backward propagation, which helps, by setting a desired resilience value in the BN, to calculate the value of improvements needed by the variables used to calculate the WF resilience.

The proposed methodology in Paper 2 is shown in Figure 7, which implies the use of conditional probability of events contributing to the calculation of the resilience of WFs in CCRs. Historical data are needed to calculate the probability of occurrence of the events, with the use of suitable probability distributions. In case historical data were not available, experts can be consulted to provide their estimated probabilities values on events, given certain operating conditions of WFs. In Paper 2 enough historical data were collected from a WF in the Arctic region of Norway. The probability values were afterwards fed into a proposed Bayesian network (BN) that was designed to calculate the resilience, as a probabilistic value, of WFs. A certain value of desired resilience can be set (90% for example) by the WF to estimate the percentage of improvement needed to achieve the desired resilience, and to locate the variables that decrease the resilience value to improve them.

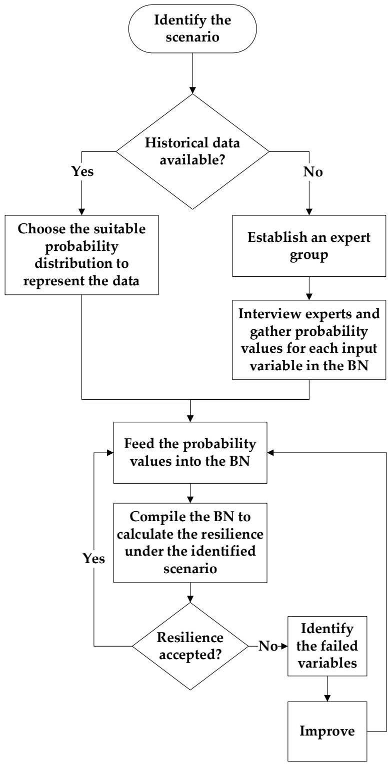

Figure 7. Methodology followed to estimate the resilience of WFs using BN.

In addition, a case study considered the WF in the Arctic region of Norway, where three distinct operating scenarios were defined, to calculate the WF resilience under each scenario. The first scenario is called the baseline scenario, where the CCR operating conditions were not present, the second scenario implied the operation of the WF under CCR conditions, and the third scenario is imaginary, called a black swan scenario, where extreme operating conditions were proposed to calculate the resilience of WFs in case they were to face such scenario.

3.2.1 The Bayesian Network

Graphically, a BN consists of nodes and links that connect the nodes. The nodes represent the variables, which can be an event or the state of a specific component, such as the state of failure or no failure of that component. Each node contains the probability of the occurrence of an event or state. The nodes are classified into parent nodes and child nodes, depending on how they are connected to each other in the graph, and which node is the predecessor (parent), and which the successor (child). The links in the BNs denote the causal relationship between the nodes. For example, in Figure 8, the nodes X1 and X2 are the parents of node X3, which is the child of both nodes. Likewise, node X3 is the only parent of node X4, which is its child (Mustafa and Barabadi, 2021).

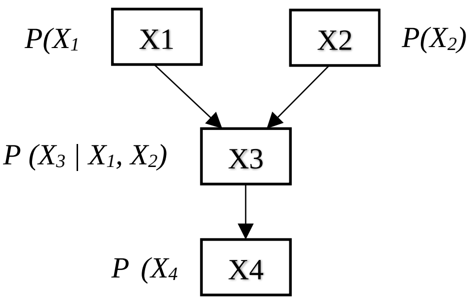

Figure 8. An example of a BN with four variables (Mustafa and Barabadi, 2021)

BNs are described as directed graphs, which means that the relationships between the nodes are directed in one direction, with no cycles or links going back to the original (parent) node. A BN is an efficient tool for calculating the posterior probability of uncertain variables (the probability of the child nodes), depending on the known condition or the evident probability of other variables (the parent nodes), in what is known as the conditional probability, which updates the probabilities of events when given a certain condition or evidence.

The conditional relationships between the variables in a BN are measured by conditional probability distributions. Eqn. 9 presents the full joint probability distribution of a BN consisting of n variables X1; X2; . . . ; Xn (Hosseini and Barker, 2016).

$$P\,(X1, X2, \ldots, Xn) = \prod_{i=1}^{n} P(X_i \mid Parents(X_i)) \qquad (9)$$

The variables/nodes used in modeling the BN are Boolean discrete variables, having values of (Yes/No), where the Yes state represents the Success state of a specific variable, and the No state represents the Fail state of that variable. For example, labor dexterity, which contributes to the successful maintenance of WTs, is reduced by 70% during the presence of extreme Arctic operating conditions. Therefore, assuming that labor dexterity has a 100% probability of being successful under normal operating conditions, the probability of successful labor dexterity is reduced to 30% under extreme Arctic conditions, which will consequently reduce the probability of carrying out successful maintenance on the WTs and, therefore, reduce the resilience of the WF (Mustafa and Barabadi, 2021).

The input and output variables, shown previously in Figure 4, are conditionally dependent on each other and are dependent on the weather conditions experienced in CCRs. This dependency is illustrated through the graphical formation of the BN, shown in Figure 8, where the nodes represent the input and output variables, and the arrows are the links between the parent nodes and the child nodes, in which the value of the child node depends on the state or the value of the parent node. For example, if excessive snow is accumulated on the roads leading to the WF, with a probability of 80% that the roads will be closed, that could mean that the successful delivery of spare parts from the suppliers to the WF will be reduced to 20%. If the opposite scenario happened, which implies no snow accumulation on the roads and no cold climate conditions are present, this leads to the roads are 100% open with no climatic hindrance that prevents or limits the delivery of spare parts to the WF, in other words, the delivery of spare parts will be 100% successful.

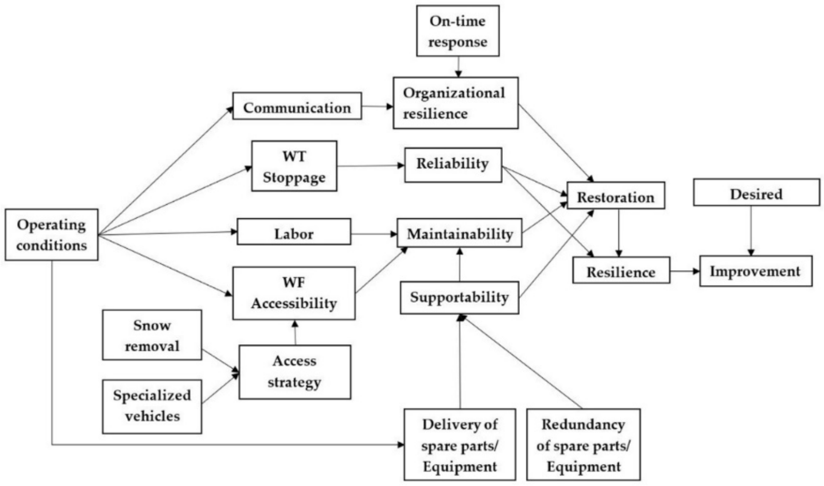

Figure 9. Graphical depiction of the proposed BN for WF resilience calculation (Mustafa and Barabadi, 2021)

Netica, a proprietary, user-friendly software, was used to build the BN and enter the different equations used, to calculate the probability distributions of the variables in the BN. As mentioned previously, the Poisson probability distribution was used to calculate the probability of the WT stoppage and communication availability variables in the proposed BN. Furthermore, the BN makes use of two other main functions to calculate the probability of the maintainability, supportability, and organizational resilience variables, these two functions are the NoisyOrDist and the NoisyAndDist functions.

The NoisyOrDist function is used when the probability value of an output variable is true when only one input variable at least is true. For example, the supportability output variable probability is true when either one of the input variables (the delivery of spare parts/ equipment or the Redundancy of spare parts/ equipment) is true. However, having both variables true would give the same success probability value of supportability. The NoisyAndDist can be expressed as the complement of the NoisyOrDist, as in Equation 10 (Fenton and Neil, 2018):

$$\text{NoisyAndDist} = 1 - \text{NoisyOrDist} \tag{10}$$

An example of the use of the NoisyAndDist function is accessing WFs under a severe accumulation of snow taking place on the roads. Normally, WFs use a combination of snow removal strategy and specially equipped vehicles to guarantee access to WTs, especially when maintenance is needed (Lehtomäki et al., 2018). Therefore, the success probability of accessing the WF depends on the success of both input variables combined, i.e., the snow removal strategy and the use of specially equipped vehicles. Table 1 in Paper 2 summarizes the modeled equations used in Netica to design the BN.

3.3 Risk analysis methodology (Paper 3)

In this paper, 6 main risks related to the operation of WFs in CCRs were identified and analyzed using the fuzzy logic methodology. Input data to the fuzzy logic tool in MATLAB were provided by experts to map the probability values, the consequences, and the risk levels membership functions. The 6 identified risks provide a holistic overview of the different risks affecting the operation of WFs in CCRs and the effects that the WFs induce on their surroundings during their operation.

Risk analysis is a systematic process of using the available information to understand the risks and estimate their level. Risk analysis provides input to the risk evaluation step in the risk management process, and to the risk treatment step (ISO 31000, 2018). The methodology followed in Paper 3, as shown in Figure 9, to analyze the 6 defined risks, utilizes fuzzy logic with inputs of data, provided by experts, to plot the membership functions of the input variables, which are the probability of risks and their consequences, and the output variable, which is the risk level.

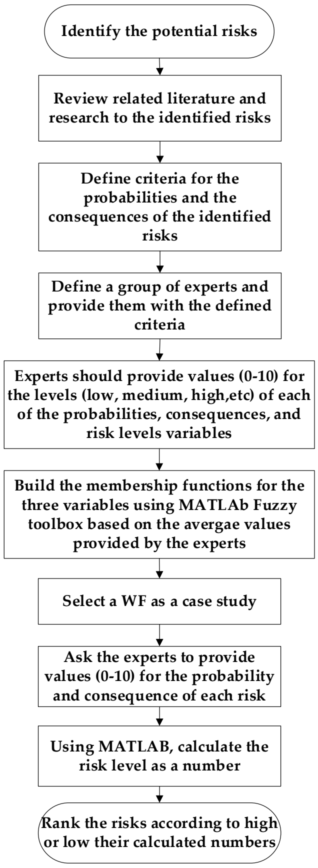

Figure 10. Methodology of analyzing risks to WFs in CCRs using fuzzy logic

The methodology starts with defining the risks to be analyzed. As previously mentioned, 6 risks were identified. The identified risks emerged from both the harsh weather conditions that affect the technical performance of WFs in CCRs and the operation of WFs that impacts the surrounding environment and community.

The second step is defining qualitative criteria, based on the literature review and available data, for the input variables levels. The defined levels for the probability of occurrence of risks are: very low, low, medium, high, and very high, and for the severity of consequences are: low, moderate, high, and very high. Experts provided numerical values for the input variables, based on the defined criteria, to plot the corresponding membership functions.

Thirdly, the membership functions that describe the levels of the probability, the consequences, and the risk level, were plotted using MATLAB fuzzy logic toolbox.

To demonstrate the methodology, a WF in the Arctic region of Norway was selected as a case study. Experts were provided with the detailed description of the WF to help them in assigning values to the input variables. The fuzzy logic toolbox in MATLAB calculated the output values, i.e., the values of the risk level, based on a set of defined rules that combine the different levels of probabilities and consequences. Based on the calculated results, the risks were ranked.

3.3.1 Fuzzy logic

Fuzzy logic is based on fuzzy set theory, which was developed by Zadeh (Zadeh, 1965), and was first used in control by Mamdani (Mamdani, 1974). Fuzzy set theory is primarily developed for reasoning and quantifying using vague and ambiguous language terms, that do not have sharp boundaries for their definitions and may be interpreted in different ways by different experts (Markowski and Mannan, 2009). Fuzzy logic can be an efficient tool in risk assessment as it compensates for the lack of knowledge, and vagueness encountered when assessing the risks related to complex technological systems, and can be very helpful when dealing with fuzzy linguistic terms such as low, medium, and high, etc., which are traditional qualitative terms used to describe the probability of happening of an event, the associated consequences with an event, and the level of the resulting risk. For example, fuzzy logic was used to assign rankings to the different failure modes of WT components, using Fuzzy Failure Mode and Effects Analysis (Fuzzy FMEA) by (Dinmohammadi and Shafiee, 2013), (Gallab et al., 2019). Furthermore, fuzzy logic was used in assessing the risks related to transporting flammable substances in pipelines (Markowski and Mannan, 2009), and offshore engineering systems (Yang and Wang, 2015).

Membership functions play an important role in fuzzy logic. Assuming a universal set X that contains all values of the inputs to the fuzzy logic process. A is a fuzzy set. $\mu_A(x)$ is a membership function associated with set A that maps every element of the universal set X to the interval [0,1], with many degrees of membership (between 0 to 1) allowed, where 0 indicates non-membership and 1 indicates total membership. The mapping of membership functions is written as follows:

$\mu_A(x): X \rightarrow [0,1]$

For simplicity, triangular membership functions were used in Paper 3. A triangular fuzzy membership function can be denoted by three points (a, b, c), where $a \leq b \leq c$ (Figure 10). Point b on the x-axis represents the variable value with the maximal grade of membership, i.e., $\mu_A(b)=1$. a and c are the lower and upper bounds of the plotted area and are used to reflect the fuzziness of the data (Hong and Wang, 2000).

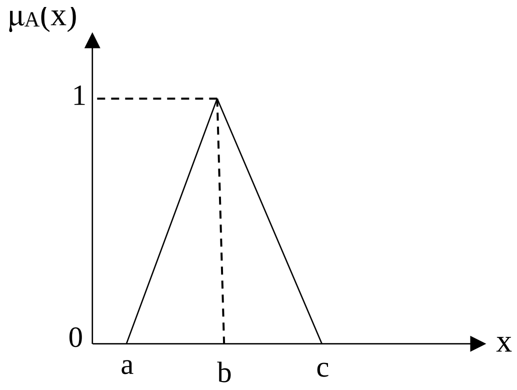

Figure 11. A triangular membership function

3.3.2 Experts' judgements

A selected group of 7 experts was asked to provide corresponding numeric values (from 0 to 10) to the levels of the input variables, based on the defined criteria to plot the corresponding membership functions. Similarly, the experts are asked to provide numeric values that correspond to the levels of the output variable, the risk level, which are the following: very low (Vl), low, moderate, moderate-high (Mh), high, very high (Vh), and extremely high (Eh). The average of the values provided by the experts is considered in plotting the membership functions for the three variables as shown in Tables 3, 4, and 5.

Table 4. Probabilities ranges for the corresponding probability levels provided by experts

	Very low			Low			Medium			High			Very high		
	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c
Average values	0	1.46	2.93	2	3.21	4.43	3.71	5.18	6.64	5.86	7.14	8.43	8	9	10

Table 5. Severity ranges for the corresponding severity levels provided by experts

	low			Moderate			High			Very high		
	a	b	c	a	b	c	a	b	c	a	b	c
Average values	0	1.68	3.36	2.36	4.32	6.29	5.00	6.71	8.43	7.64	8.82	10

Table 6. Risk levels ranges for the corresponding risk levels provided by experts

	Very low			Low			Moderate			Moderate- High			High			Very high			Extremely high		
	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c
Average values	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7	8	7	8	9	9	10.5	12

The fuzzy logic toolbox in MATLAB was used to plot the membership functions, shown in Figures 11 and 12. Moreover, a three-dimensional risk matrix, shown in Figure 13, is created. The risk matrix combines three variables, the probability, the severity, and the risk level.

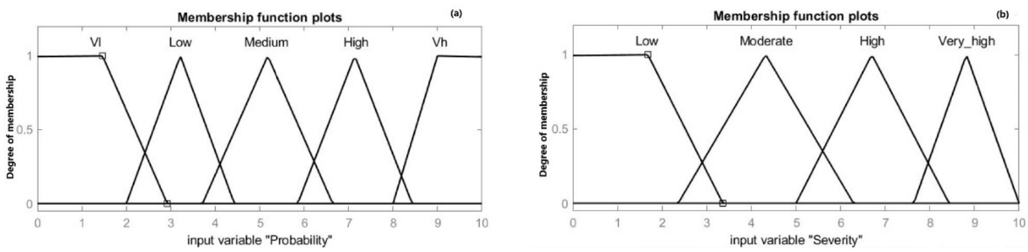

Figure 12. Membership functions of probabilities (a) and consequences (b) of risks based on experts' judgements

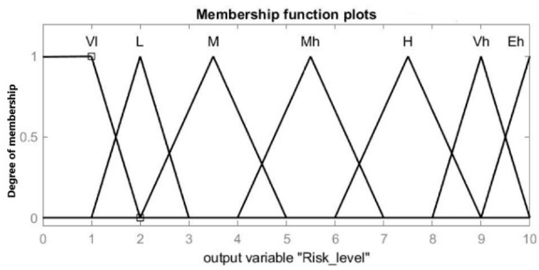

Figure 13. Risk levels membership functions based on experts' judgements

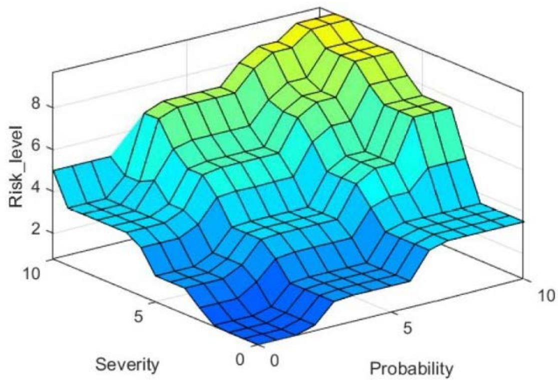

Figure 14. Fuzzy risk matrix combining the three variables for risk analysis

3.3.3 Fuzzy risk analysis

The fuzzy logic process followed in Paper 3 is based on a commonly used method called the Mamdani method (Mamdani, 1974). The Mamdani method uses the center of gravity method to calculate the output value of the risk level, unlike the Sugeno method, which uses the weighted average method to calculate the risk level (Sari et al., 2016). Figure 5 shows the three main steps to follow to calculate the risk level, and to rank the risks following the Mamdani method (Gallab et al., 2019). The steps in Figure 14 follow the plotting of the membership functions and show the process used to analyze the 6 identified risks using fuzzy logic. Similar to using experts' judgements to plot the membership functions, these steps also involve data input from the same experts, to assign values for the probability and consequences of each risk for a selected WF.

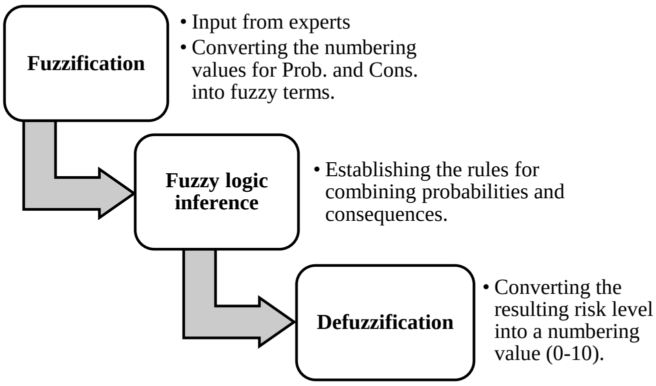

Figure 15. Overview of the Fuzzy logic process

- *Fuzzification*. in this step experts are asked to provide values (x) for the input variables. The previously defined membership functions for each fuzzy set (A) would indicate a certain degree of membership ($\mu_A(x)$) of x in A. For example, a probability of a risk being assigned a value of 5 by experts might indicate 50% low and 50% medium degrees of membership. The same applies to the consequences input variable.
- *Fuzzy logic inference*. In this step a set of rules is established with the help of the experts, to describe the output of the combinations of the input variables. By making use of fuzzy IF-THEN rules, the different combinations between probabilities and consequences of each risk can be represented. An example of such rules is: If the Probability of risk is Low and the Consequences are High, Then the Risk level is Moderate.
- *Defuzzification*. This is a counter step to the fuzzification step, where the resulting fuzzy risk levels are converted, using MATLAB fuzzy logic toolbox, into numbers, reflecting how high or low the risk level is, where the higher number reflects a higher risk level and vice versa. Following this step, the risks to WFs can be ranked.

Chapter 4

4 Results and discussion

Based on the appended papers, I here discuss and reflect on perspectives and key findings related to the three proposed research questions. The first section discusses the importance of calculating an OPI for WFs, when operating under cold climate conditions, and shows the results of the application of the OPI tool on a WF in the Arctic region of Norway. Section 4.2 presents the results of applying the BN for calculating the resilience of a WF in the same region, which also represents a measure of the performance of WFs under disruptive events, that can be experienced in that region and identifies the resilience-related variables that need to be improved and the values of improvements required. Lastly, section 4.3 provides an overview of the different risks to the performance of WFs, when operating in CCRs, as well as the risks that such WFs induce on their surroundings during their operation. Moreover, it analyzes the defined risks and ranks them according to their calculated risk level using fuzzy logic tools.

4.1 Wind farms overall performance index (OPI)

The calculation of the OPI contributes to providing an overview of different performance aspects related to the performance of WFs in CCRs. In addition, it helps in identifying which performance indicators, among the technical and sustainability performance indicators, require more attention by the WF operator to improve them. Figures (15-17) show the relative weights of the performance indicators, based on experts' judgements, which reflect the importance of these indicators to the overall performance of WFs in CCRs. According to experts, the highest relative weight was given to the technical performance indicator as 54% important to the overall performance, as shown in Figure 15, compared to the sustainability performance indicator, which had a complement value of 46%.

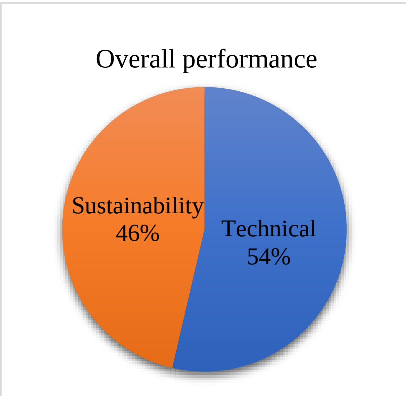

Figure 16. Relative weights of technical and sustainability performance indicators

Moving to the next level of performance indicators, shown in Figure 16, experts assigned the availability performance, which falls under the technical performance indicator of WFs, the highest relative weight of 40% among all performance indicators located in that level. In addition, the quality performance was assigned the lowest relative weight of 28% and the capacity performance had a 32% relative weight.

On the other hand, the environmental impact, as one of the sustainability performance indicators, was assigned the highest contributor to the sustainability performance of WFs with 36% relative weight. Regarding the availability performance, the three performance indicators constituting the availability performance have almost the same relative weight, as shown in Figure 17, with the reliability performance indicator having a slightly higher relative weight of 34%.

This concludes that the environmental impact of WFs in CCRs and their availability are relatively the most important performance indicators, while the social impacts and the quality of power production were assigned the lowest relative importance among the defined performance indicators in the paper.

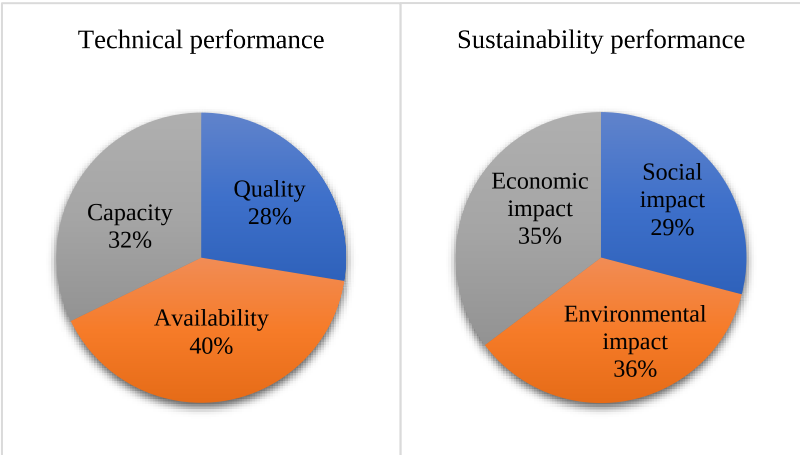

Figure 17. Relative weights of technical and sustainability sub-performance indicators

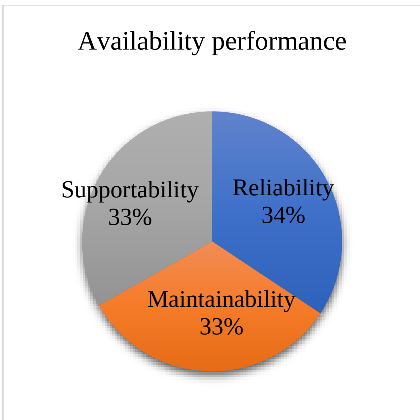

Figure 18. relative weight of the availability performance indicators

Paper 1 includes a case study of a WF called Fakken WF in the Arctic region of Norway. Data collected from the WF on the different performance aspects were used to assign the proper performance score, using Table 2 in Paper 1. Figure 18 shows the selected scores for each performance indicator, and Paper 1 includes the justification for selecting each score.

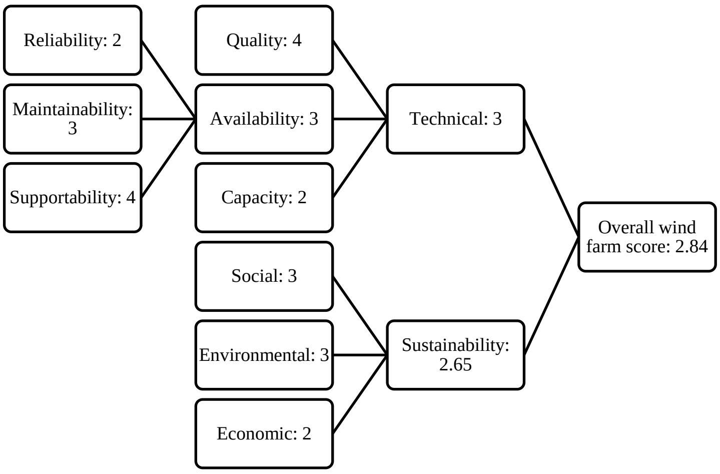

Figure 19. Performance indicators scores for Fakken WF

Afterwards, Equation 9 was used to calculate the OPI, which is a normalized value of the overall WF performance score (2.84), shown in Figure 18. The resulting OPI is 61.3%, which according to a proposed qualitative scale for expressing the OPI in Paper 1, the WF can be described as having a good overall performance when compared to the proposed qualitative scale in Table 6.

$$\mathrm{OPI} = \frac{\text{overall performance score} - \text{minimum score}}{\text{maximum score} - \text{minimum score}} = \frac{2.84-1}{3} = 0.613 \quad (9)$$

Table 7. Risk levels ranges for the corresponding risk levels provided by experts

OPI	Scale
0-25%	Bad performance
26-50%	Average performance
51-75%	Good performance
76-100%	Excellent performance

If the calculated OPI was deemed unacceptable, it will be easy for the operator to allocate the performance indicator that contributes to lowering the OPI, in this case, by referring to Fig. 18, the sustainability performance indicates a lower value than the technical performance. Moreover, it is the economic performance indicator that has the lowest score among sustainability performance indicators. This can be attributed to the high operation and maintenance (O&M) costs that lead to increasing the cost of energy produced by the WF. Based on that, it can be proposed that more efforts are required to improve the (O&M) activities. Moreover, the OPI can help in comparing the performance of two or more WFs that share similar characteristics such as WTs type, WF location, etc., and set the needed measures to improve their performance.

4.2 Resilience of wind farms in Cold climate regions

The resilience of WFs in the face of disruptions, caused by the weather conditions in CCRs, and the resulting consequence on their performance is an important issue to highlight. The different challenges that emerge from the weather conditions in CCRs that affect the performance of WFs, such as ice accretion on the blades of the WTs, snow accumulation that blocks the roads to WFs and prevents maintenance procedures, and cold temperatures that limit the dexterity of the WF staff, etc., create operational scenarios under which WFs in CCRs should operate.

System resilience is defined as the extent to which a system maintains a minimum level of performance in the face of disruptions (Firesmith, 2019). The resilience of WFs in CCRs is mainly dependent on some of the performance indicators that were discussed and calculated in section 4.1, such as the reliability, the maintainability, and the supportability performance indicators. These performance indicators, in addition to others, are calculated in this section using the concept of conditional probability, implied by the use of Bayesian networks, to calculate the resilience of WFs in CCRs as a percentage value. Using this methodology will help in calculating the resilience under various operational scenarios that WFs might be subject to, and in identifying which performance aspect/ indicator needs to be improved to reach a desired level of resilience.

A WF in the Arctic region of Norway was considered as a case study to demonstrate the methodology of calculating the resilience, under CCR weather conditions. In addition, three scenarios were defined to compare the resulting resilience of the WF when operating under different weather conditions. Table 7 summarizes the resulting calculated resilience of the three scenarios.

Table 8. Summary of calculated resilience for each operating scenario

Scenario	**Calculated resilience**
1st scenario (Baseline, non-cold climate)	99%
2nd scenario (Cold climate)	88.2%
3rd scenario (Black swan cold climate)	43.6%

The first scenario is a baseline scenario, where the WF is operating under normal operating conditions and is not subjected to cold climate operating conditions. This scenario is described in Paper 2 as non-Arctic operating conditions. The resulting resilience in this scenario showed that the WF is 99% resilient. During the operation of the WF under cold climate conditions, the second scenario, the collected data from the WF showed that the calculated probability values of the variables contributing to the WF resilience decreased, which led to a decreased resilience value of the WF, which was calculated as 88.2%.

The third scenario, the black swan scenario, implied a set of a proposed significant increases in the cold climate events that affect the operation of the WF. For example, the scenario implied a dramatic increase in the number of icing events to 10 times the number of events the WF experienced under the cold climate scenario (the 2nd scenario). In addition, the number of lost connections between the WTs and the WF staff increases tenfold compared to the second scenario, the snow removal strategy would not be efficient enough to guarantee access to the WTs, and only 50% of equipped vehicles are usable. Therefore, the accessibility to the WF is immensely reduced. Moreover, the public roads are blocked, which hinders the provision of spare parts from suppliers, and only 50% of the spare parts and tools would be redundant at the WF site. Lastly, the scenario suggests that the response of the WF to these conditions is reduced to 50%. Based on that, the calculated resilience of the WF under black swan operating conditions is 43.6%.

A backward propagation analysis is carried out in Paper 2 to calculate the percentage of enhancement needed for each variable, to improve the WF resilience, when operating under black swan cold climate conditions, from 43.6% to 90%. When running the backward propagation, the BN suggested, as per Table 8, that the reliability variable can be subjected to the utmost improvement of approximately 35% to reach the targeted resilience value. The rest of the variables are required to be improved by around 10% per each.

Table 9. Enhancement of variables when improving resilience under black swan cold climate conditions

Variables/Nodes	Resilience = 43.6%	Resilience = 90%
Reliability	34.6%	71.4%
Maintainability	51%	59.3%
Supportability	50%	58.5%
Organizational resilience	45.2%	54.5%

4.3 Wind farms-related risks analysis

To demonstrate the methodology followed in Paper 3, a WF in the Arctic region of Norway was selected as a case study. Data about the WF were gathered from different sources, to be used as input by the experts, so they provide their probability and consequences numeric values against each risk separately. The MATLAB fuzzy logic toolbox was afterwards used to calculate the level of each risk, based on the average values of the probabilities and consequences estimated by the experts. Table 9 shows the average probabilities and consequences for each risk assigned by the experts and the calculated risk level. Additionally, the table shows the ranking of the risks (from 1 to 6), where, specifically to the case-study WF, the limited accessibility to the WF risk is assigned the highest rank (1), and the social opposition risk is assigned the lowest rank (6).

Table 10. Ranking of risks considering average values of probabilities, consequences, and risk levels

Risks	Probabilities	Consequences	Risk levels	Risks ranks
Risk 1 (WT stoppage)	2.9	5.4	4.19	2
Risk 2 (Cold stress)	3.6	2.7	2.66	4
Risk 3 (Limited accessibility)	7.4	7.8	7.76	1
Risk 4 (Ice throw)	3.5	1.7	2	5
Risk 5 (Environmental risks)	3.7	4	3.5	3
Risk 6 (Social opposition)	1.8	2.3	0.826	6

Furthermore, the paper presents a comparison with a WF located in a non-CCR, to show the effects of the cold climate operating conditions on the calculated risk level, and the ranking of risks. When it comes to the new WF, the same risks are ranked differently due to various reasons, such as that the new WF experienced lower number of WT stoppages compared to the CCR-WF, and no snow accumulation on the roads of the WF, leading to higher accessibility to the WF. Therefore, Risks (1-3) would have lower risk levels compared to the CCR-WF. However, the non-CCR WF is located close to an Environmentally Protected Area and is 1.3 km away from a tourist village, which has natural and historical values, which means that risks 5 and 6 would have higher levels compared to the CCR-WF. Table 10 shows the risks levels and ranks of the non-CCR WF.

Table 11. Ranking of risks for the Kozbeyli WF in Turkey using experts' judgements and Fuzzy logic

Risks	**Probabilities**	**Consequences**	**Risk level**	**Risks ranks**
Risk 1 (WT stoppage)	1.8	4.6	2	5
Risk 2 (Cold stress)	2.2	3.4	2.57	3
Risk 3 (Limited accessibility)	2.8	2.6	2.32	4
Risk 4 (Ice throw)	1	1	0.752	6
Risk 5 (Environmental risks)	6.8	7.6	7.5	2
Risk 6 (Social opposition)	8.3	8.9	9.31	1

Chapter 5

5 Conclusions

In this thesis, I have presented added knowledge and insights to the measurement of the performance of WFs, as well as to the assessment of the resilience and the CCR-related risks, which can be encountered by WFs located in CCRs. The thesis has defined 3 main research questions, based on which the research was constructed and carried out. The proposed research questions discuss the aspects of WFs' performance installed in CCRs, their resilience, and the risks to and from WFs in CCRs.

In addition, I proposed a methodology to calculate an overall performance index (OPI) for WFs in CCRs, that consists of the technological and the sustainability set of performance indicators. The benefit of developing such an index is the ability to determine which performance indicator is responsible for lowering or elevating the calculated OPI of a WF, which will make it easier for WFs to establish measures that can help in improving the indicated weak performance aspects.

Furthermore, I proposed a methodology to calculate the resilience of WFs, when operating under different disruptive and non-disruptive operating conditions, related to CCRs. Measuring the resilience of WFs contributes to measuring their performance, as resilience is related to the ability of a WF to return to an acceptable level of performance after being subjected to a disruptive event. The methodology proposed calculates the resilience of WFs as a percentage value. Using Bayesian networks, the conditional probability concept is implemented, where the condition of the input variables, such as the stoppage rate of WTs, the labor dexterity, and the communication availability with WTs, etc., determine the values of the output variables, such as the reliability, the maintainability, and the organizational resilience, etc., which contribute to the eventual calculation of the WF resilience.

Moreover, in this thesis, I analyzed 6 types of risks that are associated with the operation of WFs in CCRs. The identified risks are either caused by weather conditions that affect the performance of WFs, such as the increased WT stoppages due to harsh weather conditions, cold stress to workers, and limited accessibility to WFs due to snow cover, or are risks caused by the WFs and their impacts on their surroundings, such as thrown ice pieces from operational WTs, environmental risks, and social opposition risk.

I proposed a methodology that utilizes experts' judgements and fuzzy logic to analyze the identified risks. The numerical values provided by experts, that express the different levels of the probabilities, consequences, and risk levels were used in the MATLAB fuzzy logic toolbox to calculate the risks levels and rank them accordingly.

5.1 Suggestion for future research

This study has contributed to proposing different methodologies, that can be used to measure different aspects related to the performance of WFs in CCRs. This opens the door to building upon my work, such as by proposing new performance indicators that can be added to the model

I proposed in paper 1, which can provide a more comprehensive overall performance index of WFs in CCRs.

Furthermore, the Bayesian network designed to calculate the resilience of WFs in CCRs can be used to identify new operating scenarios for WFs, in addition to the three scenarios I identified in Paper 2, and to calculate the resilience of WFs under many different operating scenarios, whether these identified scenarios are related to CCRs or not.

The study identified six types of risks in relation to the operation of WFs in CCRs, this can be furtherly built upon by identifying and analyzing more risks, which can provide a more holistic view of the different risks that can be encountered by WFs in CCRs or their surroundings.

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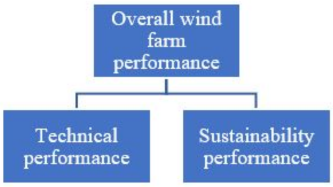
7 Appendices

Appendix 1: Questionnaire used to gather data from experts on relative weights of different performance indicators to calculate the Overall Performance Index (OPI) in Paper 1.

OPI Questionnaire:
For each of the following questions, please mark the relative level of importance of each performance category from 1 to 10, where: 1: indicates the lowest importance and 10: indicates the highest importance.

Overall performance: The overall performance of wind farms consists mainly of the Technical performance and Sustainability performance as shown below.



1. The Technical performance is mainly related to the technical functions of the wind turbines. Mark the level of importance of the Technical performance with regard to the overall performance of wind farms in cold climate regions.

2. The Sustainability performance is concerned with the Social, Environmental, and Economic impacts of wind farms in the Arctic. Mark the level of importance of Sustainability with regard to the overall performance of wind farms in cold climate regions.

Technical performance
Mark the relative importance of Quality, Availability, and Capacity performances with regards to Technical performance.

3. **Quality performance:** The quality of power production implies maintaining a balance between generated and demanded power. Unstable weather conditions can cause fluctuations in the power produced by wind farms, caused by significant fluctuations in wind speed. Mark the level of importance of quality performance with regard to the wind farm's technical performance in cold climate regions.

4. **Availability** reflects how many years wind farms can operate and yield the prospected power without failure under the prevailing conditions in the Arctic. Mark the level of importance of the availability of wind farms in cold climate regions with regard to their technical performance.

5. **Capacity performance:** Capacity reflects the highest sustainable rate of power produced by a wind farm that can be achieved given its specifications, the current resources, weather conditions, and maintenance strategies. Mark the level of importance of the capacity performance of wind farms in cold climate regions with regards to their technical performance.

Availability performance
Mark the relative importance of Reliability, Maintainability, and Supportability with regard to the Availability performance

6. **Reliability** is “the ability of a component or a system to perform its required functions without failure during a specified time interval”. Failures in wind turbines lead to downtime and loss of power production. Mark the level of importance of Reliability with regard to the availability of wind turbines in cold climate regions.

7. **Maintainability** refers to the relative ease and efficiency of performing tasks associated with machine maintenance, including both routine service and unplanned repairs (Walford, 2006). Mark the level of importance of maintainability with regard to the availability of wind turbines in cold climate regions.

8. **Supportability** can be defined as the ability of wind farms' design and planned support resources to keep the availability of wind turbines at a certain high level. Mark the level of importance of Supportability with regard to the availability of wind turbines in cold climate regions.

Sustainability performance:
The sustainability performance of wind farms refers to maintaining a certain level of performathathich will impact the environment, the economy, and the social life in cold climate regions. Therefore, sustainability is mainly concerned with the impacts of these factors.

9. **Social impacts:** Noise generated by wind turbines during construction and operation, traffic caused during construction of wind turbines, ice shedding from wind turbine blades, acquisition of lands, etc. Mark the level of importance of social impacts with regard the sustainability of wind farms in cold climate regions.

10. **Environmental impact:** threatening the biodiversity in the Arctic, pollution to water and soil during construction and use of chemicals for deicing, bird mortality when hitting the wind turbines, etc. Mark the level of importance of the environmental impacts with regard to the sustainability of wind farms in cold climate regions.

11. **Economic impacts:** reducing electricity prices, creating more job opportunities, and energy sources diversity. Mark the level of importance of the Economic impacts with regard to the sustainability of wind farms in cold climate regions.

If you have comments related to the questionnaire, please feel free to write them here.

Appendix 2: Data collected from Experts using the Questionnaire in appendix 1 (Paper 1), which shows the relative weight (importance) of each of the performance indicators.

	Availability performance			Technical performance			Sustainability performance			Overall performance	
	Reliability	Maintainability	Supportability	Quality	Availability	Capacity	Social impact	Environmental impact	Economic impact	Technical	Sustainability
Exp1	8	6	5	3		5	6	4	8	6	5
Exp2	8	5	7	4	7	6	6	4	8	7	4
Exp3	9	6	6	5	5	9	4	10	7	9	4
Exp4	8	9	10	8	9	7	4	8	6	8	7
Exp5	5	8	8	5	9	2	8	6	9	8	7
Exp6	10	10	9	8	10	9	6	10	8	8	8
Exp7	7	6	5	6	8	3	10	10	3	8	10
Exp8	9			2	9		5	9	9	9	9
Exp9	10	10	10	10	10	10	10	10	10	10	10
Exp10	9	9	9	7	9	7	3	3	7	7	4
Exp11	9	7	7	7	9	8	8	10	8	9	10
Exp12	5	8	10	6	10	10	5	8	8	7	5
Total weight	97	84	86	71	95	76	75	92	91	96	83
Combined experts' opinion	8.08	7.64	7.82	5.92	8.64	6.91	6.25	7.67	7.58	8.00	6.92
Relative weights	0.34	0.32	0.33	0.28	0.40	0.32	0.29	0.36	0.35	0.54	0.46
Standard deviations	1.68	1.75	1.94	2.27	1.50	2.70	2.30	2.71	1.78	1.13	2.47

Appendix 3: Data collected from experts to plot the triangular membership functions for each of the probability values, consequences values, and risk levels in Paper 3.

Probability membership function values:

	Very low			Low			Medium			High			Very high		
	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c
Exp. 1	0	1.5	3	2	3	4	3	5	7	6	7	8	7	8.5	10
Exp. 2	0	2	4	3	4	5	6	6.25	6.5	7	8	9	8	9	10
Exp. 3	0	1	2	2	3	4	4	5	6	6	7	8	8	9	10
Exp. 4	0	1.5	3	2	3.5	5	4	5.5	7	5	6.5	8	7	8.5	10
Exp. 5	0	1.75	3.5	2	3.5	5	3	5	7	6	7.5	9	9	9.5	10
Exp. 6	0	1.5	3	2	3	4	3	4.5	6	5	6.5	8	8	9	10
Exp. 7	0	1	2	1	2.5	4	3	5	7	6	7.5	9	9	9.5	10
Avg.	0.00	1.46	2.93	2.00	3.21	4.43	3.71	5.18	6.64	5.86	7.14	8.43	8.00	9.00	10.00

Consequences membership function values:

	low			Moderate			High			Very high		
	a	b	c	a	b	c	a	b	c	a	b	c
Exp. 1	0	2	4	3	4.5	6	5	6.5	8	7	8.5	10
Exp. 2	0	1.5	3	2	4.25	6.5	5.5	7	8.5	8	9	10
Exp. 3	0	1	2	1	3	5	4	6	8	7	8.5	10
Exp. 4	0	1.5	3	2	4.5	7	5	7	9	8	9	10
Exp. 5	0	1.75	3.5	2.5	5	7.5	5.5	7.25	9	8.5	9.25	10
Exp. 6	0	2	4	3	4.5	6	5	6.5	8	7	8.5	10
Exp. 7	0	2	4	3	4.5	6	5	6.75	8.5	8	9	10
Avg.	0.00	1.68	3.36	2.36	4.32	6.29	5.00	6.71	8.43	7.64	8.82	10.00

Risk level membership function values:

	Very low			Low			Moderate			Moderate- High			High			Very high			Extremely high		
	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c	a	b	c
Exp. 1	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7.5	9	8	9	10	9	10.5	12
Exp. 2	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7.5	9	8	9	10	9	10.5	12
Exp. 3	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7.5	9	8	9	10	9	10.5	12
Exp. 4	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7.5	9	8	9	10	9	10.5	12
Exp. 5	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7.5	9	8	9	10	9	10.5	12
Exp. 6	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7.5	9	8	9	10	9	10.5	12
Exp. 7	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7.5	9	8	9	10	9	10.5	12
Avg	0	1	2	1	2	3	2	3.5	5	4	5.5	7	6	7	8	7	8	9	9	10.5	12

Appendix 4: The estimated probability and consequences values by experts for the 6 identified risks in Paper 3, and the calculated risks levels, using MATLAB, for the case study wind farm in Northern Norway and the non-cold climate wind farm.

The probabilities values of the risks in cold climate regions

	Risk 1	**Risk 2**	**Risk 3**	**Risk 4**	**Risk 5**	**Risk 6**
Exp.1	1	2	1	1	5	1
Exp.2	2	3	2	3	4	3
Exp.3	3	4	3	5	3	5
Exp.4	1	2	3	3	2	3
Exp.5	3	1	2	4	6	4
Exp.6	2	3	1	1	1	1
Exp.7	1	4	2	1	3	1
Avg	2.9	3.5	3.6	7.4	3.7	1.8

The consequences values of the risks in cold climate regions

	Risk 1	**Risk 2**	**Risk 3**	**Risk 4**	**Risk 5**	**Risk 6**
Exp.1	1	2	1	1	5	1
Exp.2	2	3	2	3	4	3
Exp.3	3	4	3	5	3	5
Exp.4	1	2	3	3	2	3
Exp.5	3	1	2	4	6	4
Exp.6	2	3	1	1	1	1
Exp.7	1	4	2	1	3	1
Avg	1.85	2.71	2	2.57	3.42	2.57

The calculated risk levels for the cold climate region wind farm

Risk	**Probability**	**Consequences**	**Risk level**	**Risk rank**
Risk 1 (WT stoppage)	2.9	5.4	4.19	2
Risk 2 (Ice throw)	3.5	1.7	2	5
Risk 3 (Cold stress)	3.6	2.7	2.66	4
Risk 4 (Limited accessibility)	7.4	7.8	7.76	1
Risk 5 (Environmental risks)	3.7	4	3.5	3
Risk 6 (Social opposition)	1.8	2.3	0.826	6

The calculated risk levels for the non-cold climate region wind farm

Risk	**Probability**	**Consequences**	**Risk level**	**Risk rank**
Risk 1 (WT stoppage)	1.8	4.6	2	5
Risk 2 (Ice throw)	1	1	0.752	6
Risk 3 (Cold stress)	2.2	3.4	2.57	3
Risk 4 (Limited accessibility)	2.8	2.6	2.32	4
Risk 5 (Environmental risks)	6.8	7.6	7.5	2
Risk 6 (Social opposition)	8.3	8.9	9.31	1

8 Appended papers

Paper 1

An Overall Performance Index For Wind Farms: A Case Study In Norway Arctic Region

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ORIGINAL ARTICLE

An overall performance index for wind farms: a case study in Norway Arctic region

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Abstract Wind farms (WFs) experience various challenges that affect their performance. Mostly, designers focus on the technical side of WFs performance, mainly increasing the power production of WFs, through improving their manufacturing and design quality, wind turbines capacity, their availability, reliability, maintainability, and supportability. On the other hand, WFs induce impacts on their surroundings, these impacts can be classified as environmental, social, and economic, and can be described as the sustainability performance of WFs. A comprehensive tool that combines both sides of performance, i.e. the technical and the sustainability performance, is useful to indicate the overall performance of WFs. An overall performance index (OPI) can help operators and stakeholders rate the performance of WFs, more comprehensively and locate the weaknesses in their performance. The performance model for WFs, proposed in this study, arranges a set of technical and sustainability performance indicators in a hierarchical structure. Due to lack of historical data in certain regions where WFs are located, such as the Arctic, expert judgement technique is used to determine the relative weight of each performance indicator. In addition, scoring criteria are predefined qualitatively for each performance indicator. The weighted sum method makes use of the relative weights and the predefined scoring criteria to calculate the OPI of a specific WF. The application of the tool is illustrated by a case study of a WF located in the Norwegian Arctic. Moreover, the Arctic WF is compared to another WF located outside the Arctic to illustrate the effects of Arctic operating conditions on the OPI.

Keywords Wind farms · Overall performance index · Weighted sum method · Scoring criteria · Expert judgment

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1 Introduction

Wind energy investments in the Arctic region is appealing because of the higher availability of wind power, which is almost 10% higher than in other regions due to the higher density of air Fortin et al. (2005). Moreover, the Arctic region is sparsely populated, which makes it even more attractive for wind energy investments. However, the performance of wind farms (WFs) located in the Arctic is faced with a plethora of challenges. Most of these challenges are attributed to operating in severe weather conditions such as low temperatures, ice accretion on the blades and snow accumulation on roads. These weather-related challenges affect mainly the technical performance of WFs. For example, ice accretion on WT blades creates mass imbalances and instantaneous losses in power production, which, under certain conditions, can reach 30% of the power produced, even in light icing events, Laakso and Peltola (2005), or in severe icing conditions, leading to total shutdown of the wind turbine (WT).

Technical performance is related to the technical functions of WFs, in terms of the amount of electricity generated Koo et al. (2018).It also refers to the quality of the power produced by the WF, as well as their capacity and availability performances. Availability performance can be described in terms of the reliability, maintainability and supportability of the wind farms, IEC (2015). Figure 1 illustrates the proposed technical performance indicators.

The quality performance indicator reflects the design and manufacturing quality of WTs and the WF layout Zaki (2020). The availability performance indicator depends, for the most part, on the reliability, maintainability and supportability of the wind farm IEC (2015) and Naseri and Barabady (2016), and the capacity performance indicator reflects the maximum power delivered by the wind farm, considering the operating conditions in the respective region (Barabady et al. 2010).

The primary objective of this work is to devise a method for calculating the Overall Performance of WFs and to evaluate the mutual impacts of WTs on their surroundings and impact of the surrounding environment on WTs.

The impacts of WTs on their surroundings can be summarized into three categories, namely: social and safety impacts, environmental impacts, and economic impacts. According to Musango and Brent (2011) and Kucukali (2016), these three types of impacts can be grouped under sustainability performance of WFs, as shown in Fig. 1. It is worth noting that many sustainability indicators can be included to describe the sustainability of WFs; however, these three indicators are described as the traditional pillars of sustainability Diaz-Balteiro et al. (2017).

The social and safety impacts constitute hazards such as noise generated by the WTs during construction and operation, traffic on public roads caused by transporting large WTs components, and ice fall and ice throw from WTs that can harm humans, animals and nearby structures, Mustafa et al. (2019). Other concerns related to the social and safety impacts are,for example, the visual pollution that might detract from pristine views or hinder tourism, and doubts related to that WFs might interfere with the operation of military radar systems Welch and Venkateswaran (2009). In addition, there are claims such as that governments are violating the rights of indigenous communities, by approving wind energy projects, causing cultural destruction. For example, constructing wind farms on Sámi lands in northern Scandinavia, may be considered unethical and overtly political, simply because it might come across as a systematic dispossession of their lands, and a lack of recognition of their rights Lawrence and Moritz (2019).

The environmental impacts of WTs can be positive such as the carbon-free electricity production, no long-term waste and no cooling water required, for these concerns, WFs are environmentally benign. On the other hand, chemical deicing used to remove ice from the blades of WTs, and birds and bats mortalities caused by WTs, are examples of the negative impacts of WFs. However, the number of birds killed by WTs may be negligible compared to that by fossil fuels, and some other human activities Sovacool (2009). In addition, water pollution in some areas, during the construction phase of WFs Lu et al. (2019), is another example of negative environmental impacts caused by WFs.

The economic impacts are described as being crucial for wind energy investment in any country, Kucukali (2016). Examples of these impacts are the job opportunities created by WFs projects for local communities, stabilizing the prices of electricity as the country will not be dependent on a single source to produce its electricity and help in lowering the prices of electricity. This, however, is dependent on the cost of electricity produced by the WF.

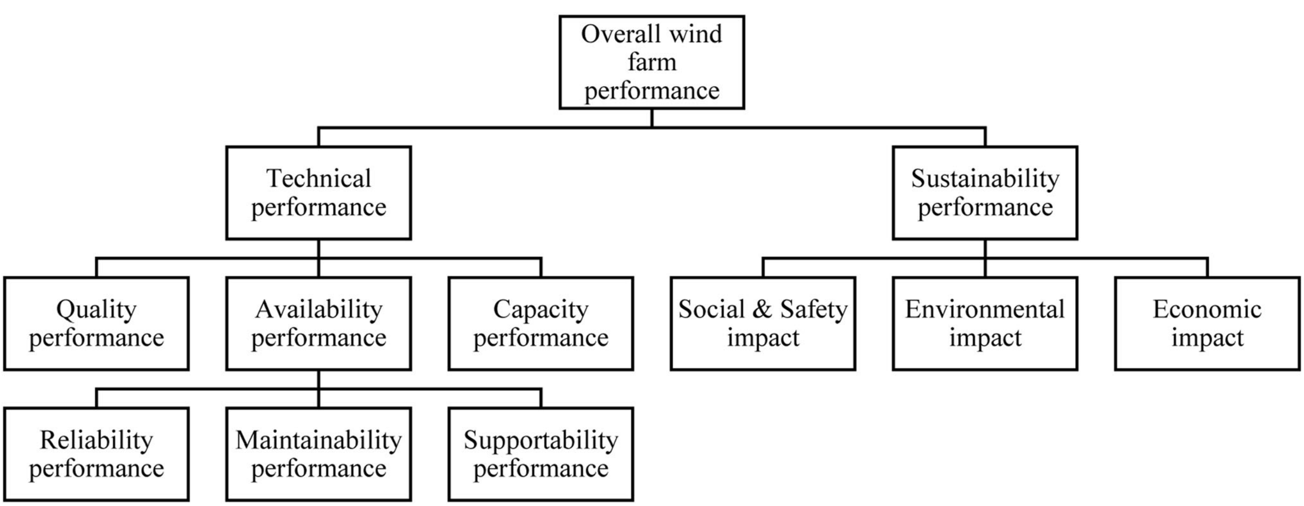


Fig. 1 The overall performance model for wind farms

Most wind energy projects are subsidized by governments due to their high capital and operational costs. Without governments' subsidies, wind energy projects will yield negative returns, and investors will find it difficult to cover for the cost of involved risks Welch and Venkateswaran (2009). However, if the capital costs of wind energy investments were reduced and the utilization rate of WTs increased, which is the percentage of time a WT can be in use during the 8760 h (365 $\times$ 24) of the year, the wind energy projects would have positive returns on investments, without even the subsidies from governments. Furthermore, as the cost of sources of energy such as oil and natural gas become more expensive, wind energy becomes more competitive. Therefore, the accelerated increase in technology development that we witness every day, and the rise in oil and gas prices, will put wind energy on a short path to become financially self-sustaining and will have positive economic impact on investors and societies.

The proposed model combines the technical and sustainability performances and can be applied to model the performance of WFs, located in cold climate regions such as the Arctic region, as well as other regions that are not characterized by cold climate conditions. In this paper, this model is used to evaluate the overall performance of a WF in Arctic Norway.

The majority of current studies on the performance of WFs in the Arctic focus on the effects of icing on WTs in terms of their structural behavior Alsabagh et al. (2013), resulting power losses Kilpatrick et al. (2020), anti/de-icing technologies Wei et al. (2020) Dai et al. (2012) Parent and Ilinca (2011) and risks caused by ice fall, ice throw and thrown blade parts Bredesen and Refsum (2015) Rastayesh et al. (2019). These studies mostly focus on the technical performance of WTs. It is observed that an integrated approach covering both the technical and sustainability performances of WFs is lacking.

The rest of this paper is organized as follows: in Sect. 2 the methodology adopted for calculating the OPI for WFs using the WSM, expert judgements, and the predefined scoring criteria is presented. Section 3 presents the application of the methodology on a WF located in Arctic Norway. The conclusions and findings of this work are presented in Sect. 4.

2 Weighted sum method for OPI calculation

There are several multiple-criteria decision-making methods that can be used in the decision-making process such as weighted sum method (WSM), weighted product method (WPM), analytical hierarchy process (AHP), technique for order of preference by similarity to ideal solution (TOPSIS), etc. The common characteristic of these methods is that the analysis of the alternatives is based on determined criteria Böğürcü (2012). WSM, which is used in this paper, is one of the oldest and most-widely used methods in multi-criteria decision-making (MCDM) Triantaphyllou (2000). For example, Stanujkic and Zavadskas (2015) used WSM to introduce an approach that helps decision makers to choose the best alternative, considering both the highest unit performance and the preferred performance, Kucukali (2016) developed a risk score card to rank the wind energy projects in Turkey using WSM and expert judgement. In addition, Williamson et al. (2014) used the WSM method to select the most appropriate low-head hydro-turbine alternatives by using quantitative and qualitative scoring.

The basic idea of the WSM is to calculate the OPI as a sum of products of performance relative weights and scores of criteria, as follows in Eq. 1, Stanujkic and Zavadskas (2015):

$$OPI = \sum_{i=1}^{n} w_i \times S_i. \tag{1}$$

where w_i is the relative weight of the performance indicator i, S_i is the criteria score for the performance indicator i. Figure 2 shows the steps followed in calculating the OPI for WFs using the WSM method. At first, the relative weight of each of the performance indicator shown in Fig. 1 needs to bdetermined. In case of lack of such data, the relative weight of performance categories is determined using expert judgment technique, explained in Sect. 2.1.

Secondly, a set of qualitative scoring criteria is to be developed to define the scores for each performance indicator. The scoring criteria reflect the different levels of performance a WF can operate according to. The scoring for each performance indicator can be divided into 4 levels, where level 1 reflects the minimum level of performance and level 4 is the highest. The scoring criteria is illustrated in Sect. 2.2.

Thirdly, the performance index for each performance indicator is calculated using Eq. (1), where the relative weight is obtained from experts and the performance score is obtained from the scoring criteria table (Table 2 in Sect. 2.2), which is based on the characteristics of the selected WF. The same process is repeated to calculate the performance index for each indicator up to the overall performance index of the WF.

Finally, we end up with a value of OPI that reflects how well or degraded the performance of a specific WF is. This index is instrumental for WFs operators and stakeholders to identify weaknesses in performance, in order to take the proper measures to alleviate them in cases, where the overall performance index was below the acceptable limit.

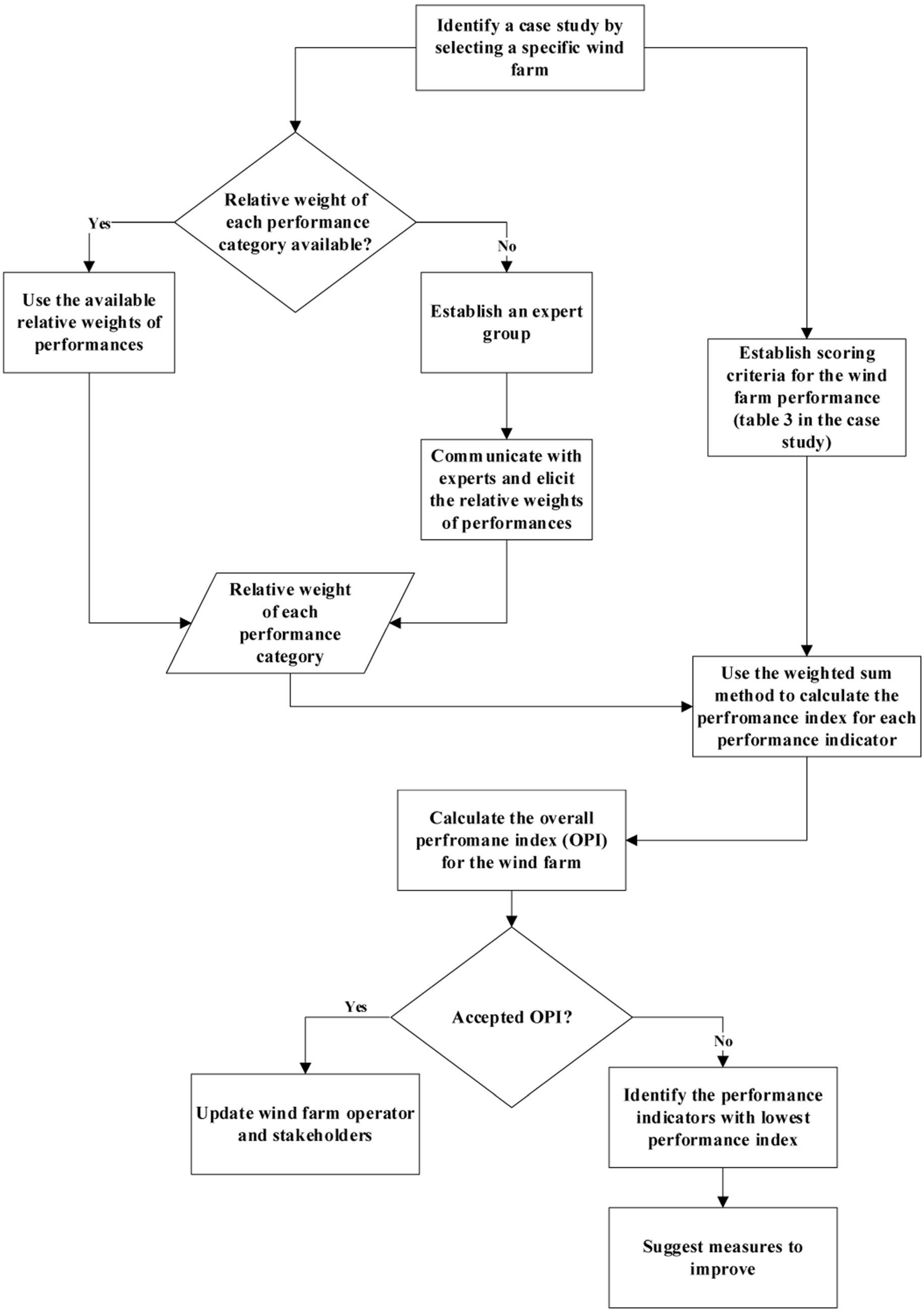


Fig. 2 Overall performance index calculation methodology

A flow chart indicating the evaluation methodology of OPI is shown in Fig. 2. A case study will be presented to demonstrate the application of this methodology.

2.1 Expert judgements

Wind energy applications in Arctic Norway are relatively new. For example, in 2010, the total installed wind energy capacity in Norway was 436 MW, with only 48 MW installed in the Arctic Battisti (2015). As such, long term data on the performance of WTs in Arctic Norway is far from satisfactory, which emphasizes the need for experts' knowledge that can contribute significantly to determining the relative weight of each performance indicator. However, expert judgement technique is indispensable even in situations where data is satisfactorily available as the statistical treatment of data cannot replace the expert judgments in the operational risk management process in hydropower plants, Mermet and Gehant (2011) as well as wind power plants.

Expert judgement is recognized as a type of scientific data and methods are developed for treating it as such. This technique is typically applied when there is substantial uncertainty regarding the true values of certain variables, Colson and Cooke (2018). It entails selecting experts with relevant experience (i.e. wind energy) and communicating with them, in order to elicit the needed information (i.e. the relative weight of each performance indicator). The Elicitation processes can involve simple correspondence, questionnaires, personal interviews (by telephone or in person) and various other combinations of interactions Beaudrie et al. (2016).

Each expert, in the elicitation process, can either be calibrated by giving his/ her answer a certain weight, that reflects the strength of the answer among other answers. The calibration process can consider, for example, the number of years of experience the expert has, the more experience the expert has the more important his answer is, compared to other experts' answers, example of that can be found in Naseri et al. (2015). In another approach, all experts can be treated as the same with having equal importance for their answers. For simplicity, the latter approach is the one used in this case study.

The selected group of experts in this study had expertise that ranged from academic doctors, and professors at universities involved in wind energy technologies to that of operators, engineers, and managers at WFs in Arctic Norway. Experts were interviewed physically or through distant conference meetings. Other means of communication with experts were telephone and email. Experts were asked to participate in a questionnaire that aimed to assess the relative weights of the performance indicators defined in the proposed model in Fig. 1. In total, 12 experts participated in answering the questionnaire. It is extremely unlikely that experts will ever be in total agreement with one another when answering questions where uncertainty is substantial.

The questionnaire consisted of 11 questions, covering all the 11 performance indicators. The meaning and aspects of each performance indicator were explained to the experts for each question to avoid ambiguity. Experts were asked to assess the relative weight of each performance indicator qualitatively, by ranking each one from 1 to 10, where 1 indicated the lowest importance and 10 indicated the highest importance.

Afterwards, experts' rankings were summed for each performance indicator, as shown in Table 1. *The average weight* of each performance indicator (*PI*) was calculated by dividing the sum of weight rankings from experts by the number of experts (n), as presented in Eq. (2).

$$PI\ average\ weight = \frac{\sum_{n=1}^{n} ranks\ of\ PI}{n}. \tag{2}$$

To calculate *the relative weight* of each performance indicator, the resulting average weight for each indicator is divided by the total weight for each group of performance indicators. For example, the availability performance represents a group of performance indicators that includes the reliability, maintainability, and supportability performance indicators. In order to calculate the relative weight of reliability performance, the average weight of reliability, which is 8.08 as per Table 2, is divided by the sum of the average weight of reliability (R), maintainability (M) and supportability (S), which is equal to 23.54. The relative weight of reliability in that case is equal to 34% as per Eq. 3. The same applies to maintainability and supportability performance indicators, with the relative weight equal to 33% for each, and to the rest of other performan indicators.

$$\begin{aligned} Reliability\ PI\ relative\ weight &= \frac{average\ weight\ of\ (R)}{\sum average\ weight\ (R, M, S)} \\ &= \frac{8.08}{8.08 + 7.64 + 7.82} \\ &= 0.34 \end{aligned} \tag{3}$$

Figure 3 summarizes the relative weight of each performance indicator assessed by the experts. According to experts, there is a slight difference between the technical and sustainability performances in terms of their relative weights; this was indicated by assigning a higher relative weight (54%) to technical performance. Through discussion, experts explained that by improving the technical performance will improve the sustainability performance aspects, i.e. the social, economic, and environmental aspects. Therefore, the technical performance was assigned a higher relative weight.

Table 1 Relative weight of performance indicators assessed by experts (1: lowest importance, 10: highest importance)

										Overall performance	
				Technical performance			Sustainability performance			Technical 1–10	Sustainability 1–10
	Availability Performance			Quality 1–10	Availability 1–10	Capacity 1–10	Social 1–10	Environmental 1–10	Economic 1–10		
	Reliability 1–10	Maintainability 1–10	Supportability 1–10								
Sum weight	97	84	86	71	95	76	75	92	91	96	83
Average weight	8.08	7.64	7.82	5.92	8.64	6.91	6.25	7.67	7.58	8.00	6.92
Relative weight	0.34	0.33	0.33	0.28	0.40	0.32	0.29	0.36	0.35	0.54	0.46

It can be seen from the Fig. 3 that all three performance indicators under the availability performance, i.e. the reliability, maintainability, and supportability, have almost the same relative weight. The experts have assigned the availability performance a higher relative weight (40%) compared to capacity and quality performances, which had relative weights of 32% and 28%, respectively as shown in Fig. 4. The experts have assessed that the environmental and economic performance indicators represent more than 70% of the total relative weight under sustainability performance, with the social performance indicator having 29% as a relative weight.

The next step, after determining the relative weights, is to define the scoring criteria for each performance indicator. The selected score from the predefined criteria is mainly dependent on the performance characteristics of the selected WF.

2.2 Performance scoring criteria

A set of criteria was defined for each performance indicator, with specific scores from 1 to 4, as shown in Table 2, which is established based on a literature review, measured data, documented evidence, and human reasoning. Selecting criteria scores are dependent on the specifications and performance characteristics of the WF under study, which can include technical characteristics, location, and WF impact on its surroundings. An example of the use of scoring criteria was shown by the Japan International Cooperation Agency JICA JICA (2011), in which a scoring criteria was used to assess the environmental and societal impacts of infrastructure projects around the world.

As can be seen from Table 2, the scores for availability, technical and sustainability performance indicators are not defined. This is because these performance indicators are functions of the performance indicators under them. In order to obtain the scores of these undefine performance indicators, the WSM can be used. As an example, Eq. (4) shows the method for calculating the criteria score for availability performance, which is equal to the sum of products of the relative weights of Reliability (R), Maintainability (M) and Supportability (S) indicators, and their criteria scores, taken from Table 2 for a specific WF.

$$\textit{Availability score}\ (S_A) = w_R \times S_R + w_M \times S_M + w_S \times S_S. \tag{4}$$

where w_R, w_M, w_S are the relative weights of reliability, maintainability, and supportability respectively, and S_R, S_M, and S_S are their criteria scores. Similarly, the overall WF score of a WF can be calculated as a function of its technical and sustainability performance indicators using Eq. (5) below:

$$\textit{Overall WF performance score} = w_{tech} \times S_{tech} + w_{sus} \times S_{sus}. \tag{5}$$

where w_{tech} and w_{sus} are the relative weights of the technical and sustainability performance indicators respectively, assessed by the experts. S_{tech} and S_{sus} are the criteria scores, calculated using equations similar to Eq. (4) for the technical and sustainability performances.

3 Calculating OPI for Fakken wind farm: a case study

The Arctic region considered in this case study is the northern rt of Norway, which experiences warmer temperatures than cities further south in the overall Arctic region, such as Canada or the United States. The coastal part of Arctic Norway is recognized to be ice free. Therefore, some WFs installed close to the coast do not need to equip their WTs with anti-icing systems, to prevent ice accretion on the blades, such as Fakken WF.

kken WF is an onshore WF, located on a small island called Vannøya to the north of Troms and Finnmark County, Norway. The WF is sited on a small hill at the southwestern edge of the island, at an altitude of 40 to 200 m above sea level Birkelund et al. (2018). A mountain range is located to the west of the WF and two large fjords to the south, forming a complex terrain surrounding the

Table 2 Scoring criteria for wind farm performance

	Score (S) = 1	S = 2	S = 3	S = 4
Technical performance				
Capacity Ozturk and Fthenakis (2020)	Wind farm capacity factor CF: 10% $\leq$ CF $\leq$ 20%	Wind farm capacity factor is 20% $\leq$ CF $\leq$ 30%	Wind farm capacity factor is 30% $\leq$ CF $\leq$ 40%	Wind farm capacity factor is larger than 40% CF $\geq$ 40%
Quality	The manufacturing quality of WTs and the quality of used spare parts are not satisfactory. The selected WTs model is not suitable for the WF site, and the WF layout is not well designed	Good quality of WTs manufacturing processes and the used spare parts. However, the selected WTs model and the WF layout could have been improved	Good quality of WTs manufacturing processes and the used spare parts. The selected WTs model and the design layout of the WF is good	High quality of manufactured WTs and the used spare parts in maintenance activities. The selected WTs model is among the most suitable for the WF site, and the layout of the WF is of high-quality design
Availability performance				
Reliability Spinato et al. (2009)	The WTs experience a high failure rate, more than 3.5 failures per WT per year	The average number of failures per WT per year is between 2.5 and 3.5	The average number of failures per WT per year is between 1.0 and 2.5	The average number of failures per WT per year is less than one
Maintainability Ozturk and Fthenakis (2020)	The time to repair a failure is more than 24 h TTR > 24 h	The time to repair a failure is between 16 and 24 h 16 h < TTR $\leq$ 24 h	The time to repair a failure is between 8 and 16 h 8 h < TTR $\leq$ 16 h	The time to repair a failure is less than eight hours TTR $\leq$ 8 h
Supportability Dao et al. (2019)	The mean downtime is more than 100 h per failure	The mean downtime is between 50–100 h per failure	The mean downtime is between 25–50 h per failure	The mean downtime is less than 25 h per failure
Sustainability performance				
Environmental impact Kucukali (2016)	The wind turbines are placed on birds' migration route, reindeers' grazing area or near to an ecologically sensitive area	The wind farm has an Environmental Impact Assessment Report which is prepared by a desk study. But the wind farm is not located in the vicinity of wetlands, protected natural areas, caves, and birds' migration routes	The wind farm has an Environmental Impact Assessment Report or study which is supported with field studies	The wind farm has a detailed Environmental Impact Assessment Report in which biodiversity issues are addressed. The environmental analysis is supported with field surveys, and a monitoring system is established at the site for relevant environmental parameters
Economic impact	The price of electricity generated by the wind farm is 26–50% higher than what households in the country usually pay to purchase electricity	The price of electricity generated by the wind farm is 1–25% higher than what households in the country usually pay to purchase electricity	The price of electricity generated by the wind farm is equal to what households in the country usually pay to purchase electricity	The price of electricity generated by the wind farm is cheaper than what households in the country usually pay to purchase electricity
Social impact Kucukali (2016)	The wind farm stops or limits local communities' ability to utilize the surrounding lands and provide a livelihood	A public consultation process has been not carried out, but the wind farm does not stop local communities' ability to utilize the surrounding lands and provide a livelihood	A public consultation process has been carried out. The locally affected community has been notified and adequate mitigation measures have been taken	A robust public consultation process has been carried out. No major objections from local communities were raised. The local community may benefit from the wind farm

WF. The WF consists of 18 Vestas V90-3.0 WTs with rated power 3.0 MW each, yielding a total installed capacity of 54 MW. The hub height of the turbines is 80 m above the ground, and the rotor diameter is 90 m. The 18 WTs are placed in two roughly parallel lines, as shown in Fig. 5, perpendicular to the southeastern inter-cardinal direction. It is assumed that the wind farm will operate for 25 years with no catastrophic operation and maintenance (O&M) events.

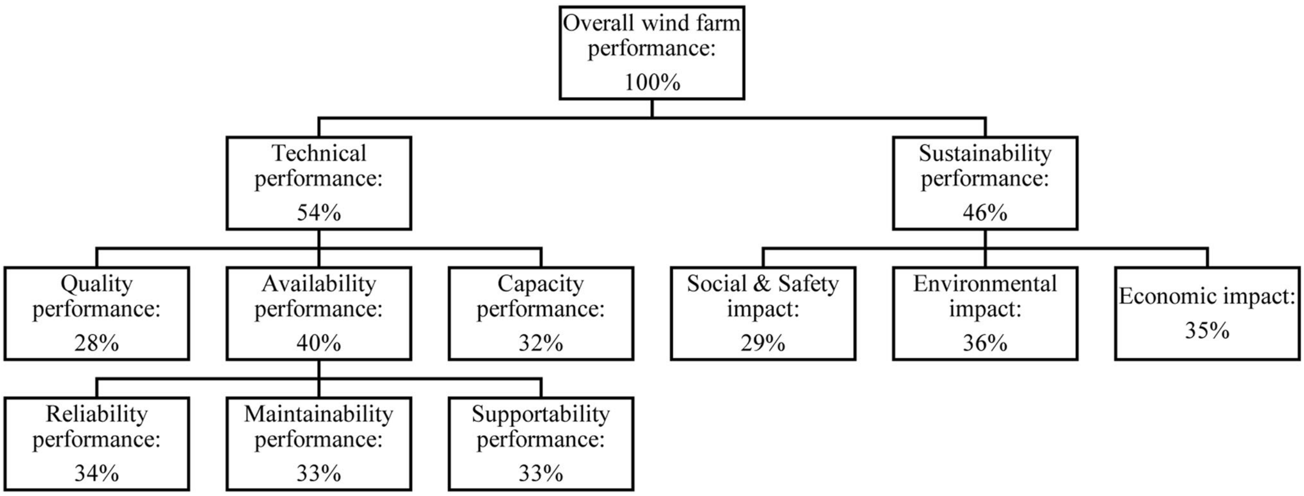


Fig. 3 Performance indicators relative weights, assessed by experts

Fig. 4 Relative weights of technical and sustainability performance indicators

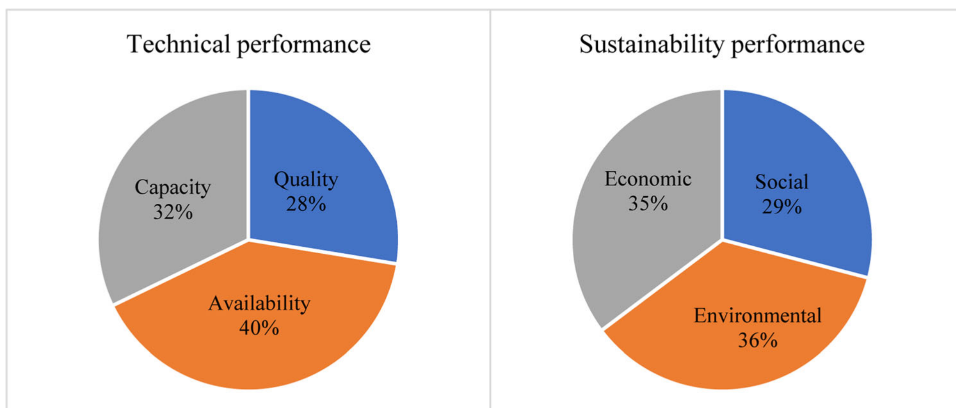
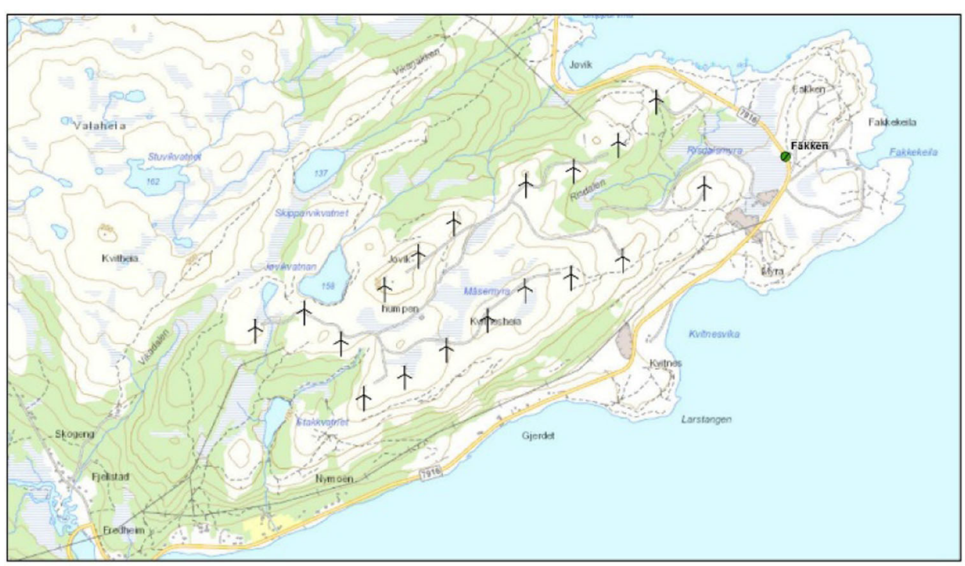


Fig. 5 Fakken wind farm layout



3.1 Fakken WF performance indicators scores

Through communication with the WF manager and operator, we were able to get our hands on 28 service reports, and more than two years of alarm logs that contained the operation and maintenance data of one wind turbine (WT No.8), for the period from January 2018 until July 2020. Based on the analysis of this data, the performance indicators criteria scores were selected from Table 2 and calculated using variations of Eq. (1), similar to Eq. (4), as can be seen in Fig. 6. The justification for the selection and calculation of the scores is shown in Sect. 3.1.1.

3.1.1 Justification of scores

Reliability. By reviewing the service reports for the reference WT (WT No. 8), it was found that the WT experienced three main failures during 2019 that led to its operation being halted: a hydraulic pump failure, a generator bearing failure, and a defective bearing on the generator's fan. Based on that, a score of 2 was assigned to the reliability performance of that WT. Moreover, an overall regular annual inspection of the WT took place twice during the period from January 2018 until July 2020. The regular inspections took place in August 2018 and 2019, with no major failures reported in either of the inspections.

Maintainability. According to the service reports, the mean time needed to replace the hydraulic pump, the generator's bearing and the generator's fan bearing were 10, 21 and 2 h, respectively. when referring to the scoring criteria Table 2, it is obvious that each time to repair of these failed components has a different criterion score as follows: the hydraulic pump has score of 3, the generator's bearing is assigned a score of 2 and the generator's fan bearing is assigned a score of 4. Therefore, by taking the average of these scores, the maintainability of the WT can be assigned a value of 3.

Supportability. Both failures, the hydraulic pump and the generator bearing failures, were repaired during the same day they failed, which means that the mean downtime for the WT per failure is less than 25 h. Referring to Table 2, the supportability score is assigned a value of 4.

Availability. The availability criteria score is a function of the reliability, maintainability and supportability performance indicators relative weights and criteria scores. By applying Eq. (4), the calculated availability criteria score is equal to 3.

Quality. The quality of the manufactured WTs is high. Vestas, the WTs manufacturer, is a well-known and a pioneer company in the WTs manufacturing, selling, installing, and servicing. Fakken WF is being monitored remotely by Vestas, and in case of failure, Vestas takes

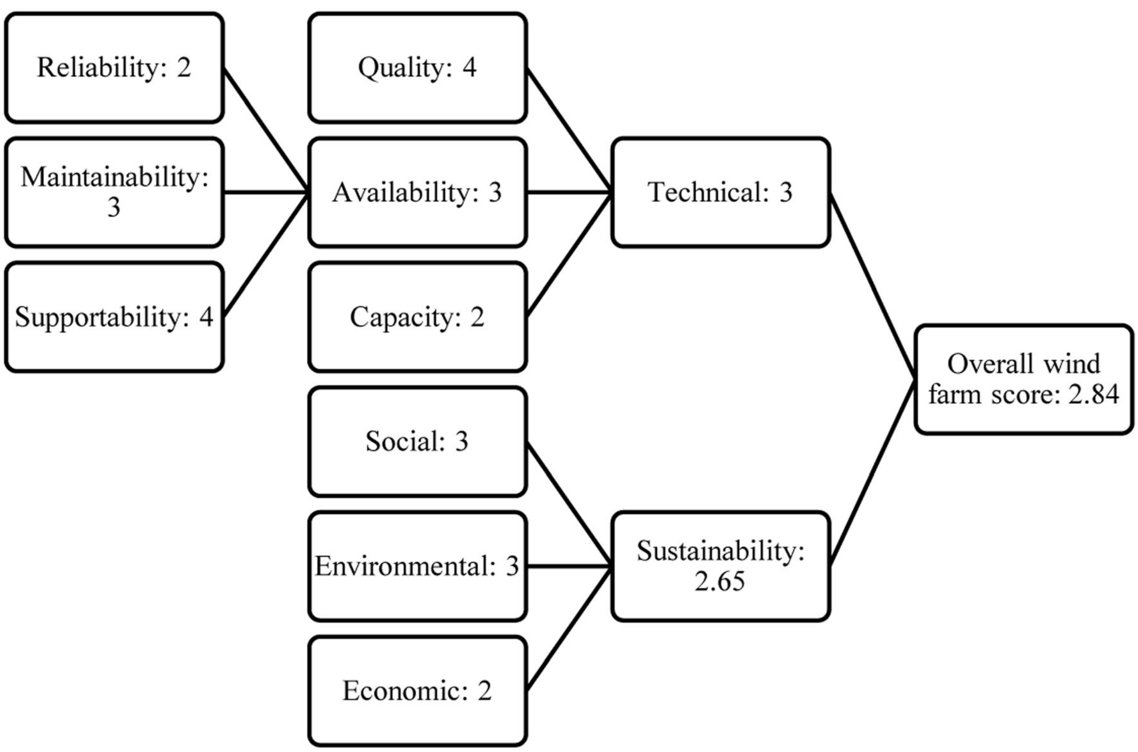


Fig. 6 Performance indicators scores for Fakken WF, based on Table 2

care of the maintenance procedure required. Therefore, the quality of used spare parts is high. The selected model of WTs (V90-3 MW) is an improved design that provides more power without an appreciable increase in size, weight, and tower loads Vestas (2013). The design of the WF layout is based on research and measurements of wind speed, humidity, temperature, and other factors, which are still being monitored until today. Moreover, a highly efficient software was being used to analyze the measured data. Therefore, the quality performance is assigned a score of 4.

Capacity. The amount of energy produced by the WF throughout the year is estimated at 130 GWh TromsKraft (2018), divided by the maximum amount of energy the WF would have produced at full capacity, which is estimated at 473 GWh. The resulting capacity factor is 27.5%. Based on that, the capacity performance is assigned a score value of 2.

Technical performance. The technical performance score can be calculated as a function of the availability, capacity and quality relative weights and criteria scores, by applying an equation similar to Eq. (4). The resulting value pf technical performance score is 3.

Environmental impact. the WF is not located in bird migration routes and does not represent threats to endangered species in the Arctic. Still, the WF was built on an important winter grazing area for reindeer. However, testing data showed that reindeer density within the wind farm area did not change significantly during and after the construction of the wind farm, Tsegaye et al. (2017). The effects on reindeer spatial use during and after WF development were negligible, according to the same study. However, some significant changes in reindeers' use of the area was noticed that might be caused by human activities during certain construction stages of the WF. Based on that, the assigned environmental impact score of Fakken WF can be equal to 3.

Economic impact. In the European Free Trade Association (EFTA) Surveillance Authority (ESA) report Sanderud and Monauni-Tömördy (2011), dated 16 March 2011, regarding the fund offered to Troms Kraft Produksjon AS to construct Fakken WF, Enova SF, a company owned by the Ministry of Climate and Environment in Norway, announced that the price of electricity from Fakken WF is calculated based on a six-month average of three year forward contracts, and it is going to be NOK 0.34/kWh. Comparing this price of electricity to the average price paid by households in Norway during the same period, i.e. the three years following the construction of the wind farm, 2012, 2013 and 2014, as taken from Statistics Norway, SSB (2020), the price of electricity generated by Fakken WF was found to be 8% more expensive.

An estimation of the levelized cost of energy produced by Fakken WF was conducted by Mustafa et al. (2020). The cost estimation shows that the WF produces energy 25% more expensive than what households in Norway normally pay. However, households in Norway pay a unified price of electricity, whether it comes from wind energy or from hydropower, which is the main source of electricity in Norway. Therefore, the economic impact of Fakken WF has a score of 2.

Social impact. The WF is located in a remote site away from residential areas, so the noise generated by the WTs does not affect the local society. The WTs are not equipped with anti/de-icing systems, as ice rarely accretes on them. Therefore, the risk of ice throw from WTs is negligible. This was confirmed when speaking to the manager of the WF. Moreover, the WF does not stop or limit local communities' ability to utilize the surrounding lands and gain a livelihood. However, some claims surfaced from the local community regarding the effects of the WTs on reindeers' use of the WF area, but these claims were disproved, by Tsegaye et al. (2017). Based on that, the social impact score is assigned a value of 3.

Sustainability performance. The sustainability performance score can be calculated as a function of the environmental, economic, and social impacts' relative weights and criteria scores, by applying an equation similar to Eq. 4. The resulting sustainability performance score is 2.65.

Overall WF performance score. The overall performance score is a function of the technical and sustainability performances' relative weights and scores. By using Eq. (5), the resulting value of the overall performance score of Fakken WF is equal to 2.84.

3.2 Fakken WF overall performance index

The proposed OPI is a normalized value of the overall WF performance score, which was calculated using Eq. 3. The value of the overall performance score is normalized to be from 0 to 1. This can be done by subtracting the lowest attainable score, which is 1 from the calculated overall performance score and dividing the result by the difference between the highest (4) and lowest (1) attainable scores, as shown in Eq. 6:

$$OPI = \frac{overall\ performance\ score - minimum\ score}{maximum\ score - minimum\ score} = \frac{2.84 - 1}{3} = 0.613 \tag{6}$$

The resulting OPI represents an absolute value that can help operators and stakeholder at a specific WF to decide whether the overall performance of that WF is acceptable or not. In case the resulting OPI was deemed to be

Table 3 A qualitative scale for expressing the OPI

OPI	Scale
0–25%	Bad performance
26–50%	Average performance
51–75%	Good performance
76–100%	Excellent performance

unacceptable, the performance indicator that contributes to lowering the overall WF performance can be easily allocated. Moreover, the resulting OPI can be expressed qualitatively by defining a qualitative scale as show in Table 3.

Based on that, the 61.3% OPI can be expressed to be good performance. In case the decision was to improve the OPI of Fakken WF, it can be seen, by referring to Fig. 5, that the sustainability performance indicates a lower impact than the technical performance. Therefore, improvements should be focused on the WF sustainability performance. Moreover, it is the economic performance indicator that has the lowest score among sustainability performance indicators. This can be attributed to the high operation and maintenance (O&M) costs that lead to increasing the cost of energy produced by the WF. Based on that, it can be proposed that more efforts are required to improve the (O&M) activities.

Another advantage of using the OPI is that it can be calculated for multiple WFs that share similar characteristics, such as WTs brands, capacity, location, etc. The OPI can help us compare the overall performance of these WFs, or their specific performance indicators, and therefore, ranke them according to how high or how low their performances are. For example, the OPI of Fakken WF can be compared with other WFs located in Arctic Norway, such as Nygårdsfjellet and Kvittfjell/ Raudfjell WFs. Based on the resulting OPI values, decision-makers can decide which WFs need to be improved to provide better performance and which performance indicators need more focus.

In order to compare the effects of Arctic operating conditions on the calculated OPI of Fakken WF, the same OPI quantification methodology is applied to a WF located in a non-cold-climate region, in Turkey. The Kozbeyli WF in Turkey has higher technical performance than Fakken WF, with a technical performance criterion score equal to 3.73 out of 4, due to higher reliability and capacity performances. This has led to an OPI value of nearly 75% if the sustainability performance of Kozbeyli WF was equal to that of Fakken WF, which is not the case. This is due to a lower environmental performance as Kozbeyli WF is located close to an Environmental Protected Area, migration route of birds, and endangered species. In addition, the Kozbeyli WF is 1.3 km away from a village that has a touristic value, which has reduced the social acceptance and performance of the WF Kucukali (2016) that consequently, reduces the sustainability performance criteria score of the WF to 1.7 out of 4. Consequently, the resulting OPI of Kozbeyli WF is nearly 60%, which is mainly due to lower sustainability performance of the WF.

4 Conclusions

The OPI is an important tool in providing a measure of the overall performance of WFs, especially in cases where performance data is scarce. The overall performance of WFs constituted the technical and sustainability performance indicators. The technical performance consisted of the quality, capacity, and availability performance indicators. The weighted sum method (WSM) is one of the most widely used methods for multiple-criteria decision making (MCDM). The use of WSM implies summing the products of the performance indicators relative weights and their scores of criteria.

Due to data scarcity, the relative weight of each performance indicator was estimated using expert judgement technique. Experts estimated that the technical performance had higher relative weight (54%) than the sustainability performance (46%). The rest of performance indicators had relative weights estimated by the experts as follows: Quality (28%), Capacity (32%), Availability (40%), Reliability (34%), Maintainability (33%), and Supportability (33%). Moreover, the sustainability performance indicators had the following relative weights: social and safety impacts (29%), environmental impacts (36%), and the economic impacts (35%).

The proposed methodology was applied to an onshore WF in Arctic Norway, called Fakken WF. The assigned and calculated scoring criteria for the performance indicators using Table 2 are found to be as follows: Reliability (2), Maintainability (3), Supportability (4), Availability (3), Quality (4), Capacity (2). The calculated technical performance score is equal to 3. The sustainability performance indicators had the following criteria scores: social and safety impacts (3), environmental impacts (3), and the economic impacts (2). The calculated sustainability criteria score is equal to 2.65. Consequently, the calculated total criteria score for the WF was found to be equal to 2.84.

The calculated OPI of the WF is 61.3%, which was deemed to be good, when compared against a proposed qualitative criteria scale. The OPI indicated that the economic performance of the WF needs to be improved, which can be attained by lowering the O&M costs to lower the cost of energy of the WF. Moreover, in order to understand the effects of Arctic operating conditions on the performance of WFs, the OPI of Fakken WF has been compared to the OPI of Kozbeyli WF, which is a WF located in a non-cold-climate region. The comparison concluded that Kozbeyli WF had higher technical performance in its reliability and capacity performances, due to the absence of Arctic operating conditions. However, the location of Kozbeyli WF has led to lowering its sustainability performance, due to its negative impacts on the environment and society, which has led a lower OPI value (60%), which was lower than the OPI of Fakken WF.

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Availability of data and material Data and used material in the paper are available upon request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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Paper 2

Resilience Assessment of Wind Farms in the Arctic with the Application of Bayesian Networks

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Article

Resilience Assessment of Wind Farms in the Arctic with the Application of Bayesian Networks

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Abstract: Infrastructure systems, such as wind farms, are prone to various human-induced and natural disruptions such as extreme weather conditions. There is growing concern among decision makers about the ability of wind farms to withstand and regain their performance when facing disruptions, in terms of resilience-enhanced strategies. This paper proposes a probabilistic model to calculate the resilience of wind farms facing disruptive weather conditions. In this study, the resilience of wind farms is considered to be a function of their reliability, maintainability, supportability, and organizational resilience. The relationships between these resilience variables can be structured using Bayesian network models. The use of Bayesian networks allows for analyzing different resilience scenarios. Moreover, Bayesian networks can be used to quantify resilience, which is demonstrated in this paper with a case study of a wind farm in Arctic Norway. The results of the case study show that the wind farm is highly resilient under normal operating conditions, and slightly degraded under Arctic operating conditions. Moreover, the case study introduced the calculation of wind farm resilience under Arctic black swan conditions. A black swan scenario is an unknowable unknown scenario that can affect a system with low probability and very high extreme consequences. The results of the analysis show that the resilience of the wind farm is significantly degraded when operating under Arctic black swan conditions. In addition, a backward propagation of the Bayesian network illustrates the percentage of improvement required in each resilience factor in order to attain a certain level of resilience of the wind farm under Arctic black swan conditions.

Keywords: wind farms; wind turbines; Arctic conditions; Arctic black swan; resilience; Bayesian network

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1. Introduction

Infrastructure systems in the Arctic are prone to disruptions in their operation caused mainly by the harsh weather conditions they face. The resilience of infrastructure systems in the face of disruptions and the resulting consequences has become a significantly recognized topic among project owners. The author in [1] defined system resilience as the extent to which a system maintains a minimum level of performance in the face of disruptions. Wind farms (WFs) are among the infrastructure systems installed in the Arctic that are prone to disruptions resulting from the weather conditions in the region. Ice accretion on the blades of wind turbines (WTs), snow accumulation that blocks the roads to WFs and prevents maintenance procedures, and cold temperatures that limit the dexterity of the WF staff are among the disruptions that affect the resilience of WFs in the Arctic.

When uncertainties are taken into consideration in resilience analyses, probabilistic resilience measures that normally have a probability value between 0 and 1 can be used [2]. For example, a system that possesses a resilience estimate of 0.8 can indicate that the system is, in general, 80% resilient against a specific disruptive event. Furthermore, it could reflect an 80% probability that the system will continue to perform under a defined disruptive event, or recover to an acceptable system performance level, within a given time interval after the disruptive event disappears.

Due to the uncertainty in energy system applications such as WFs, there are several variables that have to be determined and many explicit pieces of evidence that can be linked together through the application of Bayesian networks (BNs), which depend on the concept of probability to compute uncertainties. BNs have been used for modeling infrastructure resilience [3–5], post-disaster infrastructure recovery [6], and in applications of infrastructure system reliability [7,8].

According to Aven [9], resilience is event-dependent, and can be assessed based on the description of the disruptive event that the infrastructure system is facing. In that sense, there is a need to define the type of events that the system deals with, in order to decide whether it is resilient to them or not. Therefore, the approach adopted in this paper is to define three separate scenarios against which the resilience of a WF can be tested. The first scenario is the baseline scenario, where the WF is operating under normal operating conditions, while the second scenario tests the WF's resilience to Arctic operating conditions on the WF site. The third scenario is an imaginable scenario, defined as an Arctic black swan scenario, where the impacts of the disruptions are extreme.

The black swan concept was defined and popularized by Nassim Nicholas Taleb in his book The Black Swan [10], in which he identified three main attributes of a black swan event: 1) a black swan event is an outlier and unexpected, in the sense that nothing in the past can indicate the likelihood of it occurring; 2) its impact is extreme; and 3) after a black swan event has occurred, humans are able to find an explanation for it, making it explainable and predictable despite its outlier nature. According to Aven [11], black swan events are seen as extreme events relative to current knowledge and beliefs. Furthermore, Aven and Krohn [12] pointed out that black swan events can be events that are known to the risk analysts, but assessed to have a negligible probability of occurrence, and thus not anticipated to happen. Therefore, testing a WF's resilience to black swan events helps the WF operator to be prepared for worst-case scenarios.

This study is motivated by the observation that uncertainties emerging from the changing climate conditions might open up the possibility for unexpectedly harsh weather conditions, characterized as a black swan, to take place in regions such as the Arctic. The effects of such a scenario taking place, and affecting the operation of WFs in the Arctic, are not well addressed in the literature. Using BNs to model an uncertainty scenario and calculating the resulting resilience is effective as a BN is a practical tool for calculating conditional probabilities, and it is easy to understand its models. Most studies that have implemented BNs for applications in the Arctic are concerned with risks posed to ship transportation and collisions with ice in Arctic waters [13–15]. WF systems are relatively new in the Arctic, and as there is a corresponding lack of data in the field, the use of BNs to describe Arctic scenarios and their effects on WFs can be an interesting application.

This paper utilizes BNs to estimate the resilience of WFs located in the Arctic region of Norway, which will contribute towards enriching the literature with a unique methodology, to create multiple scenarios and assess the WF resilience against each scenario. The paper includes and assesses the WF's resilience against three main scenarios, which are the normal operating conditions scenario, the Arctic operating condition scenario, and the Arctic black swan scenario.

The remaining sections of this paper are organized as follows: Section 2 presents a conceptual definition of engineering resilience. Section 3 introduces the methodology adopted, while Section 4 explains the design and modeling of the BN. Section 5 demonstrates the use of the proposed BN by applying it to a case study of a WF in the Norway Arctic region. The conclusions of the study are then presented in Section 6.

2. Conceptual Definition of Engineering Resilience

Youn et al. [16] proposed a theoretical definition of engineering resilience, which derives its generic formula from the system reliability and the three key attributes of prognostics and health management (PHM) efficiency, which are diagnostics, prognostics, and condition-based maintenance [17]. The definition concluded that resilience can be mathematically measured as the sum of reliability and restoration, as per Equation (1) [16].

$$\text{Resilience } (\Psi) = \text{Reliability } (R) + \text{Restoration } (\varrho) \tag{1}$$

Restoration (ϱ) is defined as "the event at which the 'up' state is re-established after failure" [18], which according to [16] depends mainly on the attributes of PHM efficiency and system reliability, by focusing on transforming the system into a resilient system and minimizing its life-cycle cost (LLC). Based on that, restoration can be expressed as the joint probability of a system failure event (i.e., the reliability of the system) (Esf), and the three PHM attributes, which are a correct diagnosis event (Ecd), a correct prognosis event (Ecp), and a mitigation/recovery (M/R) action success event (Emr), expressed in Equation (2) [16].

$$\text{Restoration } (\varrho) = P\,(E_{sf}\ E_{cd}\ E_{cp}\ E_{mr}) \tag{2}$$

The authors in [19] proposed that the most important factors for consideration in assessing the resilience of a system in the Arctic are: (I) reliability of the system's components, (II) maintainability of disrupted components, (III) supportability of maintenance activities, (IV) the organizational resilience, and (V) the PHM efficiency of the system. However, the PHM elements, namely diagnosis, prognosis, and M/R action, are embedded in the maintainability, supportability, and organizational factors of restoration. This is because the organization has to gather and analyze data in order to define the potential hazards (diagnosis), estimate the remaining useful life of the impacted WT components (prognosis), and take the required M/R measures in a condition-based maintenance (CBM) sense, where the latter can be reflected by the maintainability and supportability of the WF. Based on that, and by referring to restoration equation in [19], restoration can be expressed as in Equation (3).

$$\text{Restoration } (\varrho) = (1 - R) \times M \times S \times O \tag{3}$$

where R, M, S, and O are the conditional probabilities of reliability, maintainability, supportability, and organizational resilience, respectively, which are the main factors of resilience that are important for WFs to maintain and regain their resilience during and after a disruptive event. These factors can be denoted as output variables that will depend on other input variables in determining their values. Figure 1 illustrates the input and output variables that will shape the resilience of WFs, considering Equations (1) and (3), and that will be used in establishing the Bayesian network (BN) for calculating the resilience of the WFs.

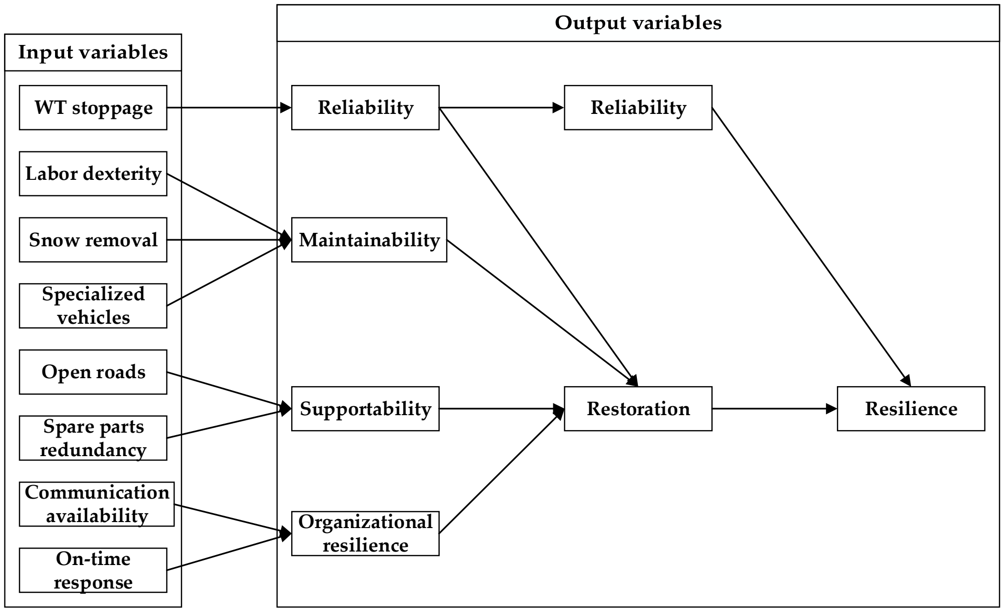

Figure 1. Input and output variables of the resilience of WFs.

2.1. Reliability

WF reliability reflects the ability of the WTs to operate as required, without failure, for a given period under given conditions. Reliability can be expressed in terms of the probability of failure [20], as in Equation (4):

$$R(t) = 1 - F(t) \tag{4}$$

where F(t) is the probability at which the WTs stop operating due to the hazards, which can be due to Arctic operating conditions or component degradation. Different statistical models have been developed for reliability modeling of complex systems like WTs, such as the Power law process (PLP), which is a special case of the Poisson process [21], and the Poisson process with covariates [22]. For the sake of simplicity, in this paper the Poisson distribution is used to represent the probability of the WT stoppage events, as shown in Equation (5) [23]:

$$p(k;(0,t), \lambda) = \frac{(\lambda t)^k}{k!} e^{-\lambda t} \tag{5}$$

where k is the number of WT stoppage events the Poisson distribution tries to find the probability of, over a fixed time interval (0, t). λ is the mean value of the distribution and is equal to the number of WT stoppage events over a specific period (e.g., a month).

2.2. Maintainability

The maintainability of an item is the ability to keep performing, or restored to a state to perform as demanded, under given conditions of operation and maintenance [18]. Maintainability is influenced by the design of the system, in terms of how easy it is to maintain it. From a different angle, the maintainability of a WF can be expressed in terms of two factors, which reflect the ability to restore the functionality of the WF: the level of labor dexterity when carrying out the maintenance activities, and the accessibility to the WF; both factors are affected by the Arctic operating conditions. In order to maintain access to the WTs, WFs can utilize snow-removing strategies, which might be costly, or equip the service team with specialized vehicles. A cost/benefit analysis must be carried out in order to determine which option is better. However, most WFs employ a combination of both solutions [24].

2.3. Supportability

Supportability is defined as the ability of a system to be supported to maintain a certain level of availability under defined operational conditions and given logistic and maintenance resources [18]. Based on this definition, the supportability of a WF involves the provision and availability of spare parts and tools that will help the service team to restore the WF's performance and availability, during and after a disruptive event. To this end, supportability depends on the redundancy of spare parts, and the accessibility of roads and routes, via which spare parts and tools can be delivered by suppliers.

2.4. Organizational Resilience

According to the BS-65000 standard [25], organizational resilience implies the capacity of the organization to prepare for disruptive events, respond and adapt to them, whether they take the organization by surprise or unfold gradually. Cutter et al. [26] argue that organizational resilience requires an assessment of the physical properties of the organization, such as communication technology, number of members, and emergency assets. Hence, the resilience of a WF can be measured in terms of (I) communication availability and (II) on-time response to events.

I. Communication availability (CA) covers the communication between staff members and the WF. Incidents involving loss of connection with WTs, which lead to loss of data, are stored in the SCADA system. A Poisson distribution can be used to estimate the probability of loss of connection events (x), taking place over a specific interval (0, t), considering an average number of loss of connection incidents (λ). Hence, the probability of connection availability can be represented as per Equation (6) [23]:

$$CA = 1 - p(x;(0,t), \lambda) = 1 - \frac{(\lambda t)^x}{x!} e^{-\lambda t} \tag{6}$$

II. On-time response to events covers the responsiveness of the operator to disruptive events and is a measure of the WF's resilience, which can be assessed by the probability of an on-time response to the events that have led to WT stoppage. For example, if 85% or more of the disruptive events that lead to or require stopping the WTs are being handled and treated by the WF operator, within the first hour of their occurrence, the WF operator can be described as resilient, and the on-time response variable can be set at 100%, and considered successful [3]. This can also include corrective maintenance activities if the treatment of the failure starts within the first hour of its occurrence.

3. Methodology

The methodology adopted to calculate resilience using the proposed BN is illustrated in Figure 2. The probability values of the input variables in the BN will either be extracted from historical data gathered from WFs or, in the event of a lack of data, from expert assessments. Afterwards, the BN is compiled to provide the posterior probabilities of the output variables, including resilience. Upon calculating the resilience value of the WF, the BN will show the probability of urgency to take measures to improve the WF resilience.

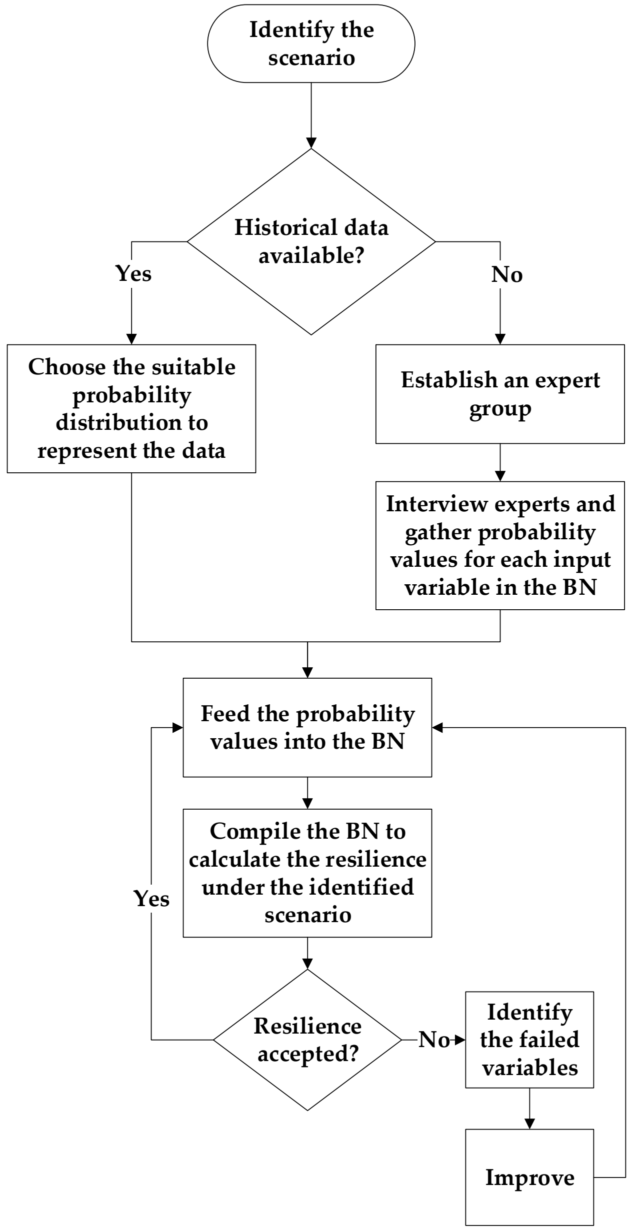

Figure 2. Methodology followed to estimate the resilience of WFs using BN.

4. Designing the Bayesian Network

Graphically, a BN consists of nodes, and links that connect the nodes together. The nodes represent the variables, which can be an event or the state of a specific component, such as the state of failure or no failure of that component. Each node contains the probability of the occurrence of an event or state. The nodes are classified into parent nodes and child nodes, depending on how they are connected to each other in the graph, and which node is the predecessor (parent), and which the successor (child). The links in the BNs denote the causal relationship between the nodes. For example, in Figure 3, the nodes X1 and X2 are the parents of node X3, which is the child of both nodes. Likewise, node X3 is the only parent of node X4, which is its child.

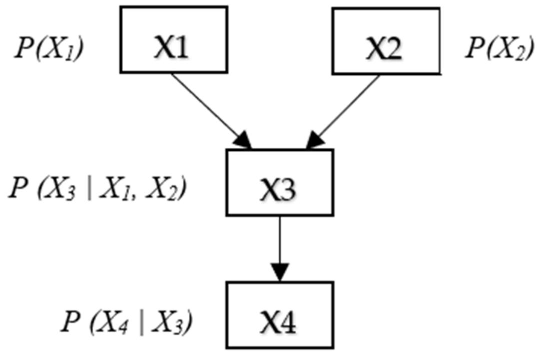

Figure 3. An example of a BN with four variables.

BNs are described as directed graphs, which means that the relationships between the nodes are directed in one direction, with no cycles or links going backwards to the original (parent) node. A BN is an efficient tool for calculating the posterior probability of uncertain variables (the probability of the child nodes), depending on the known condition or the evident probability of other variables (the parent nodes), in what is known as the conditional probability, which updates the probabilities of events when given a certain condition or evidence.

The conditional relationships between the variables in a BN are measured by conditional probability distributions. Equation (7) presents the full joint probability distribution of a BN consisting of n variables $X_1; X_2; \ldots; X_n$ [3].

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid Parents(X_i)) \quad (7)$$

The variables/nodes used in modeling the BN are Boolean discrete variables, having values of (Yes/No), where the Yes state represents the success state of a specific variable, and the No state represents the fail state of that variable. For example, labor dexterity, which contributes to the successful maintenance of WTs, is reduced by 70% during the presence of extreme Arctic operating conditions. Therefore, assuming that labor dexterity has a 100% probability of being successful under normal operating conditions, the probability of successful labor dexterity is reduced to 30% under extreme Arctic conditions, which will consequently reduce the probability of carrying out successful maintenance on the WTs and, therefore, reduce the resilience of the WF.

A graphical depiction of the proposed BN, which illustrates the interactions between the input and output variables, is shown in Figure 4. User-friendly software called Netica, which is not open source, was used to build the BN to assess the resilience of WFs under Arctic operating conditions. Netica allows for entering equations and probability distributions and converting them into conditional probability tables (CPTs).

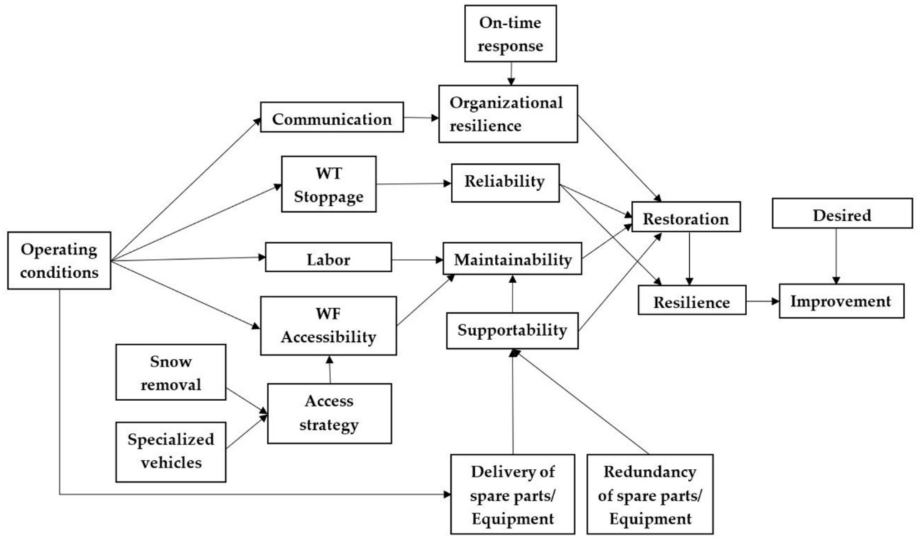

Figure 4. Graphical depiction of the proposed BN for WF resilience calculation.

In addition to the Poisson distribution function used to design the WT stoppage and communication availability nodes, two other main functions were used to design the BN nodes, which have two or more input nodes each, such as the maintainability, supportability, and organizational resilience nodes. These two functions are the NoisyOrDist and the NoisyAndDist functions.

The NoisyOrDist function is used when there are n input nodes $X_1, \ldots, X_n$ of an output node, Y, where the probability value for Y being true takes place when one and only one X_1 is true, and all input nodes other than X_1 are false. The NoisyOrDist function, based on [27], is expressed as shown in Equation (8):

$$\text{NoisyOrDist}\ (l, X_1, v_1, X_2, v_2, \ldots, X_n, v_n) \tag{8}$$

Term v_i is the probability of the output node, Y, being true if and only if that input node (X_i) is true, as presented in Equation (9) [27]:

$$v_i = P\ (Y = True \mid X_i = True, X_j = False, for\ each\ j \neq i) \tag{9}$$

Term l is called the leak probability, and it represents the probability that Y will be true when all of its input nodes are false, as expressed in Equation (10) [27]:

$$l = P\ (Y = True \mid X_1 = False, X_2 = False, \ldots, X_n = False) \tag{10}$$

Generally, the conditional probability of Y obtained using the NoisyOrDist function, based on [3], can be expressed as in Equation (11):

$$P\ (Y = True \mid X_1, \ldots, X_n) = \\ 1 - [(1 - P\ (l))\prod_{i=1}^{n}(1 - P\ (Y = True \mid Xi = True))] \tag{11}$$

The NoisyAndDist function is used when the true state of the output node Y is caused by more than one input node X being true. The NoisyAndDist can be expressed as the complement of the NoisyOrDist, as in Equation (12) [27]:

$$P\ (Y = True \mid X_1, \ldots, X_n) = 1 - \text{NoisyOrDist} \tag{12}$$

Table 1 summarizes the equations used to model the main nodes in the BN to calculate the resilience of WFs.

Table 1. Summary of the modeled equations used by Netica in the designed BN.

Node	Notes	Netica Equation Entered in the BN Nodes	Equation Number
WT stoppage	A Poisson distribution of the number of WT stoppages	P (WT stoppage ǀ ArcticConditions) = ArcticConditions == Yes? PoissonDist (k, λ)	Equation (13)
Reliability	$R(t) = 1 - F(t)$	R(t) = 1 − F(t)	Equation (4)
Access strategy	Dependent on the snow removal and the specialized vehicles nodes	P (Access strategy ǀ Snow removal, Specialized vehicles) = NoisyAndDist (Access strategy, 0, Snow removal, 0.5, Specialized vehicles, 0.5)	Equation (14)
Maintainability	Dependent on WF accessibility, labor dexterity, and supportability nodes	P (Maintainability ǀ WF accessibility, Labor dexterity, Supportability) = NoisyAndDist (Maintainability, 0, Accessibility, 0.33, Labor, 0.33, Supportability, 0.33)	Equation (15)
Supportability	Dependent on the redundancy and the delivery of spare parts	P (Supportability ǀ Redundancy, Delivery) = NoisyOrDist (Supportability, 0, Redundancy, 1, Delivery, 1)	Equation (16)
Communication	The complement of the Poisson distribution for the number of lost communication events	P (Communication ǀ ArcticConditions) = ArcticConditions == Yes? 1-PoissonDist (k, λ): 0	Equation (17)
Organizational resilience	Dependent on the communication and the on-time response of the WF	P (Organization ǀ Communication, Response) = NoisyAndDist(Organization, 0, Communication, 0.5, On-time response, 0.5)	Equation (18)
Restoration	Conditional probability of WF reliability, maintainability, support-ability, and organizational resilience	Restoration (ϱ) = (1 − R) × M × S × O	Equation (3)
Resilience	The addition of reliability and restoration	Resilience (Ψ) = Reliability (R) + Restoration (ϱ)	Equation (1)
Resilience Improvement	If the calculated resilience is higher than the desired level, then there is no need for improvements; otherwise, improvements are needed.	Improve (Resilience, Desired) = Resilience >= Desired? No: Resilience < Desired? Yes: No	Equation (19)

5. Case Study: A Wind Farm in Arctic Norway

A WF in Arctic Norway was selected for the case study, comprising three different scenarios for calculating the resilience of the WF, using the BN. The first scenario is a baseline scenario, through which the resilience of the WF is calculated under normal operating conditions, and where the Arctic conditions are not included in the analysis. The second scenario is the Arctic operating conditions scenario, which calculates the resilience of the WF under the Arctic conditions that the WF normally experiences in its location. The third scenario is an imaginable scenario, called the Arctic black swan scenario, aimed at calculating the resilience of the WF under suggested extreme Arctic events, which has a low probability of occurring, but in the event of which, the impact on the WF would be immense. In connection with the Arctic black swan scenario, a backward propagation of the BN was used to determine which resilience factors would need to be improved in order to reach a certain level of resilience, in the light of Arctic black swan events.

The data gathered from WF operators included ice detection incidents on the WTs with resulting downtime, events concerning a loss of communication between the WTs and the WF staff, the duration of each event, as well as data related to WT maintenance and service activities. In addition, data regarding the performance of the WF such as generated power, wind speed, and rotor and generator speed were gathered. However, these latter types of data were not utilized in this study.

5.1. Baseline Scenario Analysis

The baseline scenario analysis concerns the resilience of the WF when it operates under normal operating conditions (no presence of Arctic disruptive events). Figure 5 illustrates the baseline scenario with the probability of occurrence of Arctic operating conditions set to 0%. Based on the available data, the resilience of the WF and the contributing factors were calculated probabilistically as follows:

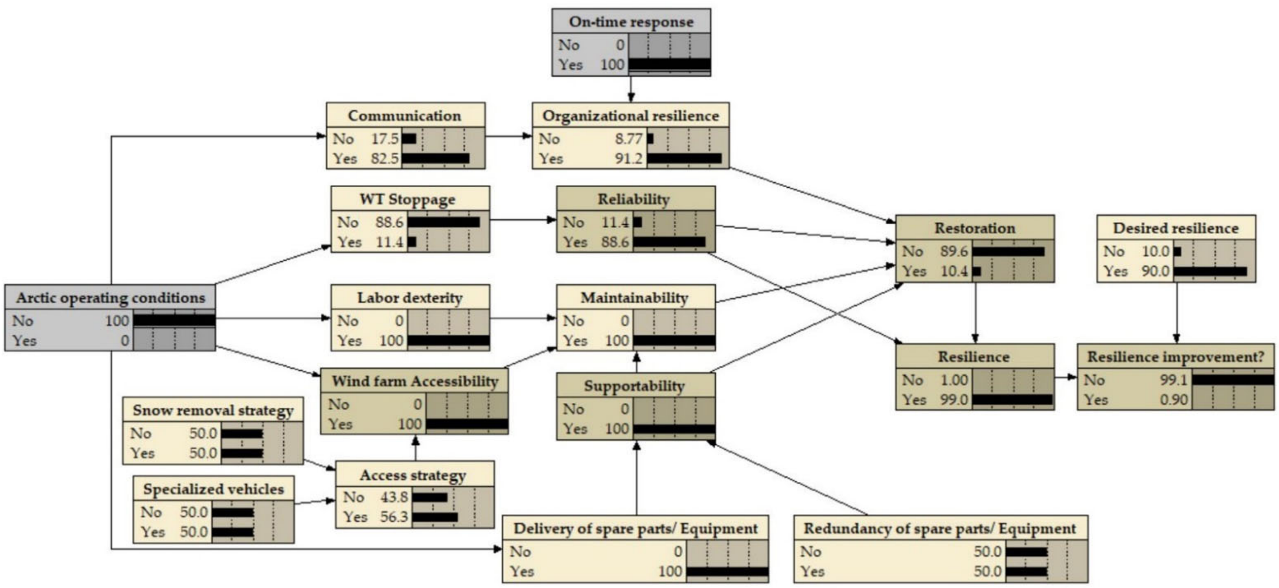

Figure 5. Baseline Bayesian network for calculating the resilience of wind farms.

Based on the gathered data, the WF experienced a total of 1993 WT stoppages during 2019. The reasons for the stoppages mainly concerned servicing and maintaining the WTs. The stoppages that resulted from Arctic operating conditions, such as icing and snow accumulations, were excluded. Based on this, the stoppage rate per WT during each month of that year was approximately 12 stoppages/WT/month. Therefore, the BN shows, by applying the Poisson distribution over the mean value of the stoppage rate (i.e., 12 stoppages/WT/month), as discussed in Equation (13), that the probability of WT stoppage is 11.4%. Consequently, the reliability of the WF, based on the BN, by utilizing Equation (4), will be 88.6% under normal operating conditions.

Labor dexterity is 100% under normal operating conditions, where the Arctic conditions are not present, which hinder the maintenance activities and limit the ability of workers to perform their work. In addition, accessibility to the WF is 100% probable since no snow has accumulated on the roads to the WF.

Regarding the supportability of the WF, the supply and provision of spare parts is 100% successful as roads are open and not affected by the Arctic conditions. Therefore, the NoisyOrDist function in Equation (16) shows that supportability is calculated to be 100% successful. Consequently, by using the NoisyAndDist function in Equation (15), it shows that the maintainability of the WF is 100% successful.

WF data show that the mean value of lost communication events between the WTs and the operator is five events per month per WT, under normal operating conditions. By applying Equation (17), the Poisson distribution over the mean value of the lost communication events shows an 82.5% probability of successful communication during non-disruptive event conditions.

In addition, by reviewing the timing and duration of the maintenance activities, it is observed that more than 85% of the maintenance procedures for failures that the WTs experience are carried out within the first hour of the failure taking place. Based on that, the on-time response is set to 100% as successful WF responsiveness. The overall organizational resilience, by applying the NoisyAndDist in Equation (18), is calculated to be successful with 91.2% probability.

By applying Equation (1) to calculate the WF resilience, the BN shows in Figure 5 that the WF is 99.1% resilient under normal operating conditions. Setting the desired resilience to be at least 90%, the resilience improvement node, which is modeled using the expression in Equation (19), in Table 1, shows that there is 99.1% no need for resilience improvement for the WF.

Table 2 summarizes the values of the BN input and output nodes, and the results of a forward propagation baseline scenario that could take place, using the modeled BN shown in Figure 5.

Table 2. Summary of baseline scenario input and output nodes.

<table>
<tr><th>Input Nodes</th><th>Yes Value</th><th>Output Nodes</th><th>Yes Value</th><th>Resilience</th></tr>
<tr><td>WT stoppage</td><td>11.4%</td><td>Reliability</td><td>88.6%</td><td rowspan="7">99%</td></tr>
<tr><td>WF accessibility</td><td>100%</td><td rowspan="2">Maintainability</td><td rowspan="2">100%</td></tr>
<tr><td>Labor dexterity</td><td>100%</td></tr>
<tr><td>Spare parts/equipment delivery</td><td>50%</td><td rowspan="2">Supportability</td><td rowspan="2">100%</td></tr>
<tr><td>Spare parts/equipment redundancy</td><td>100%</td></tr>
<tr><td>Communication</td><td>82.5%</td><td rowspan="2">Organizational resilience</td><td rowspan="2">91.2%</td></tr>
<tr><td>On-time response</td><td>100%</td></tr>
</table>

5.2. Arctic Operating Conditions Scenario Analysis

If the WF was operating under Arctic conditions, its resilience would be degraded due to the effects of ice accretion on WT blades, cold temperatures that affect the dexterity of the crew staff, and snow accumulation on roads that hinders accessibility to the WF. Figure 6 illustrates the values of the WF resilience and contributing factors. The data considered in the analysis of this scenario relate to the month of December as Arctic operating conditions are mostly witnessed during this month.

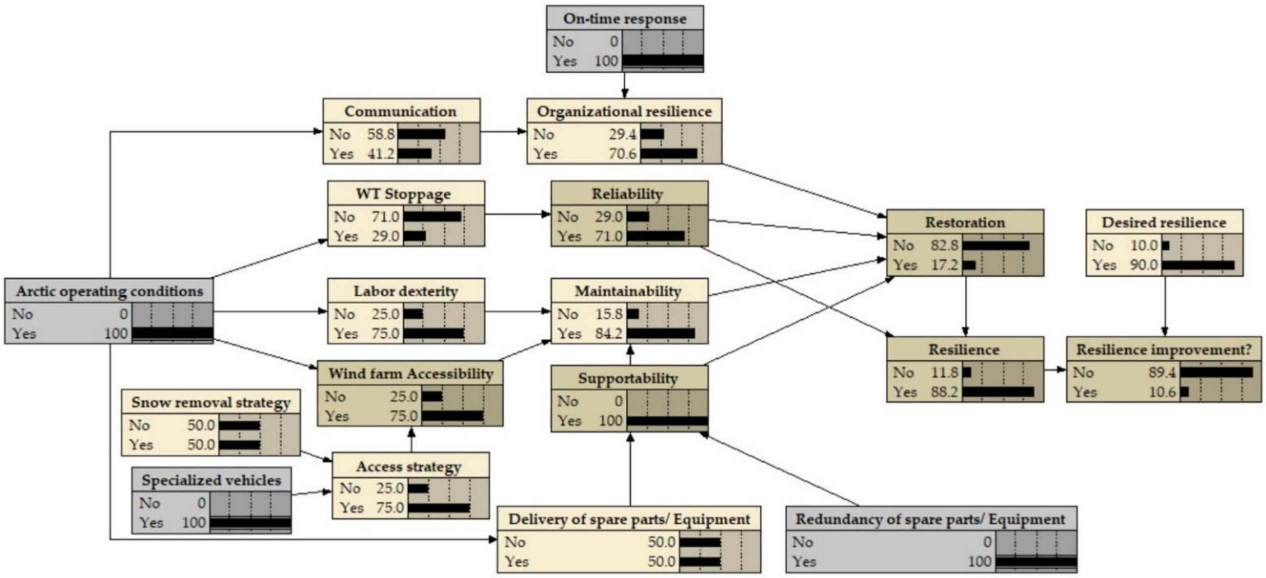

Figure 6. Bayesian network for calculating resilience in Arctic operating conditions scenario.

There were 65 WT stoppages altogether due to icing in December 2019. The average number of WT stoppages due to icing per WT during December is five. The resulting probability from applying Equation (13) to the average number of WT stoppages due to icing is 17.56%. By using Equation (20), the total WT stoppage probability is equal to the probability of stoppage due to icing events added to the stoppage probability calculated in the baseline scenario, under normal operating conditions, which was 11.4%. This results in 29% probability of stoppage under Arctic operating conditions. Based on that, by applying Equation (4), the calculated reliability probability is 71%.

$$\begin{gathered} P\ (\text{WT stoppage} \mid \text{Arctic operating conditions}) = \\ P\ (\text{WT stoppage due to icing events}) + P\ (\text{WT stoppage under normal operating conditions}) \end{gathered} \tag{20}$$

The dexterity of maintenance crews during extreme Arctic conditions is assessed to be reduced by 70% due to exposure to the cold weather [28], which can lead to decreased cognitive performance, injuries, dangerously low body temperature, and loss of sensitivity. Such conditions can directly influence the uncertainty of a person's decision or actions significantly [29]. Based on this, a simple scale can be developed to assess labor dexterity under milder Arctic conditions, such as those experienced by the WF. Table 3 proposes a qualitative scale for assessing the success of labor dexterity under different degrees of Arctic conditions. Labor dexterity success in the WF area during December falls within the range of 61–90%. By taking the average value of this range, the labor dexterity success would be approximately 75%.

Table 3. Labor dexterity success percentage according to operating conditions.

Operating Conditions	Labor Dexterity Success
Extreme Arctic conditions	0–30%
Moderate Arctic conditions	31–60%
Mild Arctic conditions	61–90%
Normal conditions	91–100%

Moreover, the WF employs a snow removal strategy to some extent, and uses specially equipped vehicles to maintain access to the WF. This can guarantee 75% successful access to the WF when applying the NoisyOrDist function in Equation (14) in the BN. By assuming that the spare parts and equipment are redundant, and available at the WF site, this would indicate 100% successful supportability, according to the NoisyOrDist function in Equation (16). This will contribute to successful maintainability of 84.2%, by applying the NoisyAndDist function in Equation (15).

According to the available data, the number of lost communication events between the WTs and the WF operator has doubled under Arctic operating conditions. In other words, the probability of successful communication between the WTs and the WF operator is halved compared to the normal operating conditions in the baseline scenario. Therefore, the probability of successful communication is reduced to 41.2%. Moreover, it is observed from the data that the responsiveness of the WF to failures did not change under Arctic conditions. Therefore, the probability of an on-time response by the operator to Arctic events remains at 100%. Based on this, the probability of organizational resilience is 70.6% when applying the NoisyAndDist function in Equation (18).

By applying Equation (3), the probability of successful restoration under the given conditions is only 17.2%. This is because the reliability of the WF is still high, even under Arctic conditions. In addition, by setting the desired resilience node to 90%, the resilience improvement node shows a slight probability of improvement urgency of 13.1%.

The resilience of the WF under Arctic operating conditions is 88.2% when calculated using Equation (1). This indicates that the Arctic conditions contributed to a 10.8% reduction in resilience, compared to the baseline scenario. Table 4 summarizes the values of the BN input and output nodes when the WF operates under Arctic conditions, using the modeled BN shown in Figure 6.

Table 4. Summary of input and output nodes in the Arctic operating conditions scenario.

Input Node	Yes Value	Output Node	Yes Value	Resilience
WT stoppage	29%	Reliability	71%	
Snow removal strategy	50%	Maintainability	84.2%	
Specialized vehicles	100%			
Labor dexterity	75%			
Spare parts/equipment delivery	50%	Supportability	100%	88.2%
Spare parts/equipment redundancy	100%			
Staff communication	41.2%	Organizational resilience	70.6%	
On-time response	100%			

5.3. Arctic Black Swan Scenario Analysis

The resilience of the WF can be tested against a scenario that is unlikely to happen but which, if it were to happen, would have an immense impact on the performance of the WF. This is classified as an Arctic black swan scenario. Proposing such a scenario can help the WF operator to prepare for the worst-case scenario that the WF might face, and to consider the best measures to take in order to mitigate the impacts of such a scenario.

The imaginable Arctic black swan scenario implies a dramatic increase in the number of icing events, which are going to be 10 times the number of icing events that the WF experiences under the Arctic operating conditions scenario. Moreover, the number of lost connections between the WTs and the WF staff during this scenario would increase tenfold compared to the Arctic operating conditions scenario, and the WF's response to such scenario events would be reduced to 50%. In addition, accessibility to the WF would be reduced as the snow removal strategy would not be efficient enough to remove the excessive accumulated snow, and only 50% of the specialized vehicles would be useable to access the WF. Lastly, the scenario suggests that roads to spare part suppliers would be blocked due to the immense amount of accumulated snow, and that only 50% of the spare parts and tools would be redundant at the WF site. Figure 7 illustrates the probabilistic values of the input and output nodes that correspond to the proposed scenario.

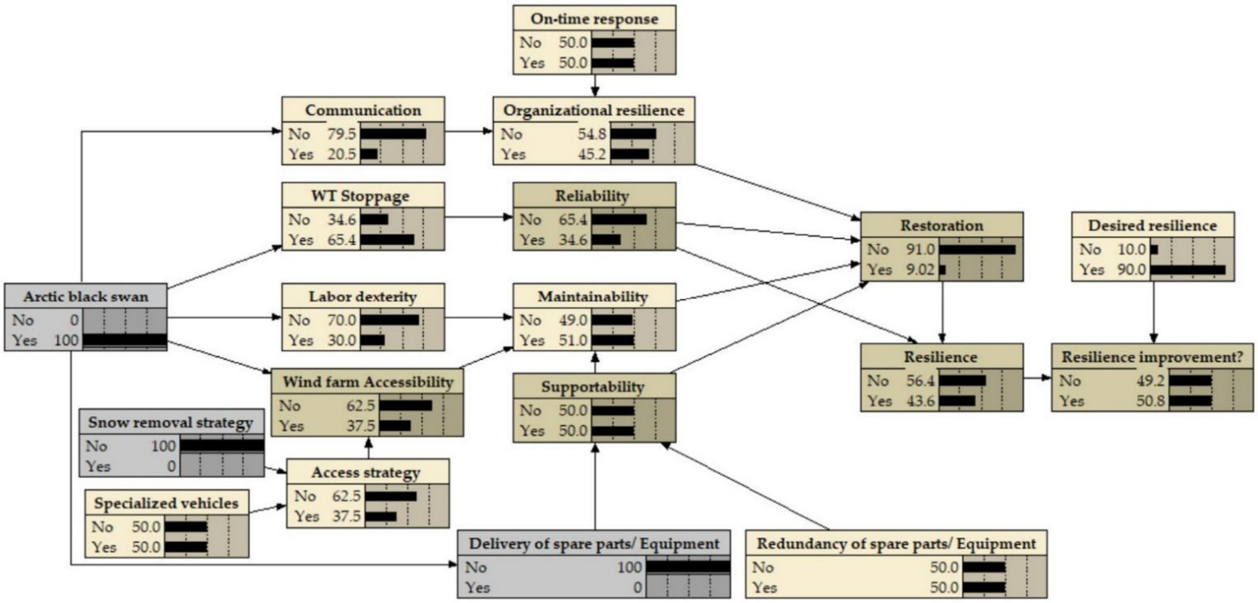

Figure 7. Arctic black swan scenario Bayesian network for resilience calculation.

By following the same methodology mentioned earlier in the previous two scenarios, it can be seen from the figure that the resilience of the WF is significantly reduced to 43.6%. All resilience factors witnessed a significant reduction in this scenario, but it is the reliability of the WF that witnessed the highest reduction, as reliability is reduced to 34.6%. Moreover, due to reduced maintainability, supportability and organizational resilience, the restoration of the WF is reduced to nearly 9%. Furthermore, the improvement of the WF resilience, shown in the resilience improvement node, is increased to 50.8%, indicating a higher urgency of implementing measures to improve the resilience of the WF.

5.3.1. Backward Propagation Analysis

Backward propagation is another practical characteristic of BNs. In backward propagation, observation is conducted of a precise variable, usually an output variable (e.g., the resilience node or the restoration node). After that, the BN calculates the marginal probabilities of unobserved variables by introducing the impact of the observed variables into the network in a backward style. For example, if the resilience value is set at 90%, as shown in Figure 8, this scenario implies enhancing the reliability of the WF from 34.6% to 72.2%, which can be achieved, for example, by installing anti/de-icing systems on the blades of the WTs. However, a cost/benefit study should be carried out to assess the feasibility of installing such systems [30]. In addition, Table 5 shows the required percentage value for each of the contributing factors to resilience in order to increase the overall WF resilience to 90% when operating under Arctic black swan conditions.

Table 5. Enhancement of variables when enhancing resilience under Arctic black swan events.

Variables/Nodes	Resilience = 43.6%	Resilience = 90%
Reliability	34.6%	71.4%
Maintainability	51%	59.3%
Supportability	50%	58.5%
Organizational resilience	45.2%	54.5%

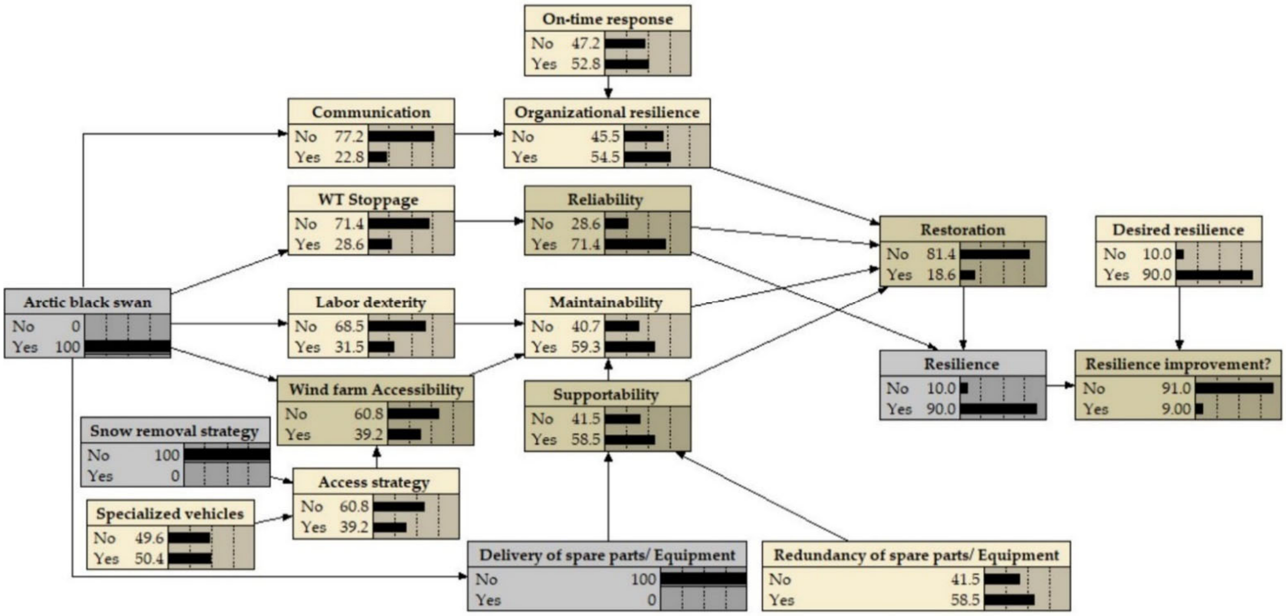

Figure 8. Backward propagation scenario when the expected resilience is set at 90%.

6. Conclusions

Infrastructure systems in the Arctic, such as wind farms, are exposed to different types of threats ranging from natural hazards to unfriendly human-induced events to accidents. Under such disruptive events, WFs need to be resilient to withstand and recover quickly and efficiently.

In this paper, resilience was probabilistically modeled using Bayesian networks. The proposed resilience model consists of variables related to the reliability, maintainability, supportability, and organizational resilience of the wind farm. The concluded resilience value is an indication of how resilient the wind farm is in the presence of Arctic disruptive events. A Bayesian network is a qualified tool for calculating prior and posterior conditional probability, through linking input and output variables in a network. Bayesian networks can be efficiently used for estimating risks and contributing to decision-making process in uncertain environments such as the Arctic region.

A WF in Arctic Norway was considered as a case study. Three separate scenarios were analyzed to calculate the WF resilience under three distinct operating conditions. The baseline scenario showed that the WF is highly resilient under normal operating conditions, with a 99% chance of being successfully resilient. The second scenario tested the resilience of the WF under Arctic operating conditions. The calculated resilience of the WF under such conditions is still high, with almost 88.2% resilience. On the other hand, the WF resilience was degraded to 43.6% under an Arctic black swan scenario. Moreover, the BN indicates that the WF needs urgent improvement actions to enhance its resilience, with a probability of nearly 51% that the WF's resilience should be improved.

A backward propagation scenario analysis would be particularly beneficial for WF decision-makers as it provides insights into achieving a specific level of resilience. The paper illustrated the values of resilience variables in the event that decision-makers want to enhance resilience to 90% when the WF is operating under Arctic black swan conditions. The enhancement of resilience to such a level requires improving the reliability significantly by more than 25%, which can be achieved by installing anti/de-icing systems on the blades of the WTs. Regarding maintainability, supportability, and organizational resilience, the improvement range is within 10% for each of them.

Author Contributions: A.M.M. performed the data collection and literature review, developed the methodology, designed the Bayesian network, ran the simulations, and wrote the paper; A.B., as the main supervisor, followed up all study steps and gave helpful advice, reviewed and edited the manuscript. Both authors have read and agreed to the published version of the manuscript.

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Nomenclature

WT	Wind turbine
WF	Wind farm
BN	Bayesian network
R	Reliability
M	Maintainability
S	Supportability
O	Organizational resilience
PHM	Prognostics and health management
ϱ	Restoration
P	Probability
F(t)	Probability of stoppage
CBM	Condition-based maintenance
k	Number of events occurring
λ	Rate of occurrence of an event

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Paper 3

Criteria-Based Fuzzy Logic Risk Analysis of Wind Farms Operation in Cold Climate Regions

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Article

Criteria-Based Fuzzy Logic Risk Analysis of Wind Farms Operation in Cold Climate Regions

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Abstract: Different risks are associated with the operation and maintenance of wind farms in cold climate regions, mainly due to the harsh weather conditions that wind farms experience in that region such as the (i) increased stoppage rate of wind turbines due to harsh weather conditions, (ii) limited accessibility to wind farms due to snow cover on roads, and (iii) cold stress to workers at wind farms. In addition, there are risks that are caused by wind farms during their operation, which impact the surrounding environment and community such as the (iv) risk of ice throw from wind turbines, (v) environmental risks caused by the wind farms, and (vi) social opposition risk to installing wind farms in cold climate regions, such as the Arctic. The analysis of these six risks provides an overall view of the potential risks encountered by designers, operators, and decision makers at wind farms. This paper presents a methodology to quantify the aforementioned risks using fuzzy logic method. At first, two criteria were established for the probability and the consequences of each risk; with the use of experts' judgments, membership functions were graphed to reflect the two established criteria, which represented the input to the risk analysis process. Furthermore, membership functions were created for the risk levels, which represented the output. To test the proposed methodology, a wind farm in Arctic Norway was selected as a case study to quantify its risks. Experts provided their assessments of the probability and consequences of each risk on a scale from 0–10, depending on the description of the wind farm provided to them. Risk levels were calculated using MATLAB fuzzy logic toolbox and ranked accordingly. Limited accessibility to the wind farm was ranked as the highest risk, while the social opposition to the wind farm was ranked as the lowest. In addition, to demonstrate the effects of the Arctic operating conditions on performance and safety of the wind farm, the same methodology was applied to a wind farm located in a non-cold-climate region, which showed that the risks ranked differently.

Keywords: wind farms; cold climate regions; risk analysis; fuzzy logic; expert judgment; probabilities; consequences

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1. Introduction

Wind energy applications in cold climate regions (CCRs) have gained more attention recently, and are growing at a rapid rate of approximately 20% per year according to the Global Wind Energy Council [1]. There are various encouraging reasons for installing wind farms (WFs) in CCRs: among others, the fact that the density of air in such regions is 10% higher than other non-cold climate regions, which results in higher availability of wind power resources [2]. In addition, abundant air resources exist in mountainous CCRs such as the Arctic region of Norway, where relatively steady winds with higher velocities [3]. Moreover, CCRs are known to be less and sparsely inhabited than other regions in the same country. Therefore, having WFs installed there will have less perceived impact on people than WFs built in large cities for example, and will likely encounter less opposition to installing WFs from residents.

CCRs are characterized by an air temperature of less than −20 °C, lasting for at least nine days per year, and an average annual temperature of less than 0 °C [4]. Wind turbines (WTs) in CCRs experience temperatures below their standard operational limits and may experience incidents of icing conditions. Therefore, such weather conditions can result in risks that will have negative impacts on WFs, and can consequently affect their surrounding environment and community.

The discussed risks in this paper are described to be emerging either from the harsh weather conditions in CCRs that affect the operation and maintenance of WFs, or risks that emerge from the WFs that affect their surrounding environment and community. The first type of risks that emerge from harsh weather conditions include the very cold temperatures and the ice accretion on the blades of WTs, which will increase the failure rate of the blades and other WT components [5,6], leading to increased operation stoppage rate of WTs. In addition, very cold temperatures can cause cold stress to workers at WFs, and might result in injuries, leading to reduced dexterity of workers and delaying maintenance of defected WTs [7]. Moreover, excessive snow precipitation can limit the accessibility to WFs, which can affect the maintenance activities required to maintain a certain level of performance. Therefore, snow removal strategies and specially equipped vehicles have to be used to overcome this risk [4]. On the other hand, the second type of risks that emerge from WFs include the ice throw from WTs caused by the centrifugal force of the WTs and the melting of ice on the blades, which can be harmful to workers at the WF, nearby residents, and other infrastructures and animals [8]. Furthermore, there are the environmental risks, which can be critical especially in the Arctic region, which is famous for its sensitive environment (with vulnerable bird and mammal species); lastly, there is the social opposition from the surrounding community that can negatively affect the wind energy investments in CCRs [9].

Careful analysis of the aforementioned risks is mandatory to control them and mitigate their probability of occurrence and the severity of their consequences. Moreover, analyzing these risks represents an input to the risk evaluation step in the risk management process and to the risk treatment step [10]. Additionally, this paper provides inputs to several wind energy research fields such as the optimization of the WT performance [7,11,12], in which the cold climate operating conditions are a major contributor to degrading the performance of WFs installed in that region, which likewise applies to WT power curves [13,14], WT blades [15,16], and WT life [17,18] research fields.

Furthermore, this paper aims at providing an overall analysis and ranking of these risks, which can help designers of WFs, risk managers, and operators acquire a holistic image of the potential risks, which will contribute to the prioritizing of their decisions in case of the lack of sufficient data that is usually encountered in CCRs, due to the fact that wind energy applications in that region are relatively new [4].

One of the effective tools for analyzing and ranking risks in the absence of quantitative probability models is fuzzy logic [19]. Fuzzy logic can make use of experts' judgments and available data to model the inaccuracy and uncertainty in human thinking [20], which can create confusion when using vague linguistic terms such low, medium, high, etc. Risks are measured quantitatively using fuzzy logic, which increases the accuracy of ranking the risks and accurately prioritizes risk control measures. Fuzzy logic has been applied in different applications. For example, Fuzzy Failure Mode and Effects Analysis (Fuzzy FMEA) has been developed and applied by [19,21] to rank the failures in different WT components, and in determining the costs of failure to WTs [22]. Fuzzy logic was also used for risk assessment of pipelines transporting flammable substances [23], and offshore engineering systems [24].

This paper utilizes fuzzy logic and experts' judgments to rank six types of risks to and from WFs in CCRs, mainly in the Arctic region. Furthermore, the paper compares the ranking of the same risks to a similar WF that is installed in a non-cold-climate region, to demonstrate the Arctic effects on the WF.

The paper is organized as follows: Section 2 presents the methodology followed to analyze the risks. Section 3 explains the fuzzy logic process. Section 4 identifies six risks to WFs in CCRs. Section 5 defines the criteria for the risks, considering five levels of probabilities (very low, low, medium, high, very high) and four for the severity of consequences (low moderate, high, very high). Section 6 considers a WF in Arctic Norway as a case study to demonstrate the proposed methodology and ranks the six risks; finally, conclusions are presented in Section 7.

2. Methodology

The methodology adopted in this work, shown in Figure 1, starts with identifying the potential risks usually WFs in CCRs are subjected to. The risks-relevant literature and research are being reviewed to define criteria for the inputs to the risk analysis, which are the probabilities of occurrence and the severity of consequences of the identified risks. Afterwards, the defined criteria are sent to a selected group of experts who will provide estimated values (between 0 and 10) for the different levels of the probabilities and consequences, which represent the input to the risk analysis and for the risks' levels, which represents the output. Based on the data collected from the experts, and by using MATLAB fuzzy logic toolbox, membership functions are graphed to represent the levels of the inputs and the output.

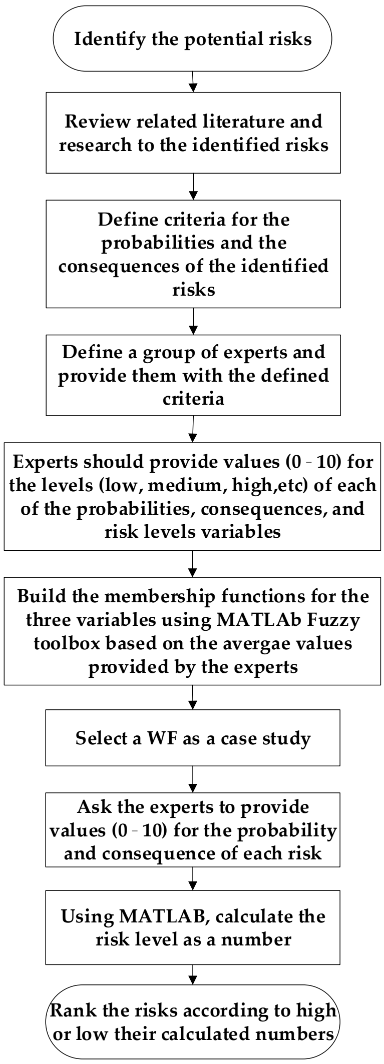

Figure 1. Methodology of analyzing risks to WFs in CCRs using fuzzy logic.

This methodology is implemented to a WF in Arctic Norway as a case study for demonstration. Initially, data regarding the WF are gathered from the WF operator, research articles, and weather stations that publish their data online. Afterwards, the collected data conceded to a selected group of experts, who are asked to quantitatively evaluate the corresponding probability of occurrence and severity of consequences of each of the identified risks on a scale from 0 to 10. Experts' judgments were then fed into MATLAB fuzzy logic toolbox, which calculated the risk level, using specifically defined rules. Eventually, the risks are ranked depending on the resulting risk level, the highest risk level was assigned a rank of (1) and the lowest risk was assigned a rank of (6).

3. Fuzzy Logic Process

Fuzzy logic is based on fuzzy set theory developed by Zadeh [25]. Fuzzy sets are a generalization of the classical set theory, indicating that the classical set theory is a special case of the fuzzy set theory [26]. Fuzzy logic is an efficient tool in risk assessment as it compensates for the lack of knowledge and vagueness encountered when assessing the risks related to complex technological systems, and can be very helpful when dealing with fuzzy linguistic terms such as low, medium, high, etc., to describe the risks, as these terms do not have sharp boundaries for their definitions and can hold different interpretations when interpreted by different experts [23].

For example, taking X as a universal set that contains all objects used in the risk analysis process. Probability, consequences, and risk levels are the input and output variables used in the risk analysis. Each one of these variables contains a number of objects (fuzzy terms) that were previously defined in X as follows:

X = {very low, low, medium, moderate, high, very high, moderate-high, extremely high}
Input variable (probability) = {very low, low, medium, high, very high}
Input variable (consequences) = {low, moderate, high, very high}
Output variable (risk level) = {very low, low, moderate, moderate-high, high, very high, and extremely high}

Each fuzzy term in the universal set X is described as a fuzzy subset (A), characterized by a membership function μ(x), which assigns to each object a degree of membership that has values between zero (no-membership) and one (complete membership). Based on that, a fuzzy subset A can be written as a set of pair: $A = \{(x,\mu_A(x)); x \in X\}$, where x is a numbering value provided by the experts to describe the input variable (i.e., the probability or the consequences) [23].

The fuzzy logic process followed in this paper is based on Mamdani method [27], which is the most commonly used method in fuzzy logic, using the center of gravity method to calculate the output value of the risk level during the defuzzification step, unlike the Sugeno method, which uses the weighted average method to calculate the risk level [28]. Figure 2 shows the three main steps (fuzzification, fuzzy logic inference, defuzzification) followed in applying the fuzzy logic process to calculate the risk level and ranking the risks [19]:

- Fuzzification: In this step experts are asked to provide values (x) for the input variables. The previously defined membership functions for each fuzzy subset (A) would indicate a certain degree of membership ($\mu_A(x)$) of x in the subset A. For example, a probability of a risk assigned a value of 5 by experts might indicate a 50% low and 50% medium degrees of membership. The same applies to the consequences input variable.
- Fuzzy logic inference: In this step a set of rules is established with the help of the experts to describe the output of the combinations of the input variables. By making use of fuzzy IF-THEN rules, the different combinations between probabilities and consequences of each risk can be represented. An example of such rules is: If the Probability of a risk is Low and the Consequences are High, Then the Risk level is Moderate.
- Defuzzification: This is a counter step to the fuzzification step, where the resulted fuzzy risk levels are converted, using MATLAB fuzzy logic toolbox, into numbers

reflecting how high or low the risk level is, where higher number reflects higher risk level and vice versa. Following this step, the risks to WFs can be ranked.

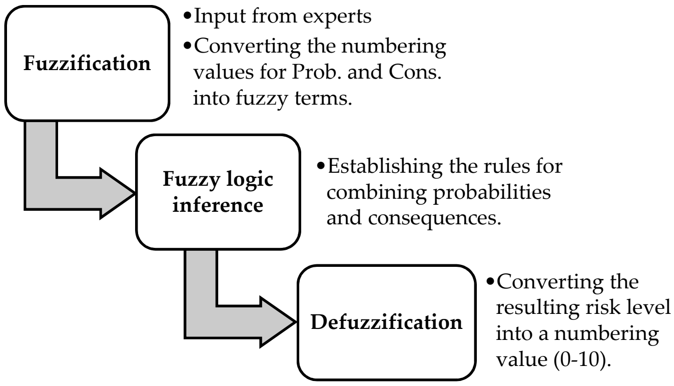

Figure 2. Overview of the fuzzy logic process.

4. Risks Identification

The risks to WFs in CCRs are mainly caused by the harsh weather conditions they experience, which degrade their overall performance and resilience. In addition, WFs impose risks on their surroundings, these risks can be associated with environmental concerns and social opposition to WFs being installed in CCRs, such as the Arctic region. The following description of the six risks will be used in Section 5 to define the criteria for the probabilities and consequences of the risks.

Risk 1. Increased WT stoppages due to harsh weather conditions (WT stoppage): Low temperatures affect the physical properties of materials and the normal operation of electronic devices [29], leading to increased failure rate in WT components. Lubrication oil viscosity, for example, changes under low temperatures and has an impact on the dimensions and mechanical properties of different components in the WT. This results in possible overheating and higher fatigue charges on components, with one of the most affected being the gearbox, as its lifetime is considerably reduced [30].

Moreover, ice accretion on WTs, which mostly takes place on the leading edge of the blades, increases mass and aerodynamic imbalances, and might render the operation of the WT unsafe, leading to the shutting down of the WT and the loss of power production until the ice is removed or melted [31]. The probability P of stoppages of WTs, due to failures and ice accretion, can be calculated using the Poisson distribution in Equation (1) [32]:

$$p(k;(0,t),\ \lambda) = \frac{(\lambda t)^k}{k!} e^{-\lambda t} \quad (1)$$

where λ denotes the rate of stoppages per WT per a specific period t (e.g., a month or a year), and k is the number of WT stoppages the distribution calculates the probability of.

Risk 2. Cold stress to workers (Cold stress): Cold temperatures cause cold stress to crew workers, and limit their dexterity [33]. Serious cold-related illnesses and injuries, caused by trench foot, frostbite, and hypothermia, may occur in case of extreme cold temperatures, in addition to permanent tissue damage, and death that may result as a consequence to major cold-related injuries.

High wind speeds and cold temperatures are the two main factors contributing to cold stress to workers [34]. Wind Chill Temperature (WCT) is a measure that determines the likelihood that workers are subjected to the risk of frostbite, which can be calculated using Equation (2), where V is the wind speed (km/h) 10 m above the surface and T is the air temperature (°C) [34]:

$$WCT[^\circ C] = 13.12 + 0.621T - 11.37V^{0.16} + 0.3965TV^{0.16} \quad (2)$$

Table 1 has been generated using Equation (2). The table is used to determine whether the workers at WFs in CCRs are subjected to the risk of frostbite or not, where the shaded region indicates an increasing risk of frostbite [34].

Table 1. Wind chill temperature (WCT) chart.

		Air Temperature (°C)												
		10	**5**	**0**	**−5**	**−10**	**−15**	**−20**	**−25**	**−30**	**−35**	**−40**	**−45**	**−50**
Wind Speed (km/h)	**10**	9	3	−3	−9	−15	−21	−27	−33	−39	−45	−51	−57	−63
	15	8	2	−4	−11	−17	−23	−29	−35	−41	−48	−54	−60	−66
	20	7	1	−5	−12	−18	−24	−31	−37	−43	−49	−56	−62	−68
	25	7	1	−6	−12	−19	−25	−32	−38	−45	−51	−57	−64	−70
	30	7	0	−7	−13	−19	−26	−33	−39	−46	−52	−59	−65	−72
	35	6	0	−7	−14	−20	−27	−33	−40	−47	−53	−60	−66	−73
	40	6	−1	−7	−14	−21	−27	−34	−41	−48	−54	−61	−68	−74
	45	6	−1	−8	−15	−21	−28	−35	−42	−48	−55	−62	−69	−75
	50	6	−1	−8	−15	−22	−29	−35	−42	−49	−56	−63	−70	−76
	55	5	−2	−9	−15	−22	−29	−36	−43	−50	−57	−63	−70	−77
	60	5	−2	−9	−16	−23	−30	−37	−43	−50	−57	−64	−71	−78
	70	5	−2	−9	−16	−23	−30	−37	−44	−51	−59	−66	−73	−80
	80	4	−3	−10	−17	−24	−31	−38	−45	−52	−60	−67	−74	−81

Risk 3. Limited accessibility to wind farms due to snow cover: CCRs are known for their diverse landscape, especially the Arctic region, including tundra, glaciers and steep mountains. The Arctic terrain can be challenging to move around. Snow accumulation on WFs roads and pathways will reduce accessibility to the WTs, this is especially significant when it comes to the maintainability of WTs, which might be reduced under such conditions [4]. The severity of snow accumulation determines whether the WF needs to implement snow removal strategies, using special snow removal vehicles, or if it would be enough to use specially equipped vehicles to access the WTs, such as snow mobiles and snowcats, in case normal vehicles were not useable.

Risk 4. Thrown ice pieces from operational wind turbines (Ice throw): This phenomenon can occur when pieces of ice are either thrown away from an operational WT, see Figure 3, due to the aerodynamic and centrifugal forces, or dropped down if the WT was idle. In both cases, ice pieces landing on the ground will represent a hazard to the safety of the WF including the WTs, WF facilities, crew personnel, and animals [8]. A simple equation (Equation (3)) can be used to measure the distance of thrown ice pieces from an operational WT as follows [35]:

$$d = 1.5\ (D + H) \quad (3)$$

where (d) is the throwing distance, (D) is the rotor blade diameter, and (H) is the hub height.

Figure 3. Ice piece thrown from a WT in Arctic Norway WF [36]. Reprint with permission from author [Matthew Homola], 2022, NTNU Norwegian University of Science and Technology.

The probability of ice throw from operational WTs depends on the probability of ice formation on the WT blades, the probability of being thrown away to a location where ice pieces may represent a hazard to WF surroundings, and the probability of members of the public, crew personnel, and animals being present within the range of landing ice pieces [37]. The probability of ice accretion on WT blades depends on many factors such as the air temperature, wind speed, liquid water content (LWC), median volume diameter (MVD), and the elevation of WT from the sea level [38].

Rime ice and glaze ice are the two most common types of ice to accrete on the blades of WTs. Rime ice forms when supercooled water droplets freeze immediately upon impacting the surface of the blade, while glaze ice forms when the liquid water freezes shortly after impacting the surface of the blade [39]. Glaze ice accretion forms near the freezing point (0 °C) and has strong adhesion to the surface; it is transparent and has a higher density than rime ice. On the other hand, rime ice has lower adhesion to the surface and has a white or opaque color [40].

The probability of ice formation on WTs can be reflected by estimating the daily intensity of the icing events in kg/m^2. Table 2 summarizes five site icing index categories that can be used to determine the intensity of icing on WTs in the WF location on a daily basis [41].

Table 2. Site icing index categories.

Site Icing Index	Intensity of Icing kg/m^2/day	Icing Severity
S1	>120	Heavy
S2	61–120	Strong
S3	25–60	Moderate
S4	12–24	Light
S5	0–12	Occasional

Risk 5. Environmental risks: The Arctic, as an example of CCR, is known for its sensitive environment. Locating WFs in the Arctic will lead to possible impacts on the critical habitats and threatened species. For example, bird mortalities caused by WTs have been debatable [42] for several years, even though it is stated that wind energy killed 20 times fewer birds compared to fossil fuels, and the number of birds killed by WTs can be negligible compared to some other human activities [43]. In addition, the construction phase of wind farms might result in pollution of nearby surface or underground water [44]. Similarly, the use of liquids such as the gearbox lubricating oil might result in pollution in case it leaked from the WT. Moreover, the Arctic area is known for reindeer grazing, therefore, having WFs built on winter grazing areas for reindeer might affect their density, especially during the construction phase or even after it.

Risk 6. Social opposition: The visual presence of WTs can be annoying, especially to residents living nearby WFs. The presence of WFs might stop or limit the ability of local communities to utilize the surrounding lands and might affect its economy [45]. In addition, the generated noise by WTs might be annoying to residents living nearby WFs. The sources of the generated noise by WTs are the mechanical components such as the gearbox and control mechanisms, and the rotation of the WT blades through the air. Noise levels are measured by decibels (dB(A)), which is a scale designed to measure how the human ear perceives the sound frequencies. The day–evening–night noise level (L_{den}) is a European standard to express the noise levels from machines throughout an entire day [46]. The institution of occupational safety and health (IOSH) designed a scale for classifying noise levels [47], which can be used to assess the severity of noise emitted by WTs, as shown in Table 3.

Table 3. Noise levels classification.

WF Noise Level Class	Noise Level L_{den} dB(A)
Very low	0–40
Low	41–70
Medium	71–100
High	101–140
Very high	>140

5. Probabilities of Risk Occurrence and Severity of Consequences Criteria

Table 4 determines the criteria for estimating the probability of each of the identified risks. The criteria are based on reviewed research studies, measured data, and human evidence. Selecting the probability level for each risk type is primarily dependent on the WT or WF under the study.

Table 4. Criteria for the probabilities of risks experienced by WFs in CCRs.

Risk	Very Low (Vl)	Low	Medium	High	Very High (Vh)
Increased WT stoppage rate [48]	The probability of stoppage using Equation (1) is between 0–20%	The probability of stoppage using Equation (1) is between 21–40%	The probability of stoppage using Equation (1) is between 41–60%	The probability of stoppage using Equation (1) is between 61–80%	The probability of stoppage using Equation (1) is between 81–100%
Cold stress [34]	Mild wind chill conditions. The wind chill temperature can be larger or equal to −10 °C WCT ≥ −10 °C	Low wind chill temperature −10 °C > WCT ≥ −25 °C	Very cold wind chill temperature −25 °C > WCT ≥ −35 °C	Danger of frost bite −35 °C > WCT ≥ −60 °C	Great danger of frostbite WCT < −60 °C
Limited accessibility [4]	No snow cover on the roads. The WF is easily accessible.	The roads of the WF are covered with snow but is still accessible with normal cars.	Accessing the WF requires the use of snowcats and snow mobiles due to snow cover.	There is a need to remove the snow off the road using special vehicles and equipment such as snowplows, blowers, loaders, and deicer trucks, etc.	The accessibility is very low due to extreme weather conditions and excessive snow cover on the roads.
Ice throw [41]	The site icing index according to Table 2 is S5, indicating occasional icing. No roads, residential areas, or facilities are in the range of thrown ice pieces.	The site icing index according to Table 2 is S4, indicating light icing. Most roads residential areas, and facilities are not in the range of thrown ice pieces.	The site icing index according to Table 2 is S3, indicating moderate icing. Roads and facilities in the surroundings are in the range of thrown ice pieces.	The site icing index according to Table 2 is S2, indicating strong icing. The probability of being hit by ice pieces is high.	Excessive ice accretion on the WT blades, S1. the main road is very close to the WF site; therefore, surroundings are in great danger of being struck by ice pieces thrown from the WTs.
Environmental risks	The WF is not built on a migration route for birds and is not built on winter grazing area for reindeer. No records of water or environmental pollution by the WF exist.	The WF is built on a migration route for birds and on a winter grazing area for reindeer, but the effects are not significant. No records of water or environmental pollution by the WF exist.	The WF is built on a migration route for birds and on a winter grazing area for reindeer and affect their existence. No records of water or environmental pollution by the WF exist.	The WF is built on a migration route for birds and on a winter grazing area for reindeer and affect their existence significantly high. There is a record of water and environmental pollution by the WF.	The WF affects the existence of migrating birds and reindeer density in the area very significantly, with significant water and environmental pollution record by the WF.
Social Opposition [45,49]	The WF is located far from residential areas, does not have an impact on the livelihood of local communities, and the noise level is very low, L_{den} = 0–40 dB(A).	The WF is located far from residential areas, does not have an impact on the livelihood of local communities, and the noise level is low, L_{den} = 41–70 dB(A).	The WF is located near residential areas, with bearable effects on the livelihood of local communities, and the noise level is moderate, L_{den} = 71–100 dB(A).	The WF is located near residential areas, with high effects on the livelihood of local communities, and the noise level is high, L_{den} = 101–140 dB(A).	The WF is located close to residential areas, with very high effects on the livelihood of local communities, and the noise level is very high, L_{den} > 140 dB(A).

Table 5 shows the criteria selected for measuring the consequences of the identified six risks. The consequences of risks are defined differently based on the type of risk being assessed. The consequences can be evaluated depending on the resulting system deterioration, injuries or loss of lives, maintenance delays, and short- or long-term effects.

Table 5. Criteria for the consequences of risks experienced by WFs in CCRs.

Risk	Low	Moderate	High	Very High
Increased WT stoppage [21]	The WT stoppage did not cause deterioration in the WF operation and was slightly noticed by the operator.	The WT stoppage caused slight deterioration in the WF performance and was highly noticeable by the operator.	The WT stoppage was caused by a failure that significantly deteriorated the WF performance or led to minor injuries to humans nearby.	The WT stoppage would seriously affect the ability of the WF to continue operating, or cause damage, serious injury or death.
Cold stress [50]	No injury or illness.	Minor injury or minor occupational illness.	Medium injury or medium occupational illness.	Serious injury or death of humans.
Limited accessibility [51]	No delay in carrying out maintenance activities to the failed WTs.	Maintenance is slightly delayed, with slight loss of power production	Maintenance is significantly delayed, with significant loss of power production.	Maintenance of the failed WT is highly delayed, with so highly increased power losses.
Ice throw [50]	No injury or illness.	Minor injury or minor occupational illness.	Medium injury or medium occupational illness.	Serious injury or death of humans.
Environmental risks [50]	Minor environmental damage, readily repaired and/or might incur slight costs to correct and/or in penalties.	Short-term environmental damage, with slight costs to correct and/or in penalties.	Medium-term environmental damage, with significant costs to correct and/or in penalties.	Long-term environmental damage, with very high costs to correct and/or in penalties.
Social Opposition [50]	The WF has minor effects on the touristic activities in the area. The WF noise levels do not cause hearing impairments.	The WF has short-term effects on the touristic activities in the area. The WF noise levels cause minor hearing impairments.	The WF has medium-term effects on the touristic activities in the area. The WF noise levels cause severe hearing impairments.	The WF has long-term effects on the touristic activities in the area. The WF noise levels might cause permanent hearing loss.

6. Experts' Judgments

The preceding criteria were sent to seven experts, who were asked to provide their range of values for each fuzzy linguistic term used to assess the probability (Very low (Vl), Low, Medium, high, Very high (Vh)) and the consequences (Low, Moderate, High, Very high) term, as well as the risk levels, which are described as Very low (Vl), Low (L), Moderate (M), Moderate-high(MH), High(H), Very high (Vh), and Extremely high (Eh). Afterwards, the data gathered from the experts were used to design the membership functions that reflected these fuzzy terms.

The selected experts have backgrounds ranging from university professors working on wind energy to experienced staff at wind farms in Arctic Norway. Experts were assumed to have equal weights for their answers. Based on the average values for the probabilities, consequences, and risk levels collected from the experts, and by using MATLAB fuzzy logic toolbox, the triangular membership functions for the input variables (i.e., probabilities and consequences) and the output variable (the risk levels) were defined, as shown in Figures 4 and 5, where the x-axis represents the input values provided by the experts (from 0 to 10), and the y-axis represents the degree of membership (from 0 to 1) for each membership function. The combination between these three variables can be represented by a 3-dimensional surface plot, in Figure 6, which shows a fuzzy risk matrix.

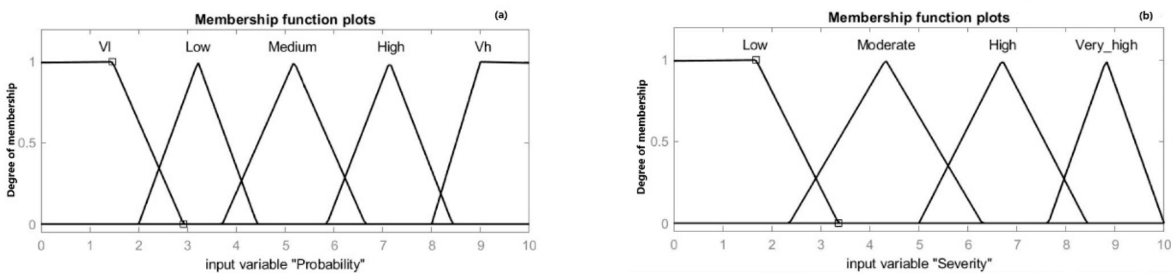

Figure 4. Membership functions of probabilities (**a**) and consequences (**b**) of risks based on experts' judgments.

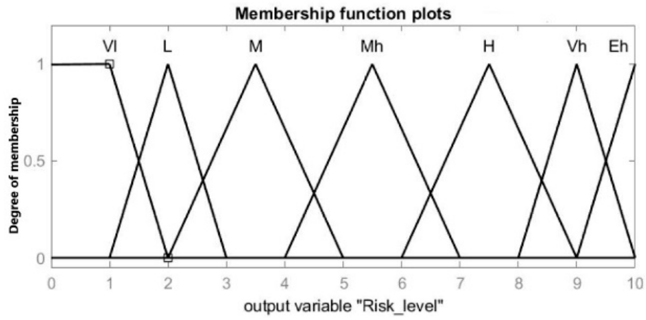

Figure 5. The membership functions of risk levels based on experts' judgments.

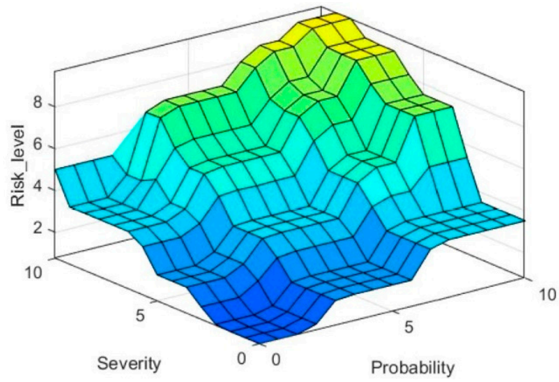

Figure 6. Fuzzy risk matrix combining the three variables for risk analysis.

For more illustration, the y-axis in Figure 4a,b represents the degree to which a certain input (a probability or a consequence) can be described as low, medium, high, etc. For example, if the average value of the probability of a certain risk, given by experts, was 5, that means that the degree of membership of the probability of that risk is 80% medium, as per Figure 4a. Similarly, if the severity of a specific risk was determined by experts to be 9, that means that the severity of that risk is 100% very high, as per Figure 4b. Following that, the defined inference rules will determine the level of the risk in fuzzy terms. A logical inference rule that applies to this example can be: if the probability is medium and severity is very high, then risk level is high. The degree of membership of the risk level is determined using the minimum operator as in Equation (4) [20]:

$$\mu\ (\text{Risk is high}) = \min\ (0.8; 1) = 0.8 \tag{4}$$

where μ (Risk is high) is the degree of membership of the risk level as a high risk. Afterwards, the risk level is determined by referring to Figure 5, where the *x*-axis value for the risk level that corresponds to 80% high risk is equal to 7.5.

The fuzzy inference functions in MATLAB used in this risk analysis application are shown in Table 6. The membership functions defined by the experts are used to generate the fuzzy rules that will be used to rank the risks. A total of 5×4 = 20 rules were generated. Examples of these rules are as follows:

- *Rule 1*: If probability is very low and consequence is low, then the risk level is very low.
- *Rule 11*: If probability is medium and consequence is high, then the risk level is moderate-high.
- *Rule 19*: If probability is very high and consequence is high, then the risk level is very high.

Table 6. MATLAB fuzzy inference functions used.

Type	andMethod	orMethod	defuzzMethod	impMethod	aggMethod
Mamdani	min	max	centroid	min	max

A detailed description of the WF was sent to the experts, who were asked to provide their numeric values for the probabilities and consequences of each risk. Afterwards, the fuzzy logic toolbox in MATLAB was used to calculate the risk level using the centroid method [52]. Figure 7 illustrates the different probability and consequence combinations, based on the defined 20 fuzzy rules, to calculate the risk level values.

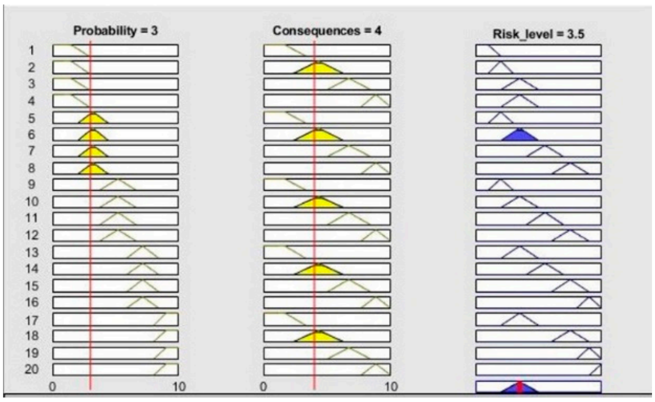

Figure 7. Rules of probabilities and consequences for risk level calculation.

Case Study: Wind farm in Arctic Norway

A WF in Arctic Norway, with a layout shown in Figure 8, was selected to demonstrate the proposed methodology. The selected WF is located in a valley at around 420 m above the sea level. The WF consists of fourteen 2.3 MW WTs. In order to support the experts in their estimations, operational and site specifications data about the WF were acquired from different sources. For example, data regarding failure rates, icing rates, maintenance reports, and WTs performance were acquired from the WF operator; this data covered two years of WF operation, from 2019 to 2020. In addition, data regarding the WF's site specifications and weather data were acquired from published research articles and manufacturers' technical publications, as well as weather stations that publish their data online.

Figure 8. Wind farm location and layout.

6.1. Analysis

MATLAB fuzzy logic toolbox was utilized to calculate the level of each risk on the basis of the average values of the probabilities and consequences of each risk provided by the experts. Table 7 shows the average probability and consequence values determined by the experts as well as the resulting risk level calculated by MATLAB. In addition, the table shows the ranking of the risks, where limited accessibility to WF risk is assigned the highest rank (1), and social opposition risk is assigned the lowest rank (6).

Table 7. Ranking of risks considering average values of probabilities, consequences, and risk levels.

Risks	Probabilities	Consequences	Risk Levels	Risks Ranks
Risk 1 (WT stoppage)	2.9	5.4	4.19	2
Risk 2 (Cold stress)	3.6	2.7	2.66	4
Risk 3 (Limited accessibility)	7.4	7.8	7.76	1
Risk 4 (Ice throw)	3.5	1.7	2	5
Risk 5 (Environmental risks)	3.7	4	3.5	3
Risk 6 (Social opposition)	1.8	2.3	0.826	6

Risk 1 (WT stoppage). From the data gathered from the WF operator, there were 1993 stoppages experienced by the WTs during 2019, mainly due to maintenance. In addition, December 2019 was the month that witnessed the highest rate of WT stoppages due to icing, which was 65 stoppages. Equation (1) was applied separately to determine the probability of stoppage per WT per month due to failure and per month due to icing. It was found out that the probability of stoppage was 29% per WT per month. Those stoppages did not result in deterioration of the WF production and operation was resumed as regular, according to the WF operator.

Risk 2 (Cold stress). The coldest average ambient temperatures impacting the WF occur during January, February, and March, according to Figure 9a, with the coldest average temperature of as low as nearly −12 °C recorded in February. In addition, the average monthly wind speed during the same month is 13.6 km/h, as shown in Figure 9b [53]. By applying Equation (2), the WCT during February is calculated to be about −19 °C, which indicates no risk of frostbite to workers at the WF. In addition, according to the WF operator, there are no injuries recorded or illnesses caused to workers at the WF by very cold WCTs.

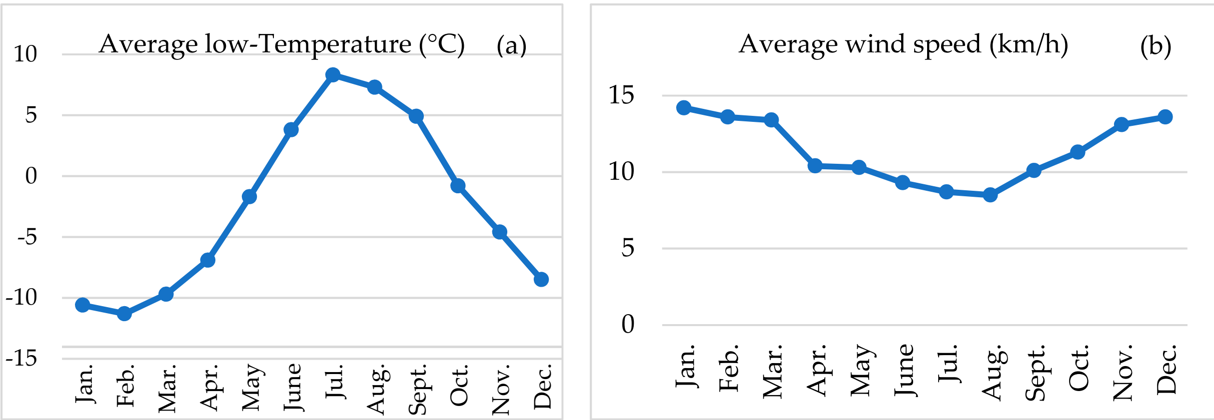

Figure 9. Monthly average temperatures (**a**) and wind speeds (**b**) at the WF's location [54]. Data were gathered from Weather Atlas.

Risk 3 (Limited accessibility). The Norwegian Meteorological Institute [55] provides information about the snow depth of specific sites in Norway through weather stations distributed in different areas of the country. The closest weather station to the WF is located in Straumsnes. Figure 10 shows that the highest recorded snow depth in 2020 occurred during February until May, with a maximum snow depth of 75 cm recorded in April. Such accumulation of snow requires specially equipped vehicles, such as snowcats and snowmobiles to be available all the time, to maintain access to the WF under severe weather conditions, which was confirmed by the WF operator during a visit to the WF by the authors. Besides that, during periods of peak snow accumulation, snow removal strategies are implemented, which can be costly [4].

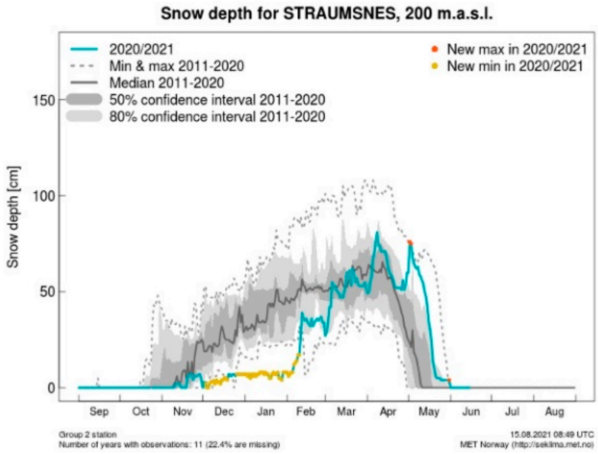

Figure 10. Snow depth in an area close to the WF [55].

Risk 4 (Ice throw). A field study shows that the daily intensity of icing in Narvik, a city close to the WF, is approximately 14.5–18.5 kg/m^2 during January, February, and March, as shown in Figure 11 [56]; those measurements can be assumed close enough to be applicable to the site under consideration. This indicates a light icing intensity with site icing index for the WF site, according to Table 1. By applying Equation (3) to calculate the throwing distance of ice pieces, it is found that the throwing distance is 255 m. The closest residential area to the WF is kilometers away. Moreover, a main road passes next to the WF, but it is around 500 m away from the closest WT, which means that no residents or personnel exist within the range of ice throw risk.

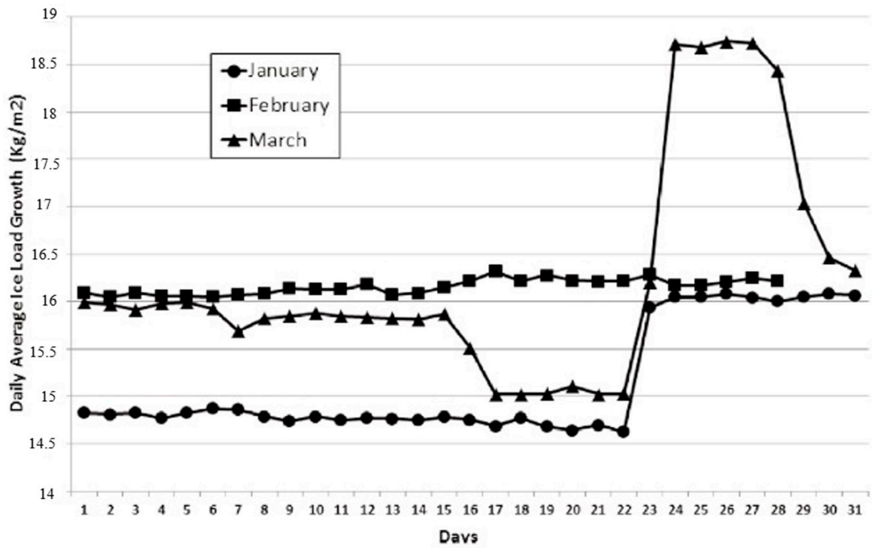

Figure 11. Icing intensity close to the WF site during January, February, and March [56]. Reprint with permission from author [Muhammad S. Virk], 2022, The International Journal of Ocean and Climate Systems.

Risk 5 (Environmental risks). A study by Jacobsen et.al. [57] revealed that the number of registered birds migrating through the WF area was low, where the average number of observed birds passing through the WF was around five birds during 4 h of observation in a day. This is primarily due to the topography and local conditions of that area, which is not inviting to migrating birds. However, the area around the WF has great value for reindeer husbandry and is used for reindeer grazing during autumn and winter. In this respect, field results show that the density of reindeer in WF areas in Arctic Norway do not change significantly, and that reindeer can adapt and keep using WF areas for grazing [58]. With regards to environmental pollution, there is no evidence that the WF caused pollution to nearby waters or to the environment in general.

Risk 6 (Social opposition). The presence of the WTs and the noise they generate are not expected to cause annoyance to humans due to the fact that the WF is located away from residential areas, in a valley with surrounding mountains as high as 2000 m above sea level from the north and south. Besides, the location of the WF is not classified as a touristic area. However, there is a main road that passes next to the WF, which means that drivers and passengers passing by the WF will be subjected to this noise level for very short time. According to one study, the level of noise generated by a similar WT located at approximately 500 m far, which is nearly the distance between the closest WT and the main road, would be 48 dB(A) at a wind speed of 10 m/s [59], meaning that the noise severity can be described as low.

6.2. A Wind Farm under Normal Operating Conditions

In order to compare the effects of cold climate operating conditions on the calculated risk level and ranking of risks, the same methodology is applied to a WF located in a non-cold-climate region. The Kozbeyli WF [45], in Turkey has higher reliability, with lower rate of WT stoppages, no ice accretion on the blades of the WTs, less snow accumulation on the roads of the WF, and a 3.1 km access road built to guarantee access to the WF. However, the WF is close to an Environmentally Protected Area in Foça, with a bird migration route 4 km to the south of the WF [60]. Moreover, in the WF area, there are endangered species such as Passer Domesticus and Crocidura Russula, that were identified and listed by the Bern Convention [45].

Furthermore, the WF is located 1.3 km near to a touristic village, which has natural and historical values. Social acceptance of the WF was determined to be poor due to its impact on tourism in that area. Based on the preceding information, Table 8 demonstrates the ranking of risks using experts' judgments and MATLAB fuzzy logic toolbox. It can be seen from the table that the social opposition risk ranked the highest, followed by the environmental risks, while the risk of ice throw from WTs ranked as the lowest risk, flowed by the risk of WT stoppage.

Table 8. Ranking of risks for the Kozbeyli WF in Turkey using experts' judgments and fuzzy logic.

Risks	Probabilities	Consequences	Risk Level	Risk Rank
Risk 1 (WT stoppage)	1.8	4.6	2	5
Risk 2 (Cold stress)	2.2	3.4	2.57	3
Risk 3 (Limited accessibility)	2.8	2.6	2.32	4
Risk 4 (Ice throw)	1	1	0.752	6
Risk 5 (Environmental risks)	6.8	7.6	7.5	2
Risk 6 (Social opposition)	8.3	8.9	9.31	1

7. Conclusions

In this paper, six types of risks that are related to the operation of WFs in CCRs. These risks were distinguished as being caused by the harsh weather conditions, and risks caused by the WFs on their surrounding environment and community. The identified risks were analyzed using expert judgment and MATLAB fuzzy logic toolbox. The identified risks are the increased WT stoppages risk, cold stress to workers risk, limited accessibility to WFs risk due to snow accumulations on the roads, ice throw from WTs risk, environmental risks, and social opposition risk.

Based on a research review, gathered data, and published data, and experts' reasoning, two criteria tables were defined for the probability of occurrence and the severity of consequences of each risk. Furthermore, experts' judgments and MATLAB fuzzy logic toolbox were used to graph the membership functions for the probabilities and consequences of each risk (the inputs), as well as risk levels (the output). The risk levels were calculated based on a set of 20 rules generated using the experts' data.

A WF in Arctic Norway was selected to illustrate the proposed methodology. Experts were provided with a description of the WF and were asked to deliver their assessed values for the probabilities and consequences of each risk. Through the calculated risk level, it was concluded that limited accessibility to the WF ranked as the highest risk, followed by WT stoppage. On the other hand, social opposition was ranked as the lowest risk followed by the ice throw.

In order to demonstrate the methodology further, a WF that is not subjected to cold climate operating conditions, located in Turkey, was selected. The social opposition to the WF was ranked as the highest risk followed by the environmental risks, where the ice throw risk and WT stoppage risk were deemed to be the lowest-ranked risks. This was due to the fact that the Turkish WF was installed close to a village with touristic value and in a area that is a home for endangered species.

Author Contributions: A.M.M. developed the methodology, conducted the literature review, and gathered the data to establish the probabilities and consequences criteria, gathered the data from the experts, performed the risk analysis using MATLAB fuzzy logic toolbox, and wrote the paper; A.B., as a main supervisor, followed up all study steps and gave helpful guidance and reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data gathered from the wind farm are subjected to a non-disclosure agreement. Therefore, an approval from the wind farm is required in case the data are needed. The data gathered from the experts can be provided upon request from the editors.

Conflicts of Interest: The authors announce no conflict of interest.

Nomenclature

WT	Wind turbine
WF	Wind farm
CCR	Cold climate region
X	Universal set
A	A fuzzy subset
$\mu(x)$	Membership function
λ	Stoppage rate per wind turbine per year
L_{den}	day–evening–night noise level
WCT	Wind chill temperature
V	Wind speed (km/h)
T	Air temperature (°C)
P	probability
dB(A)	decibels
IOSH	The institution of occupational safety and health

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Paper 4

Risk assessment of wind farm development in ice proven area

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Risk Assessment of Wind Farm Development in Ice Proven Area

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ABSTRACT

There many risks associated with wind farms operating in cold harsh areas, a number of these risks is caused by icing. Atmospheric and super-structure icing can cause ice accretion on wind turbines' structure, and lead to public safety risks caused by ice throw and the failure of wind turbine's components. Other risks can affect wind farm's maintenance crew and their activities. Such risks are caused by snow accumulation and forming of sea ice, which can lead to limiting the access to wind turbines, and reducing their availability and the overall power production of the wind farm.

Snow accumulation and ice accretion on wind turbines specifically and the wind farm generally induce different types of risks. Therefore, an analysis should be carried out to determine how the different types of icing and snow accumulation affect each part of a wind turbine and wind farm. A risk matrix is usually utilized to determine the rank of these risks and prioritize them, which will help in the decision-making process for risk mitigation.

KEYWORDS: Wind farm safety; Public safety; Icing types; Icing effects; Risk matrix.

1. INTRODUCTION

The global average capacity of installed wind power throughout the past couple of years exceeded 50 GW per year, where 2015 marked a record-breaking year in which the global installed wind power capacity exceeded 60 GW (Sawyer, 2017). It is expected that the growth of installed wind power will exceed 840 GW by 2022, this will be supported by an increased growth in the installed capacity of offshore wind turbines, which only represented 3.5% of global installed capacity in 2017 (Sawyer, 2018). Figure 1 illustrates the projected wind power capacity in Gigawatt (GW) to be installed during the following four years until 2022. It is noticed from the figure that the cumulative installed wind power capacity will grow at nearly a constant rate of 10% until 2022.

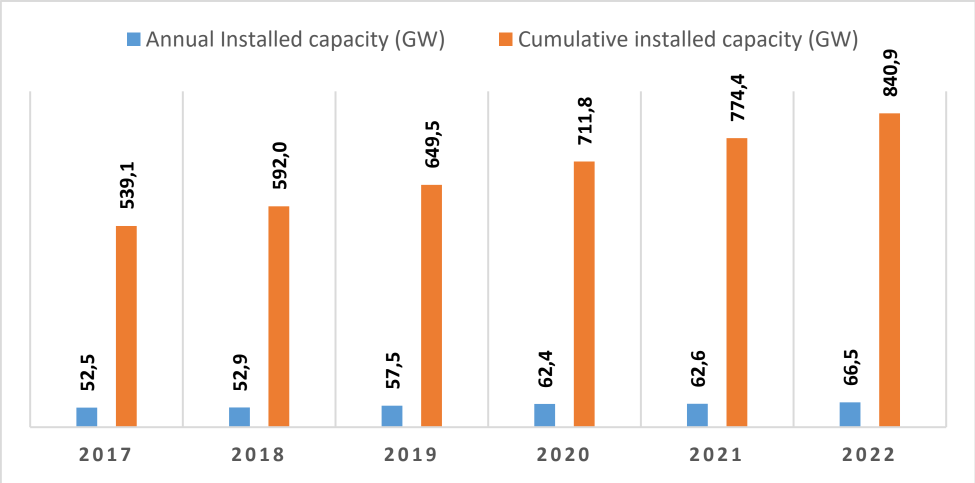

Figure 1. Annual and cumulative wind power forecast, reproduced from (Sawyer, 2018)

Air density in the arctic is higher compared to the other regions. According to (Tammelin and Säntti, 1996), air at -30 °C is almost 27% denser than at 35 °C. Knowing that power output of a wind turbine is proportional to air density, the available wind power in Arctic is almost 10% higher than in other regions (Fortin et al., 2005). Therefore, northern areas in Norway are appealing for wind energy investments. For example, Kvitfjell/ Raudfjell Wind Park, located in Troms County in Norway, will be launched in November 2019. Kvitfjell wind farm consists of 67 wind turbines, each with 4.2 MW capacity, a total of 281 MW (Sivam et al., 2018). To develop an effective and safe offshore wind farm, the available experience of onshore wind farms plays an important role.

2. ICE TYPES AFFECTING WIND FARMS

Ice accretion can be categorized into atmospheric icing and super structure icing caused by sea water sprayed on the wind turbine's structure during low temperatures, forming ice on it. Onshore structures like wind turbines and power lines are affected by atmospheric icing. Offshore stationary structures like offshore wind turbines and oil drilling platforms are affected by both types of icing (Battisti et al., 2006). Moreover, a third category of ice can be added to this classification of ice types affecting offshore wind turbines, which is land-fast and floating frozen sea water applying static and dynamic loads on the foundation and the tower of the wind turbine. Figure 2 shows the classes of ice affecting onshore and offshore wind farms. Following is an analysis regarding which of the main components (foundation, tower, nacelle and blades) of a wind turbine operating under icing conditions are mostly affected by the different types of icing. The analysis is summarized in Table 1, where the sign (✓) indicates the type of icing that affects each wind turbine's component. Moreover, different aspects of effects and risks are furtherly discussed in Section 3.0.

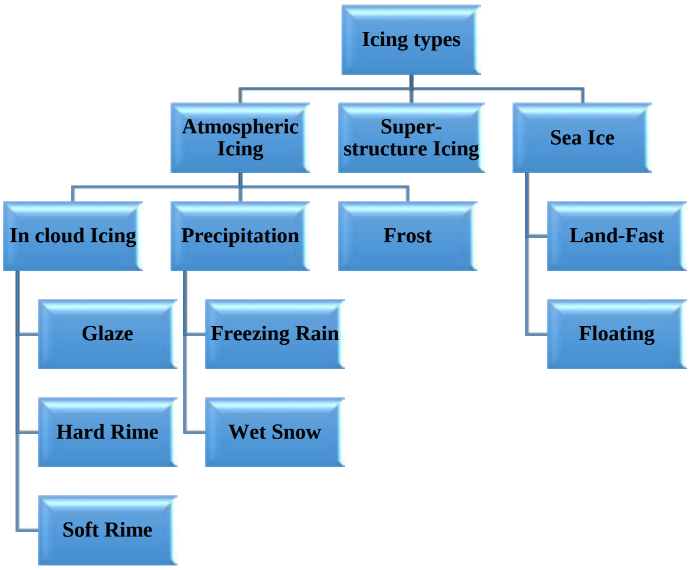

Figure 2. Ice types affecting onshore and offshore wind turbines

2.1. Atmospheric Icing

The process of atmospheric icing formation is that super cooled water particles in the form of droplets and drizzle or rain at temperatures ranging between -15 °C and 0 °C are found in the atmosphere (Ingvaldsen, 2017). These particles freeze immediately upon hitting a surface exposed to the atmosphere. Atmospheric icing can be divided into three types: In-cloud icing, precipitation and frost (Parent and Ilinca, 2011).

The main icing types of interest when it comes to ice build-up or ice affecting wind turbines' structure and performance are in-cloud icing and precipitation icing. Frost has very low density and persistency and is believed to not cause any problems to wind turbines (Dalili et al., 2009). Therefore, frost is excluded from the following analysis and from Table 1.

2.1.1. ***In-cloud icing***: includes rime ice and glaze ice (Parent and Ilinca, 2011). Several factors like liquid water content (LWC), median volume diameter (MVD) of water droplets, wind speed, pressure, temperature, etc. determine the form of in-cloud icing.

A. *Glaze ice*: often associated with precipitation, and can be witnessed mostly on flat surfaces such as the top of the nacelle (Parent and Ilinca, 2011). It forms when portion of water droplets does not freeze immediately upon impact, but runs back on the surface and freezes later. The resulting ice density and hardness is very high, which makes it difficult to remove. Glaze can also, with the presence of wind, accumulate on vertical surfaces, such as the tower and blades when facing the wind direction.

B. *Rime ice* is the most common type of in-cloud icing, and is classified into soft rime and hard rime (Ryerson, 2011). Soft rime has lower density and adhesion than hard rime. Hard rime is more difficult to remove. The probability and frequency of rime ice formation depends on the geographical location and elevation of the wind farm. Rime ice accumulates on objects facing the wind like the wind turbine's blades and tower, smaller diameter objects have higher collection efficiency of rime ice, such as cables, stair case railings and lattice structures which is a form of offshore wind turbines' towers (Sundina, 1998).

2.1.2. ***Precipitation***: consists of rain or snow freezing upon impact with below zero ^{o}C surface, forming freezing rain and wet snow (Ryerson, 2011). The accretion rate from precipitation can be much higher than in-cloud icing. Wet snow and freezing rain accumulate mostly on all components of a wind turbine, especially on horizontal surfaces such as top of the nacelle. In case of severe precipitation, snow can add considerable weight to the wind turbine's structure. Snow and freezing rain accumulate also on the wind turbine's foundation and wind farm's roads, which makes it even more challenging for maintenance crews to reach wind turbines and perform the needed maintenance. Moreover, snow occurs during sea-spray icing and can enhance superstructure ice accumulation.

2.2. Super structure icing:

In an open sea where offshore wind turbines are installed, ice accretion becomes a complex phenomenon as both types of icing i.e. atmospheric and superstructure icing take place (Battisti et al., 2006). However, the intensity of superstructure ice accretion on wind turbine blades depend highly on the elevation of the wind turbine above sea level and the type and size of the wind turbine. In case the offshore wind turbine elevation was relatively low, sea water can spray on the blade's tip when it is pointing downward, and if air temperature was below freezing, ice accumulates on the lower part of the tower and the blade tip. Sea spray ice can form on the wind turbine of up to 16 meters above the sea surface. However, it is expected that waves can carry sea spray above that limit.

		Atmospheric Icing				Super Structure Icing	Sea Ice
		In-Cloud Icing		Precipitation			
Configuration	Component	Glaze	Rime	Wet Snow	Freezing Rain	(Sea Spray Ice)	
Onshore Wind Turbine	Blades	✓	✓	✓	✓		
	Tower	✓	✓	✓	✓		
	Nacelle	✓		✓	✓		
	Foundation			✓	✓		
Offshore Wind Turbine	Blades	✓	✓			✓	
	Tower	✓	✓			✓	✓
	Nacelle		✓	✓	✓		
	Foundation					✓	✓

Table 1. Wind turbine main components affected by different types of icing

3. ICING EFFECT ON WIND TURBINE AND WIND FARM

Ice effects on a wind farm can be categorized into four main aspects:

- Mechanical equipment performance
- Operation and maintenance crew performance
- Wind farm accessibility
- Public safety risks

3.1. Mechanical equipment performance

Generally, an equipment performance is a function of reliability, maintainability (how easy the failed component can be repaired), which are both main factors comprising the availability performance of an equipment such as a wind turbine. Therefore, fast and frequent maintenance is important in keeping the wind turbine functioning and in minimizing the loss of power production. Figure 3 shows the relationship between production performance and availability and functional performance (Markeset, 2010).

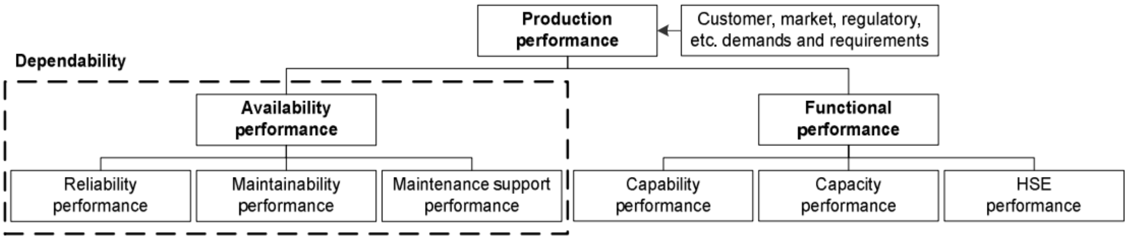

Figure 3: Production performance concept (Markeset, 2010)

Icing may reduce the reliability of wind turbine's components, decrease their maintainability, reducing the availability of the wind turbine as a result (Markeset, 2010). Furthermore, icing can reduce the capability, capacity and HSE performance of the wind farm, affecting its functional performance and resulting in loss of power production. In addition, icing disturbs the accuracy of measuring devices, such as anemometers, wind vanes, temperature sensors and ice detectors. For example, 30% wind speed-reading error was recorded during the assessment phase of a site prone to icing conditions (Laakso et al., 2003).

Ice accretes on different parts of a wind turbine creating mass and aerodynamic imbalance, increases the structural loads on the turbine significantly, shortens the wind turbine's components' lifetime and increases blade generated noise (Andersen et al., 2011). However, the most critical part of a wind turbine that can be affected by different types of the ice is the blade. Ice accretes differently from one blade design to another. The accretion process of ice is not uniform along the same blade; most accretion takes place on the tip and leading edge of the blade due to the existence of stagnation point there, see Figure 4.

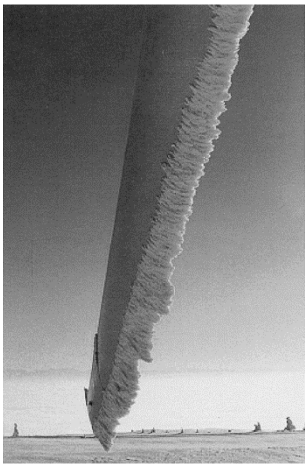

Figure 4. Iced turbine blade in Switzerland, (Tammelin et al., 2000)

Ice accretion leads to increase in blade's surface roughness and increasing the drag coefficient, leading to reduction in power production, which can be in range of 20-50% under sever icing conditions (Laakso et al., 2005). Continuing in operation under sever icing conditions and heavily accreted ice will harm the wind turbine and decrease its fatigue life as the wind turbine's components are subjected to excessive loads, which can be up to 50% of the blade's weight (ISO, 2001). Therefore, wind farm operators tend to shut down the wind turbine until the accreted ice is removed. Stoppage of the wind turbine can happen without the interference of the operator as the heavily accumulated ice can slow down the rotation of the blades or stop them completely. Figure 5 shows the percentage of main causes resulting in wind turbines' downtime in Finland between the year 1996 and 2008 for 72 wind turbines. As this figure shows, 4% of downtime is caused by icing (Stenberg and Holttinen, 2010). Icing increases the probability of failure of components and shortens the lifetime of the wind turbine. Therefore, it is important to focus on icing issues and solutions.

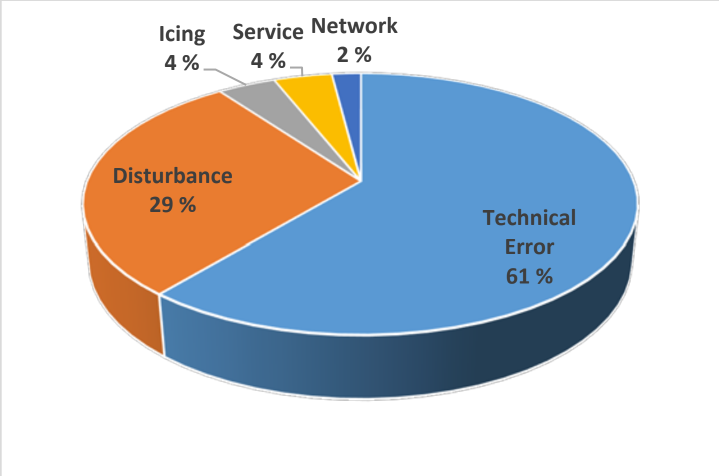

Figure 5. Percentage downtime causes, redesigned from (Stenberg and Holttinen, 2010).

Not only accreted ice on wind turbine's structure affects it, but also static and dynamic loads on offshore wind turbine's tower and foundation caused by land-fast and drifting sea ice pieces or even ice fields is another effect of icing. Drifting ice masses can hit the wind turbine's tower at velocities even higher than 1 m/s, causing damages to the tower and the foundation of the wind turbine through increasing the overturning moments (Battisti et al., 2006). Moreover, floating ice pieces hitting the tower increase the vibrations in the wind turbine's structure and can damage the tower due to the brittle behavior of low carbon steel that the tower is normally made of. In addition, sea ice accumulation can increase the corrosion process of the tower and the support structure (Morcillo et al., 2004). Also, in some cases the sea water around an offshore wind farm freezes completely, such state can last for several months, and will block the access to the wind turbines for maintenance purposes for a long periods of time and will therefore influence the output power from the wind farm.

3.2. Operation and maintenance crew performance

Ice affects the operator and maintenance crews' performance as well as their safety. Icing can decrease worker's visibility and limit the entrance to the wind turbine due to snow accumulation on the roads within the wind farm and at the entrance of each wind turbine. Figure 6 shows how workers' visibility is reduced during snowy weather conditions in Fakken wind farm in northern Norway. Snow and ice can cause personnel slipping hazards. Snow can melt and refreeze on lattice structures and hatches (for example the nacelle hatch) (Ryerson, 2011), which makes it even more difficult to open to perform maintenance. Icing increases the probability of accidents and injuries, and it is a reason for workers to be absent from work due to sick leaves and hospitalization.

Figure 6. Unclear visibility in Fakken wind farm due to snowy weather conditions (Mæhlum, 2013)

Maintenance crews will need to climb up to the nacelle where most mechanical rotating equipment are inside in order to carry out the required maintenance including replacing worn parts, oil and filters change and carry out required inspections. In addition, cleaning blades off accreted ice requires the use of cranes and lift workers to pretty high elevations at which workers are subject to higher wind speeds and low temperatures and, thus, more prone to falling risks. Moreover, glaze ice and snow accumulate on top of the nacelle, which can undoubtedly be a reason to the risk of slipping, tripping and falling off the wind turbine. Snow accumulated on top of the nacelle can melt and fall down on the wind turbine's vicinity. Ice throw is another risk to wind farm's workers. Pieces of ice either are thrown off an operational wind turbine due to aerodynamic and centrifugal forces or they fall down in case the wind turbine was idle. In both cases ice pieces represent a hazard to personnel, animals, roads and surrounding structures including other wind turbines. With the aid of Monte-Carlo simulation Battisti et al., 2005, have shown that the odds to be hit by a piece of ice (between 0.18 and 0.36 kg) on a site with moderate icing conditions (5 days per year) is 1 in 10. This is valid for a person walking 10 hours under an operating turbine that uses a de-icing system, considering a total ice accretion of 75 kg/ rotor/ day.

Tammelin et al., 2000, and Seifert et al., 2003, developed two equations (1&2) for measuring the distance of thrown ice pieces from an operational and idle wind turbine:

$$d = 1.5\,(D+H), \text{ when the wind turbine is operating.} \tag{1}$$

$$d = v\,\frac{D/2+H}{15}, \quad \text{when the wind turbine is idle.} \tag{2}$$

Where (d) is the throwing distance, (D) is the rotor blade diameter, (H) is the hub height, and (v) is the wind speed at hub height in m/s.

Despite these equations are empirical, they do not consider all necessary parameters to calculate the throwing distance of ice pieces, such as relative wind direction and speed, temperature, humidity, speed of rotation of the blades, and also the initial position and velocity of the ice piece being detached from the wind turbine. All these mentioned parameters can be different from one site to another and from one wind turbine to another. Therefore, the severity of risks evolving from ice throw and ice fall is not the same for all wind farms, and should be thought of during the early stages of the design phase of the wind farm. International recommendations for ice fall and ice throw risk assessments has been provided by (Krenn et al., 2018) in which the development of trajectory models of ice throw and ice fall have been reviewed. Moreover, it is stated that the properties of the ice piece itself should be considered in order to understand the trajectory of a given particular ice piece.

3.3. Wind farms' accessibility:

Onshore wind farms are subject to snow accumulation on the roads and pathways leading to the wind turbines. Snow accumulation on staircase and wind turbine's door can reduce accessibility to the failed components and consequently it will reduce the availability and performance of the wind turbine. Snow drifting on road and against wind farm's buildings can limit movability, and make transportation of personnel and equipment a challenging task. Consequently, specialized vehicles may be needed.

Another solution is to employ a snow removal strategy as shown in Figure 7. However, a feasibility study to determine the best option must take place. This should include parameters such as the cost of each solution, distance travelled (length of access roads), estimated annual snowfall accumulation and frequency, health & safety training, etc. noting that a combination of both solutions can be more feasible than depending on only one of them (Lehtomäki et al., 2018).

Figure 7. Snow removal employed (Lehtomäki et al., 2018)

Accessing offshore wind farms for maintenance and inspection purposes is carried out utilizing one out of three possible transportation strategies (Nielsen and Sørensen, 2011), taking into consideration the presence of ice:

- *Option 1*: always use boat to perform repairs.
- *Option 2*: repair as soon as possible (ASAP) using either boat or helicopter. In case of good enough weather conditions, boats are used, otherwise helicopters are used. The boat is assumed to require a mean wind speed less than 10 m/s and wave length less than 1.5m, or it will more difficult to move from the boat to the wind turbine. The helicopter is assumed to operate at wind speeds less than 20 m/s.
- *Option 3*: Risk-based alternative, where the cheapest type of transportation is used whether it is a boat or a helicopter, assuming perfect weather forecast while performing the repair, which is not the case in reality. This option implies finding the first coming days where repair is possible by boat or helicopter, and the cost of repair and lost production until that day is found for each transport type.

Using a boat only to perform repairs will result in high costs due to high production loss, leading to large total costs, see Figure 8. When the ASAP option is used, most repairs are performed using a helicopter, which is the main contributor to the increase in the total costs of ASAP strategy option. In the risk-based strategy, most repairs are performed using the boat. The total costs are smallest for in risk-based option since the less costly usually should be used, given a good weather forecast.

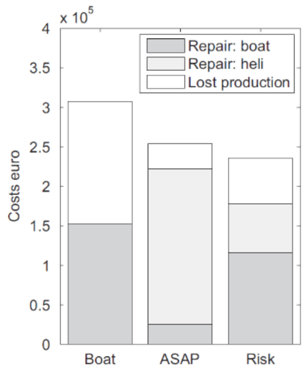

Figure 8. Cost of each transport strategy (Nielsen and Sørensen, 2011)

3.4. Public safety risks:

Wind turbines can cause external safety risks to public and wild life in the wind farm's surrounding area. As mentioned in Section 3.2, ice accreted on wind turbine's blades can detach, break in pieces and fly away, representing a risk to people, cars driving on roads near the wind farm, animals and other nearby public buildings and infrastructures, which can be described as public safety risks. Many countries define a buffer distance, also called setback distances, between wind turbines and existing public roads and infrastructure to reduce the safety risks from wind turbines to them (Larwood, 2005). For example, the setback distance defined in Denmark is four times the wind turbine's height.

Ice and snow accumulation on wind turbine's structure can decrease its fatigue life and might lead to components' failure. Complete or partial detachment of components, such as the wind turbine's blade or the nacelle/ rotor combination and the collapse of the tower are all modes of failure that can be caused by ice and snow accumulation on wind turbines and can result in safety risks to the surrounding area. A fault tree analysis was used by (Brouwer et al., 2018) to describe an analysis of wind turbine failures that can lead to public safety risks. The analysis concluded that the most common failure was complete or partial loss of a blade, which is also the component that is most prone to ice accretion.

Following the snow removal strategy mentioned in Section 3.3 to remove snow off wind farm's roads, snow-blowing machines used for that purpose can increase the traffic around the wind farm and develop hazardous situations for users of nearby roads.

Using anti/de-icing chemicals, in particular glycol compounds (e.g. ethylene, propylene, diethylene, alkylene) to clear ice off wind turbine's blades has many disadvantages. For example, chemicals can create human safety and health problems, cause environmental harms, damage roads and vehicles and may not be cost effective (Back et al., 1999). Anti-icing chemical compositions represent a threat to surface and ground water. De-icing chemicals can pollute drinking water and cause diseases to humans. They also may increase water's salinity, alter its density, change the physical and ecological properties of lakes, and suppress convective motion of water in spring (Dai et al., 2012). In addition, water polluted by ant/de-icing chemicals harms living plants and animals in the surrounding areas.

4. RISK ASSESSMENT OF ICING EFFECTS ON WIND FARMS

A cross tabular methodology similar to (Ryerson, 2011) was developed to assess the risks imposed by different types of icing on different wind farm's safety aspects. Based on the expertise of the authors of this paper, ice types were ranked according to the expected hazards they might inflict on the function and safety of wind farm as shown in Figure 9. Ice types were ranked from 1 to 10 starting from lowest to highest potential hazards on safety. For example, glaze ice is assigned a hazard value of 10 because it affects many wind turbine's components like the blade, nacelle and tower, and it accumulates on both onshore and offshore wind turbine components. Glaze ice has high density and strong adhesion, and is more difficult to remove compared to rime ice (Parent and Ilinca, 2011).

Freezing rain and wet snow impact the structures and foundations of wind turbines as well as roads within onshore wind farms. Thus it affects functions related to the wind farm's safety such as wind farm's accessibility and maintenance. Both freezing rain and wet snow are assigned a hazard value of 8.

Rime ice accretes mainly on small diameter objects like cables, railings and latticed tower structures. Rime ice accretion on blades can result in power losses. For example, a 28.7 m diameter wind turbine demonstrated a 20% power loss due to rime ice accretion (Alsabagh et al., 2013). Rime ice is assigned a hazard value of 6.

Sea ice collides with the tower and foundation of offshore wind turbines and causes damages to them. It also limits the access to offshore wind farms, and reduces their maintainability and availability. For these reasons the hazard value assigned to sea ice is 4. Super structure icing represents a substantial threat to offshore oil platforms as it causes structural damages and disable many of the platform's safety-related functions (Ryerson, 2011). However, in case of offshore wind turbines, with tubular cross section of the tower, unlike offshore platforms, the tubular cross section does not allow for intense ice accretion from sea spray. Moreover, sea spray ice can only accrete on the tip of the blade when the blade is at the lowest point. Therefore, superstructure icing is assigned a hazard value of 2.

Structural and functional safety aspects of the wind farm were ranked by the relative importance of each structure/ function to overall wind farm safety, taking into account the effects of different icing types on each structure and function. For example, the blade is assigned a safety rating of 10, due to a number risks induced by the blades, such as the risk of ice throw and ice fall. Also, ice accretion can cause blade's failure, which is of high safety concern to public safety in case of complete or partial blade detachment from the wind turbine.

The tower carries each of the nacelle, hub and blades, therefore its stability is of high importance to the wind farm's safety. The intensity of ice and snow accumulation on the tower is small compared to the blade due to the tubular shape of the tower. In case of offshore wind farms, the tower is prone to sea spray ice accretion and sea ice collision, which can cause serious damages to it. Furthermore, speaking of the probability of tower failure, it is considered less probable than blade failure (Brouwer et al., 2018). Wind turbine's tower is assigned a safety value of 8.

Operation and maintenance crew performance is highly important for consistent availability of the wind farm and to prevent interruptions in inspection and repair activities. Crew performance is assigned a safety value of 7.

Snow accumulation on wind farm's roads and paths limits the access to wind turbines and can create unsafe condition to carry out the required inspection and maintenance, which will affect the availability of the wind turbines and lead to loss of power production. Wind farm's accessibility is assigned a safety value of 6.

Wind turbine's foundation is important for stability and integrity of wind turbine's structure and for wind farm's safety. The foundation can be damaged by collision of sea ice in case of offshore wind farms. Snow accumulation takes place on the foundation in onshore wind farms. However, it is rare that snow accumulation will lead to foundation's failure. As such, offshore wind turbine's foundation is assigned a safety value of 5.

The nacelle contains the main mechanical components responsible for power generation, such as the gearbox and generator. Snow and ice accumulation on top of it can cause slipping hazards to personnel. Failure and detachment of a nacelle due to icing is less probable than a blade's detachment. Therefore, the nacelle is assigned a safety value of 4.

		Icing hazard rating				
		Glaze	Freezing Rain & Snow	Rime	Sea Ice	Super Structure Icing
Wind farm's structure and function relative safety rating		10	8	6	4	2
Blades	10	100	80	60	40	20
Tower	8	80	64	48	32	16
(O&M) crew performance	7	70	56	42	28	14
Wind farm accessibility	6	60	48	36	24	12
Foundation	5	50	40	30	20	10
Nacelle	4	40	32	24	16	8

Figure 9: Cross tabular assessment comprising impacts of icing types on functional and structural safety of onshore and offshore wind farms

It is noticed from Figure 9 that glaze ice and freezing rain and snow induce the highest impact on wind turbine's structure, mainly the blades and the tower, through changing the blade's profile and adding considerable weight to the wind turbine's structure. In addition, operation and maintenance crew performance is highly affected by glaze ice as it may cause slipping, tripping and falling hazards while performing operation and maintenance activities.

5. CONCLUDING REMARKS:

Wind farms operating in ice proven areas experience multiple safety risks induced by different icing types. The effects of different icing types on onshore and offshore wind farms have been investigated and listed in Table 1. Ice accretion on wind turbines' structure increases its components' failure process and creates risks such as ice throw and detachment of an entire or partial component, resulting in public safety risks. Moreover, ice and snow accumulation on the roads of a wind farm and land-fast and floating sea ice reduce accessibility to wind farms to perform the required maintenance, which affects the availability of the wind turbines and wind farm's overall power production. The effect of each icing type on wind turbine's components and wind farms' safety aspects have been illustrated in Table 2.

The design of the wind turbine's components and foundation should be resistant to the damages and vibrations caused by ice accretion and sea ice. Cold weather packages and offshore corrosion protection systems have to be adopted. Inspection and maintenance planning should be designed to accommodate limited access to wind turbines due to seawater freezing.

Maintenance crews must receive the required training and work only when their health and psychological conditions are appropriate. Moreover, workers have to use proper equipment and clothing and follow regulations like using safety ropes and cranes and working in pairs, etc. There are techniques used to clean blades off accreted ice, such as the use of drones that can spray de-icing liquid to the blades.

There are other aspects of risks that can be witnessed in wind farms operating under icing conditions, which were not mentioned in this paper such as the effects of icing on wind farm's communication tools, and the increased noise hazards due to ice accretion on wind turbine's blades. Further investigation of the effects of the use of chemical Anti/De-icing systems (ADIS) on the environment can be included.

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Paper 5

Wind Turbine Failures Review and Gearbox Condition Monitoring

Mustafa, A. M., A. Barabadi and T. Markeset (2020)

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Paper 6

Downtime Cost Estimation: A Wind Farm in the Arctic Case Study

Mustafa, A. M., A. Barabadi and T. Markeset (2020)

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