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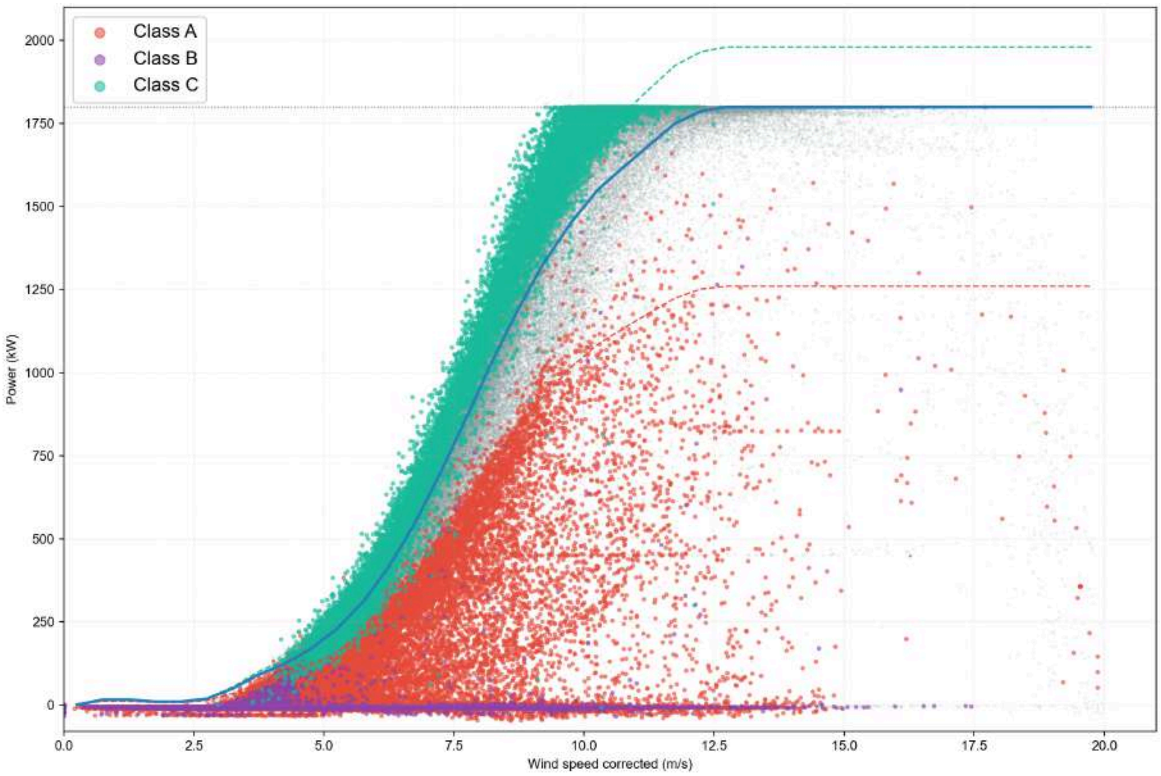
Master's Thesis

Icing Power Loss forecasting for wind farms in cold climates using machine learning



Chuong Dang Ta
Master in Decentralised Smart Energy Systems (DENSYS)

*Thesis carried out at **rebase.energy** supervised by:*

S. Haglund (CEO) & **I. Dimoulkas** (Senior Data Scientist)
Industrial Supervisors | [rebase.energy]

Dr. Giuseppe Giorgi
Academic Supervisor | Politecnico di Torino

Stockholm, Sweden

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Author:

Chuong Dang Ta

Industrial Supervisors:

S. Haglund (CEO)

I. Dimoulkas (Senior Data Scientist)

rebase.energy, Stockholm

Academic Supervisor:

Dr. Giuseppe Giorgi

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Abstract:

Atmospheric turbine icing in cold climates causes aerodynamic degradation, structural standstills, energy losses, and operational uncertainty. This thesis forecasts wind power icing loss at 1- to 36-hour lead times using multi-year Swedish turbine SCADA and ERA5-Land data. Icing labels are established using an extended IEA Wind Task 19 Sigmoid Performance Ratio framework. Data investigation reveals inter-annual non-stationarity and wind speed–temperature overlap between icing and non-icing events. Biases between SCADA and ERA5-Land inputs are corrected using Quantile Mapping and LightGBM. From numerous candidate features across multiple physical groups, Spearman and SHAP screening remove unstable predictors. A two-stage LightGBM classifier-regressor is trained using walk-forward cross-validation over multiple winters.

Evaluation on a blind winter test set spans several scenarios: Persistence, Oracle, Realistic NWP, and SCADA-only. Persistence yields high short-term accuracy but collapses rapidly as lead time increases. Oracle (using weather observations) defines the performance ceiling. Realistic NWP tracks the Oracle classifier but suffers a regression penalty from forecast errors. SCADA-only (no weather forecasts) collapses beyond the near term. Thus, local SCADA signals dominate near-term forecasts, but meteorological forecasts are essential for longer horizons.

Keywords:

Wind turbine icing, Power loss forecasting, Feature stability screening, Non-stationarity, SCADA, ERA5-Land, Cold climates.

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Stockholm, Sweden **Chuong Dang Ta**
June, 23rd, 2026

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The **DENSYS 2.0** Erasmus Mundus Joint Master Degree (EMJMD) is a collaborative two-year (120 ECTS) program designed to provide advanced training in the interdisciplinary fields of Decentralised smart ENergy SYStems. Strongly anchored in the UN Sustainable Development Goals 7, 9, and 13, the program aims to educate a new generation of engineers and researchers capable of designing, optimizing, and operating the decentralized energy systems essential for a low-carbon society.

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The curriculum is jointly implemented by a consortium of four leading European institutions:

- **Université de Lorraine** (Nancy, France) - Core multiphysics and system basics.
- **KTH Royal Institute of Technology** (Stockholm, Sweden) - Global decentralized systems.
- **Politecnico di Torino** (Turin, Italy) - Energy-to-X innovative storage pathways.
- **Universitat Politècnica de Catalunya** (Barcelona, Spain) - Thermal energy engineering.

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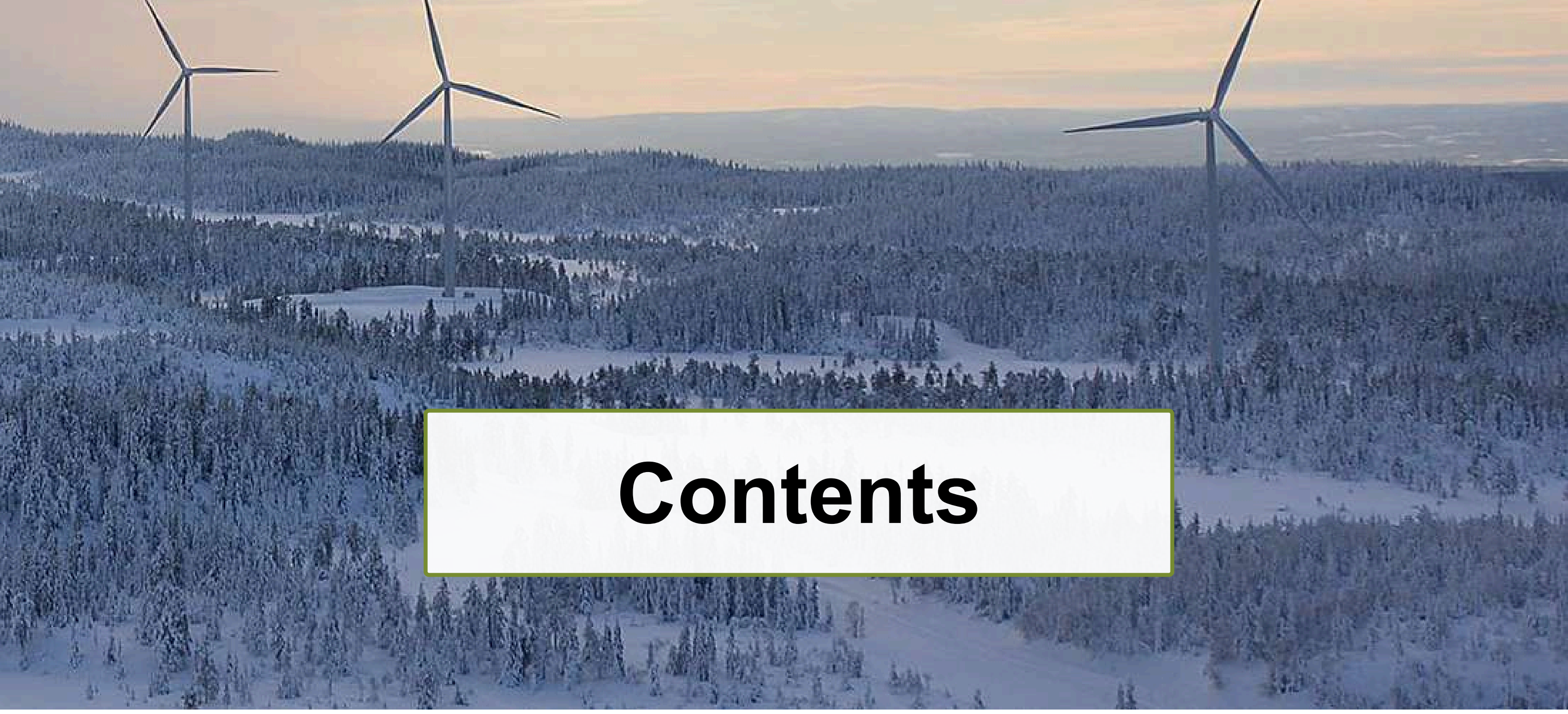

Contents

Abbreviation List

ANN	Artificial Neural Network.
CC	Cold Climate.
CDF	Cumulative Distribution Function.
CV	Cross-Validation.
DJF	December, January, February (winter months).
EBA	Energy-based Availability.
EFB	Exclusive Feature Bundling.
ERA5-Land	Fifth generation ECMWF reanalysis for land surface variables.
FNN	Feedforward Neural Network.
GBDT	Gradient-Boosted Decision Tree.
GOSS	Gradient-based One-Side Sampling.
GRU	Gated Recurrent Unit.
IEA	International Energy Agency.
IEC	International Electrotechnical Commission.
ISO	International Organization for Standardization.
JJA	June, July, August (summer months).
LightGBM	Light Gradient Boosting Machine.
LSTM	Long Short-Term Memory.
MAE	Mean Absolute Error.
ML	Machine Learning.
NWP	Numerical Weather Prediction.
OOF	Out-of-Fold (diagnostics computed on held-out validation folds).
PCA	Principal Component Analysis.
PR	Performance Ratio.
QM	Quantile Mapping.
QRF	Quantile Regression Forest.
RF	Random Forest.
RMSE	Root Mean Square Error.
ROC	Receiver Operating Characteristic.
RQ	Research Question.

SCADA	Supervisory Control and Data Acquisition.
SHAP	SHapley Additive exPlanations.
SVM	Support Vector Machine.
TBA	Time-based Availability.
TCN	Temporal Convolutional Network.
TIGER	Tensor-based Icing dEtection and pRediction.
XGBoost	Extreme Gradient Boosting.

Notation List

Wind Energy & Icing

$P(t)$	Measured active power output at time t [kW].
$P_{\text{ref}(u)}$	Sigmoid reference power curve evaluated at wind speed u.
$\text{PR}(t)$	Performance Ratio at time t; ratio of measured to reference power.
$u(t)$	Hub-height wind speed at time t [m/s].
$T_{\text{air}(t)}$	Ambient air temperature at time t [°C].
τ	Forecast lead time [hours]; ranges from 1 h to 36 h.
$y(t)$	Binary icing label at time t (1 = icing, 0 = healthy).
$\hat{y}(t)$	Predicted binary icing indicator.
$f_{\text{icing}(t)}$	Icing power loss fraction; target variable for the regressor stage.

Machine Learning & Statistics

ρ	Spearman rank correlation coefficient.
$\text{CV}(\rho)$	Coefficient of variation of Spearman ρ across training winters; used as the cross-winter stability metric.
F_1	F1 score: harmonic mean of precision and recall.
R^2_{icing}	Coefficient of determination computed on icing-flagged rows only.
w_t	Recency decay sample weight assigned to training observation at time t.
K	Number of walk-forward cross-validation folds ($K = 11$).
θ	Classification decision threshold applied to the predicted icing probability.
$\boldsymbol{x}(t)$	Feature vector at time t (dimension 93 after stability screening).

Threshold Scoring

score	Energy-penalised threshold score.
α	Penalty weight on false-positive energy in threshold scoring.
E_{FP}	Cumulative energy of false-positive icing predictions [MWh].
$E_{\text{icing,real}}$	Cumulative energy of true icing events [MWh].

1. Introduction

In the first chapter, the critical context of wind energy in cold climates (CC) were introduced. There is paradox between high winter power potential vs severe consequences caused by atmospheric icing (aerodynamic, structural and economic consequences). In addition, current mitigation strategies ranging from active de-icing to advanced machine learning-based detection were evaluated. Then, by synthesizing existing research on icing label construction, two-stage architectures, probabilistic forecasting, and tensor-based feature engineering, four specific research questions are posed.

1.1 Context of the Work

The share of wind energy among clean energy sources in cold climates has been substantially growing in recent years wtih 156 GW on shore in the share of 700 GW Global onshore wind capacity in 2020 and total around 300 GW in 2025 [1], [2]. In addition, in the Nordic countries, the wind energy capacity is substantially higher in winter due to stronger wind and higher air density. Winter is the windiest season, and generally the wind speed is highest over sea and in the Scandinavian mountain range (The WPD is about four times larger in wintertime (December–February) than during summer (June - August)) [3]. Consequently, countries with high wind potential and intensive cold climates are rapidly advancing wind power development. By 2050, wind energy capacity in cold climate regions throughout Scandinavia, North America, Europe, and Asia is projected to reach approximately 250-400 GW [1].

Despite this potential, wind turbines in severely cold climates must withstand challenging conditions, particularly frequent subzero temperatures and ice formation. As illustrated in Fig. 1.1, average January temperatures in core wind-producing regions such as Sweden and Norway drop as low as −6.5°C to −10.8°C, while neighboring regions face even more extreme conditions, reaching −21.4°C [4].

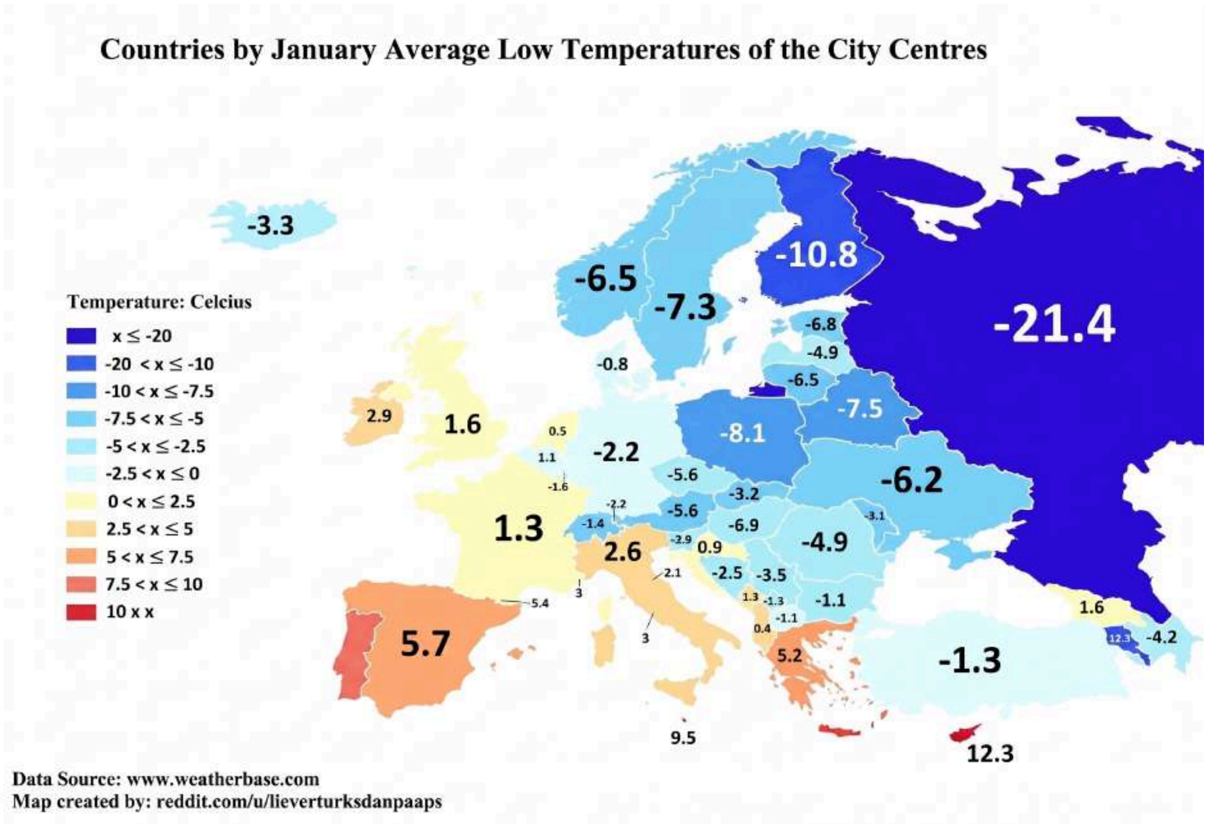

Fig. 1.1: Map of European countries by January average low temperatures highlighting the severity of the Nordic climate [4]

1.1.1 Icing consequences

Icing formation can affect on the aerodynamic, rotation imbalance, leading to the structure getting damaged. Also, beyond physical damage, icing results in significant power production efficiency drops or total system downtime. These operational interruptions lead to substantial revenue losses for wind farm operators.

Aerodynamic & structural impacts

According to [5] and [6], icing accretion on wind turbine blades is a highly localised phenomenon. The consequences are shownn below as well as illustrated in Fig. 1.2 and Fig. 1.3 how icing affects the aerodynamics of an airfoil.:

- Leading edge: It is one of the most prone areas for icing, as it directly faces the incoming wind, causing water droplets in the air to collide and accumulate. Ice buildup on the leading edge changes the aerodynamic shape of the blade, increasing air resistance and reducing the turbine's energy conversion efficiency. In addtion, this part icing can cause airflow separation, resulting in reduced lift and raised vibration of the blades.
- Blade root: connection part with the turbine's rotating shaft, is vulnerable to ice accumulation due to centrifugal force during rotation. Root icing can increase the weight of the blade, leading to higher structural stress and affecting the overall stability of the blade and turbine
- The suction side and pressure side: The suction side faces direct airflow and has a likelihood of water droplets condensing into ice.
- Blade tip: High rotational speeds cause rapid freezing of any moisture, and detached ice chunks can pose safety hazards.

- Irregularities: Seams, joints, and surface imperfections can act as focal points for icing and increase surface roughness, affecting airflow and the overall aerodynamic performance of the blade.

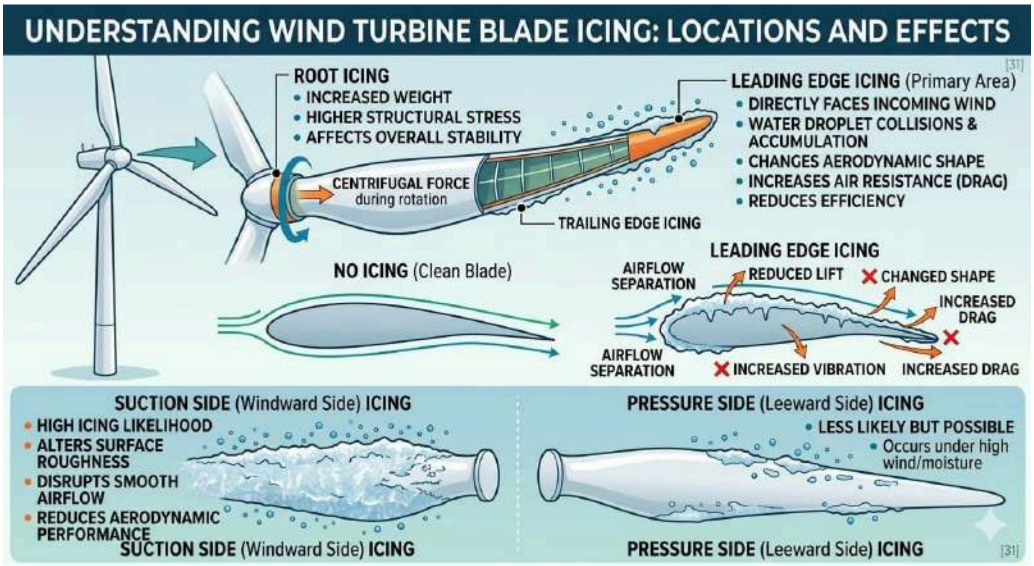

Fig. 1.2: Icing accumulation on blade components and consequences [Generated by AI]

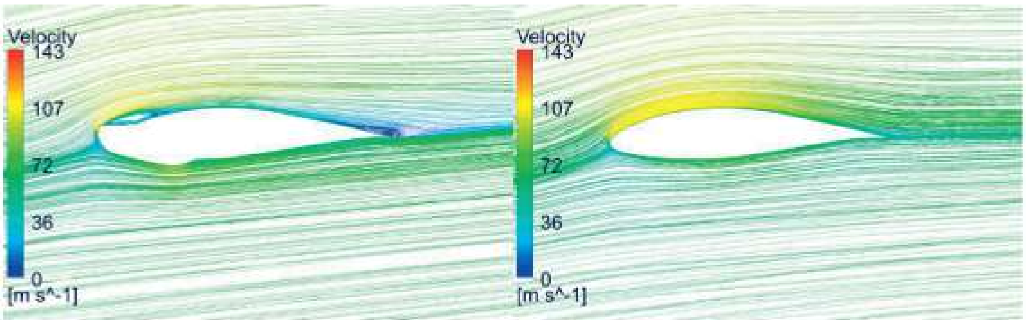

Fig. 1.3: Comparison of airflow patterns on an iced (left) versus a clean (right) airfoil [7].

Economic & operational consequences

As reported in [8], ice accumulation on turbine blades directly reduces energy yield, resulting in substantial financial setbacks. In extreme cold climates, severe icing can reduce power output by up to 20% or force a complete operational standstill, preventing wind farms from achieving their projected generation targets. Even marginal ice buildup can cause chronic underperformance; these cumulative efficiency drops create a widening gap between forecasted and actual revenue, ultimately threatening the long-term financial sustainability of the project.

Beyond production losses, icing significantly increases maintenance expenditures by accelerating component fatigue. Ice-induced rotor imbalance creates excessive vibrations that strain the gearbox, bearings, and structural integrity of the blades, necessitating more frequent and costly technical interventions. Moreover, ice formation introduces critical safety hazards, such as “ice throw” onto public roads or equipment that often restrict technician access. These safety-related delays, combined with the need for specialized de-icing equipment and winterized logistics, further escalate the total cost of ownership for assets in cold climates.

1.1.2 Icing mitigation approaches

Anti-icing and de-icing techniques

In [9], the authors reviewed passive and active anti-icing and de-icing techniques. In order to mitigate icing in energy systems, two main strategies are recruited: anti-icing and de-icing strategies. [6]. Anti-icing strategies are often preventative by slowing down ice accretion while de-icing approaches are focused on ice removal. Regarding the system input, both anti-icing and de-icing strategies involve active and passive methods. Active methods require an external energy to remove the ice while passive methods are applied by taking the advantage of physical and chemical properties of surfaces. Table 1.1 summarizes the major ice mitigation techniques.

Table 1.1: Comparison of ice mitigation techniques.

Techniques	**Active/ Passive**	**Effectiveness**	**Roughness increase**	**Cost**	**Energy consumption**
Anti-icing surfaces and coatings	Passive	Limited	Medium/High	Low	N/A
Thermal (passive)	Passive	Limited	Low	Very low	N/A
Thermal (active)	Active	Effective	Medium/Low	High/ Medium	High/Medium
Expulsive	Active	Effective	High	High	Low
Pneumatic	Active	Very effective	Very high	High	Low
Ultrasonic waves	Active	Very effective	Very low	Medium	Low

Icing detection

Icing detection addresses the question “Is there ice now?” on a turbine. Effective ice management relies on a combination of direct and indirect detection methodologies to initiate mitigation protocols. The authors in [10] direct methods as those measuring the physical properties of ice on the blade surface, such as ultrasonic sensors, capacitive systems, and optical devices.However, there exists installation, operation, and maintenance costs associated with these sensors which can pose a challenge for their use.

In contrast, indirect methods infer icing by monitoring performance deviations, primarily through Supervisory Control and Data Acquisition (SCADA) data and power curve analysis. The researchers conclude that while indirect methods are cost-effective, they often lack the precision required for early-stage detection; therefore, integrating autonomous, blade-mounted sensors is essential for the timely activation of anti-icing and de-icing systems to prevent significant aerodynamic degradation.

Icing Forecasting

Icing forecasting is the prediction of icing on wind turbines. The prediction of icing before it occurs allows operatios to proactively initiate mitigation measures, such as de-icing technologies or turbine shutdowns, to hedge against safety hazards and minimize revenue losses. Moreover, icing forecasting would allow one to conduct a cost/benefit analysis by comparint the cost of the mitigating action with the revenue losses due to icing [11].

cite{} Recently, data driven method using SCADA data arises as a choice for develop a prediction model as well as meteorological data when available. Along with that,by leveraging advancement in machine learning (ML) to learn the unique signatures of icing events.However, a fundamental challenge remains, one needs to address the following key question:

> *how to "mine" the complex and hidden signatures of icing events from large streams of multivariate (and often noisy) SCADA data? [12]*

The following literature review systematically examines existing research to evaluate how various methodologies have addressed these data-driven challenges, focusing on the evolution from physics-based models to advanced machine learning architectures.

1.2 Literature Review

ML for Production Loss Prediction

Early applications of ML focused on transforming meteorological data into actionable power loss forecasts. Scher and Molinder demonstrated a statistical approach using Random Forest (RF) regression, training their model on Numerical Weather Prediction (NWP) and on-site observational data [13]. Their results achieved a forecast skill comparable to traditional physics-based icing models. Similarly, Kreutz et al. utilized neural networks to capture the majority of icing events, further validating the shift toward data-driven forecasting [14].

Icing Label Construction and the IEA Wind Task 19 Standard

A prerequisite to any data-driven icing model is a reliable ground-truth label, and the overwhelming majority of the reviewed studies derive this label directly from the IEA Wind Task 19 (IEA T19) recommended practice, which discretizes SCADA power deviations into fixed classes (e.g. Class A partial loss, Class B full shutdown, Class C production stop with high wind) [15] [16]. Felding (2021) and Sjökvist (2023) both rely on strict percentile-based thresholds (e.g. the 10th percentile of an empirical reference power curve) to assign these hard class boundaries. While this discretization is convenient for classification, it forces an inherently continuous physical process, gradual aerodynamic degradation, onto a small number of abrupt categories, discarding information about partial or transitional icing severity and making the resulting labels sensitive to the arbitrary choice of threshold. Very few studies question whether the IEA T19 classes themselves are the most reliable representation of icing severity, or benchmark an alternative labelling scheme against them.

Two-Stage ML Architectures

Building on the success of individual classifiers, recent studies have adopted two-stage methodologies that bridge icing detection and power estimation. Haugen (2025) introduced a sequential framework where an RF classifier first predicts binary icing events up to 36 hours in advance using NWP and SCADA data. This predicted boolean status is subsequently utilized as the primary input feature for advanced regression models such as Feedforward Neural Networks (FNN) and Long Short-Term Memory (LSTM) networks to estimate the magnitude of the resulting power loss [17]. Similarly, Sjökvist (2023) evaluated multiple supervised learning models and demonstrated that an XGBoost regression model combined with empirical reference curves specifically classifying data points falling below the 10th percentile as iced yields highly accurate detection of production losses [16].

Advanced Feature Engineering and Data Processing

Recent frameworks have introduced sophisticated data processing to handle high-dimensional SCADA streams. The TIGER framework proposed by Ye and Ezzat reshapes SCADA data into tensors to extract low-dimensional, information-rich features. By combining these with power-curve-derived physics and a TabNet classifier, TIGER outperforms existing methods in both detection and short-term prediction with significantly fewer false alarms [12]. Additionally, Zhang et al. (2024) provided a systematic framework comparing original, PCA-reduced, and engineered physical features. Their evaluation of multiple algorithms showed that RF can exceed 99% accuracy when using a three-category classification (un-iced, initial ice, and severe ice) to provide more nuanced predictions than binary models [6]. However, none of these frameworks formally screen candidate features for cross-winter stability (e.g. via rank-correlation) or interpret feature contributions through modern explainability tools such as SHAP before selecting the final input set, leaving the risk that unstable or spuriously important predictors remain in the model.

Probabilistic and Temporal Forecasting

As the field matured, research shifted toward quantifying uncertainty and modeling time-series dependencies. Molinder et al. (2021) extended deterministic models by applying Quantile Regression Forests (QRF) to generate probabilistic forecasts of icing-related power losses. By integrating physical icing model outputs, this approach provides valuable uncertainty estimations critical for energy trading decisions, although they noted that RF-based methods often tend to underestimate extreme icing events [18]. Complementing this, Andersen (2023) demonstrated the utility of implementing ensemble prediction systems into established physical icing models (e.g., IceLoss2.0) to capture initial condition uncertainties. To address temporal complexities, Zhang et al. employed Temporal Convolutional Networks (TCN) to predict icing from SCADA time series, achieving an average prediction accuracy of 77.6% for lead times up to 48 hours [11]. Notably, these studies train and validate on winter periods without explicitly testing whether the underlying meteorological and operating regimes are stationary from one winter to the next; a model tuned on one season’s ice climatology may silently degrade when the following winter departs from it.

Physical Modeling and Reference Curve Integration

Despite the rise of deep learning, physical thresholds and empirical SCADA analysis remain foundational for validating machine learning outputs. Felding (2021) utilized strict SCADA filtering to construct dynamic reference power curves, identifying ice losses based on strict temperature thresholds and production deviations from the 10th percentile [15]. Furthermore, Uusitalo (2022) highlighted the importance of meteorological variables beyond temperature and wind speed; analyzing Finnish wind farms, she revealed that factors such as cloudiness and precipitation are critical predictors of ice breakage points. Understanding these physical transition phases, particularly during severe glaze ice events, offers a crucial physical mechanism to improve data-driven ice shedding models [19].

Meteorological Data Quality

A further, largely unaddressed gap concerns the input meteorological data itself. Most studies above feed NWP or reanalysis products (e.g. ERA5-Land) directly into their models, or otherwise interchange them with on-site SCADA meteorological sensors, without first quantifying or correcting the systematic bias between the two sources [13] [11]. Since forecast products are the only meteorological input available operationally at the lead times required for proactive de-icing decisions, uncorrected bias between forecast and SCADA-observed temperature and wind speed propagates directly into icing detection and power loss errors.

Summary of Gaps

Synthesizing the reviewed literature reveals four gaps that motivate this thesis: (i) icing labels are almost universally constructed from the discrete IEA T19 classification without benchmarking against a continuous alternative; (ii) the non-stationarity of winter meteorological and operating regimes across seasons is rarely tested explicitly, despite its direct bearing on model generalisation; (iii) the systematic bias between forecast/reanalysis data and SCADA measurements is seldom quantified or corrected before being used as model input; and (iv) feature sets are rarely screened for cross-winter stability and interpretability (via Spearman correlation and SHAP) before being fed into two-stage detection-estimation architectures evaluated under realistic, operationally-relevant input scenarios.

1.3 Research Questions

To address the four gaps identified above, icing label construction, non-stationarity of winter data, meteorological data bias, and feature screening for two-stage forecasting, this study investigates the following research questions:

RQ1: Instead of the discrete IEA Wind Task 19 classification, can a continuous, sigmoid-shaped reference power curve derived directly from SCADA data serve as a more physically faithful icing severity label, and which of the two labelling schemes, discrete IEA T19 classes or the proposed continuous sigmoid label, more reliably captures true icing severity when the two are benchmarked against each other and against independent icing indicators?

RQ2: To what extent do winter meteorological and turbine operating regimes exhibit non-stationarity from one winter season to the next, and how does this seasonal non-stationarity, largely unexamined in prior icing studies, affect the stability and generalisation performance of icing detection and power loss models trained on one winter and evaluated on another?

RQ3: What systematic bias exists between forecasted meteorological variables (temperature and wind speed) and on-site SCADA measurements across multiple winter seasons, and how effectively can a quantile mapping transformation combined with a LightGBM residual-correction model remove this bias to produce calibrated forecast inputs suitable for turbine-scale icing forecasting?

RQ4: Having constructed a comprehensive candidate feature set from raw SCADA and meteorological variables, which predictors survive a two-stage screening process combining Spearman rank correlation stability across winters with SHAP-based importance analysis, and how does feeding this screened feature set into a two-stage LightGBM detection-estimation cascade perform when compared across four input-data cases, oracle NWP, raw forecast NWP, bias-corrected NWP, and SCADA-only, in detecting icing events and estimating power loss?

The remainder of this thesis is organised to address these four research questions in turn. Section 2 presents the raw SCADA and meteorological dataset and establishes a rule-based icing detection baseline, including the construction of the proposed sigmoid reference-curve label against the IEA T19 classification (RQ1). Section 3 investigates the SCADA data in detail and quantifies the bias between reanalysis/forecast weather data and on-site measurements, introducing the quantile mapping and LightGBM residual correction strategy (RQ3), while

Section 4 builds the candidate feature set, screens it via Spearman rank correlation stability and SHAP-based importance (RQ4), and then trains, tunes, and evaluates the two-stage LightGBM cascade across the four input-data cases, while also examining the non-stationarity of winter regimes and its effect on model generalisation (RQ2). Finally, **Section 5** concludes the thesis and outlines future research directions.

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