

UAV Icing at Low Reynolds Numbers: RG-15 Airfoil Drag Increase Prediction Based on Batch-Automated CFD Simulations

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ABSTRACT:

Accretion of ice on aircraft wings can severely degrade aerodynamic performance, posing safety risks and operational challenges for both manned and unmanned aircraft. Predicting the drag increase caused by ice accretions can improve mission planning and the operation of ice protection systems. While few analytical expressions predict the drag increase of iced airfoils based on atmospheric and flight parameters, all were developed for the Reynolds numbers of manned aircraft (mostly between 1,500,000 and 15,000,000). Unmanned aerial vehicles (UAVs) typically operate at lower Reynolds numbers (typically between 250,000 and 1,000,000), requiring specialized research in icing conditions. This study compares existing drag correlations to drag increases simulated numerically with Ansys FENSAP-ICE on the wing of a small UAV. The results show a significant difference between the predicted and the simulated drag coefficients. Based on the numerical results, new predictions are developed based on the mass that has

impinged on the aircraft and the freezing fraction. Using separate equations for different freezing fractions, all data points can be predicted within 23% of the simulated values, with an average error of less than 6%. Although the training dataset is limited, applying the equations to cases outside the original dataset still presents good predictions. Even though this study relies on numerical results without direct experimental validation, the results are promising for developing more accurate wing drag prediction methods for low-Reynolds-number cases.

AUTHOR KEYWORDS: icing; unmanned aerial vehicle (UAV); drone; computational fluid dynamics (CFD); numerical simulations; icing penalties; drag prediction

INTRODUCTION:

Atmospheric icing, also known as in-cloud icing or in-flight icing, is a weather condition that can be dangerous for aircraft (Cao et al. 2018). It occurs when an aircraft flies through a cloud containing supercooled liquid water droplets. When supercooled droplets hit the aircraft, they can freeze on the surface, either completely or partially. Depending on where the droplets freeze, the aircraft's performance can be negatively influenced in different ways (Hann 2024). Ice accretion on the propeller reduces the thrust and increases the torque (Liu et al. 2019; Müller et al. 2023; Müller and Hann 2022). Ice accumulating on antennas and sensors can lead to communication problems and faulty measurements (Cao et al. 2018). Ice growth on wings can lead to reduced lift, increased drag, and a reduced stall angle (Bragg et al. 2005; Lindner et al. 2023). The severity of the effect of the ice shape on the wing depends on the freezing fraction, a parameter describing how much of the impinging liquid water freezes on impact. When the outside temperature is only slightly below freezing, droplets only partially freeze on impact and instead flow back and freeze downstream. This type of ice is called *glaze ice*; it has a freezing fraction

significantly smaller than 1, and it can result in significant performance penalties. At temperatures well below freezing, all droplets freeze on impact, resulting in a freezing fraction of 1. The resulting ice type is called *rime ice*; it has a streamlined appearance, and it has a less significant influence on performance. *Mixed icing* is an intermediate state where the ice shape is mostly in the form of glaze at locations close to the leading edge and in the form of rime ice at locations further downstream.

Ice protection systems (IPS) can mitigate the adverse effects of ice accretion and enable aircraft to operate in icing conditions. According to Thomas et al. (1996), these systems can be classified into systems that only remove ice once the accreted amount has reached a threshold (*de-icing*) and systems that prevent any ice accretion (*anti-icing*). Anti-icing systems have the advantage of keeping the aerodynamic performance constant, but they require large amounts of energy because they are active continuously in icing conditions. De-icing systems require less energy because they are only activated cyclically but allow some ice accretion and, as a result, induce some degradation in aerodynamic performance (Wallisch and Hann 2023).

Ice accretion is a challenge for all types of aircraft, whether they are manned or unmanned (Gao et al. 2021; Hann and Johansen 2020). Certified ice protection systems exist for manned aircraft (Leary 2002; Sinnett 2007), but equivalent technologies for unmanned aircraft are still under development. The application of these certified IPS to small UAVs with a wingspan of a few meters is limited by their lack of bleed air and by weight and electrical energy constraints. As a result, drone operation can be severely limited, and icing conditions can lead to crashes (Bello et al. 2022). Unmanned aircraft without ice protection systems might experience cancellation rates of up to 40% in winter, depending on where they are operated (Borup et al. 2024). The market for unmanned aerial vehicles (UAVs), often also called unmanned aerial systems (UAS), remotely piloted aerial systems (RPAS), or drones, is growing (Federal Aviation Administration 2024). This growing market leads to an increased focus on developing ice protection systems for unmanned aircraft (Hann et al. 2021; Kozomara et al. 2024; Yugulis et al. 2023).

De-icing systems are more popular for the IPS on UAV wings (Hann et al. 2021; Wallisch and Hann 2022) because they are more energy-efficient than anti-icing systems. Optimizing these de-icing systems requires a good understanding of the intercycle time, the interval during which the de-icing system is inactive and allows ice to form. The drag of the resulting intercycle ice shapes must be compensated by increasing the aircraft's thrust. Hence, an accurate estimate of the drag of intercycle ice shapes is required to optimize IPS operations.

The most accurate way to measure the drag of iced airfoils is to either conduct flight tests or conduct experiments in icing wind tunnels. However, these tests are expensive and time-consuming, especially when the aim is to test in all potential icing conditions. Numerical simulations can be a faster and cheaper option. When wide parameter ranges must be explored, however, the costs for simulations also become significant. Additionally, predicting drag using numerical simulations is subject to uncertainty, particularly for iced geometries (Chi et al. 2005). Analytical expressions are a quicker and cheaper way to determine drag. They require existing data to be optimized and are strictly only valid within the parameter range of the training data, but they provide almost immediate results. Analytical expressions for the drag increase caused by wing icing have been developed since the 1960s. The first documented equation was developed by Gray (Gray 1964). The prediction was based on experimental results of glaze ice (Bragg 1982). It was later shown that the equation does not provide good predictions for drag increases outside the parameter range (Olsen et al. 1984). Later, Bragg (1982) investigated the aerodynamic performance of rime ice shapes and developed a correlation for the increase in drag caused by rime ice. Flemming and Lednicer (1985) developed separate predictions for drag increases caused by rime and glaze ice. The correlations contain Mach number influences and rotor blade oscillation effects, as they were designed for helicopter applications. Later, Bragg et al. (2000) developed an equation for glaze ice drag to model the performance of an aircraft in icing conditions. Han and Palacios (2013) developed a method for predicting the drag increase in both glaze and rime conditions based on existing data, and their results

showed good agreement with those of additional experiments. However, all analytical expressions were developed for manned aircraft cases with large Reynolds numbers (mostly between 1,500,000 and 15,000,000) and were not tested for typical UAV flight conditions (typically between 250,000 and 1,000,000). UAVs are typically slower and smaller than manned aircraft, resulting in lower Reynolds numbers. Lower Reynolds numbers increase the laminar portion of the airflow and influence heat transfers and droplet trajectories (Szilder and McIlwain 2011). Accordingly, confirming whether the results for manned aircraft also hold true for unmanned aircraft is crucial.

Analytical expressions to estimate the drag based on atmospheric and flight conditions could help drone operators and developers in multiple ways. In short, these equations enable the estimation of drag without additional experiments or simulations. Existing predictions for the drag increase of an iced airfoil are used during the design of wings and their ice protection systems to identify the most severe icing conditions for which the IPS must be designed (Han and Palacios 2013). Additionally, existing expressions can assist in characterizing the icing severity in flight and optimizing the IPS operation (Bragg et al. 2000). Finally, existing correlations are used to predict the required rotor power of an unprotected helicopter blade in icing conditions (Gent et al. 2000).

There are more potential use cases for an accurate drag prediction. However, for the following examples, it should be noted that the increase in drag may not be the primary driver. Reduced lift, deteriorated stall behavior, or loss of control-surface effectiveness may be more challenging than increased drag. As mentioned, for aircraft equipped with a de-icing system, the prediction can be used to calculate when the ice should be removed from the wings to minimize energy consumption. For aircraft without an ice protection system, a drag equation could calculate how long the aircraft can fly in the current or predicted conditions before the drag becomes problematic. Additionally, a more precise estimate of the remaining endurance and range is possible with an accurate drag correlation. This is because the aircraft must increase its thrust to compensate for the additional drag, thereby decreasing the remaining energy.

Finally, a good estimate of the drag caused by icing could improve the definition of icing severity. In current models, the icing severity value typically depends on the ice accretion rate (Federal Aviation Administration 2015a) or the liquid water content (Jeck 2001). Estimating the performance degradation might be more beneficial, considering that the same amount of ice accretion can result in different performance penalties for different-sized aircraft (Hann and Johansen 2021) and at different ambient temperatures (Bragg et al. 2000).

The objective of this paper is the development of analytical expressions for the drag increase of iced wings of a typical small-scale fixed-wing UAV. An automation process was used to set up and start several numerical simulations with Ansys FENSAP-ICE with the same structure but with different ambient conditions more easily. The automation process is explained in the methods section, but ultimately not the main objective of this study. The numerical results are compared to existing analytical expressions for drag increase that have been shown to produce inaccurate predictions of drag. New predictions are presented and compared to the same numerical results. Additionally, the equations developed are applied to a wider parameter range than the training dataset to present the usability of the prediction outside the limited range. Finally, it is demonstrated how these equations can be applied to real-world scenarios. These considerations include scenarios with limited information about icing parameters, as most aircraft are not equipped with a sufficient number of sensors to measure all icing-relevant parameters.

METHODS:

The analyzed case

The case investigated in this paper describes a typical small to medium-sized fixed-wing UAV with a maximum take-off weight of 25 kg (Hann and Wallisch 2020). A wing with a mean aerodynamic chord of 0.27 m and the RG-15 airfoil is assumed. The RG-15 airfoil has good characteristics for low Reynolds

numbers (Selig et al. 1995) and is a popular choice for UAVs. An airspeed of 25 m/s and an angle of attack of 4° are typical for a UAV of this type and size (Hann and Wallisch 2020). This results in a Reynolds number of 450,000.

All investigated environmental conditions for the simulations were selected from the certification requirements in FAA 14 CFR part 25, Appendix C (Federal Aviation Administration 2015b). The certification document summarizes combinations of ambient static temperature, median volume diameter (MVD) of the droplets, and maximum expected liquid water content (LWC) in two different types of clouds. Continuous maximum clouds are defined with a horizontal extent of 17.4 nm and can be crossed in 1,290 s at 25 m/s. Intermittent maximum clouds have a larger LWC than continuous maximum clouds, but a smaller horizontal extent of only 2.6 nm. An aircraft flying at 25 m/s would cross these clouds in 200 s. Nine different temperatures and six different droplet sizes are investigated for continuous maximum, as shown in Appendix A. Because intermittent clouds are defined with a wider temperature and droplet size range, eleven different temperatures and eight different droplet sizes are analyzed, as shown in Appendix A.

The numerical simulations

All numerical simulations were performed using the state-of-the-art icing computational fluid dynamics (CFD) solver *Ansys FENSAP-ICE* 2022 R2 (Beaugendre et al. 2006). *FENSAP-ICE* comprises an airflow solver, a droplet solver, and an ice accretion code. Additionally, *FENSAP-ICE* offers the possibility of quasi-steady simulations known as *multishot simulations* (Ozcer et al. 2019, 2011). The total icing time is divided into multiple steps, and the ice shape of the previous step serves as the geometry for the subsequent airflow calculation. The unsteady nature of ice accretion can be captured more accurately using the multishot approach than with a single time step (Prince Raj et al. 2020).

The clean grid used in the numerical simulations was generated using *Pointwise* V18.6R1. All grid settings are based on previous work (Fajt et al. 2019). The mesh is 2.5-dimensional, consisting of a 2D mesh extruded by a single cell in the third dimension. A hybrid O-grid shape (Steinbrenner 2015) captures the boundary layer well with structured cells and a y^+ value < 1 . More information on the grid and grid dependency studies can be found in Lindner et al. (2023).

The airflow was calculated with the Reynolds-averaged Navier-Stokes solver and the Menter k - ω -SST turbulence model. Menter's k - ω -SST model was chosen because it showed better agreement with experimental results than the Spalart-Allmaras model in previous tests and because it is better able to capture flow detachment zones (Ozcer et al. 2019). The initial clean simulation employed a one-equation intermittency transition model. For the following steps, the airflow was assumed to be fully turbulent (Chung and Addy 2000). A shorter first step was simulated with a uniform sand-grain roughness of 0.0005 m, as is recommended by ANSYS (ANSYS Inc. 2021, 2022). The roughness for the following steps is calculated automatically by *FENSAP-ICE*'s beading model (Ozcer et al. 2011). *FENSAP-ICE*'s Eulerian droplet impingement solver was used for the droplet impingement. The ice shapes are calculated based on the impingement and a heat balance. Afterwards, the new wing geometry including the ice shape was re-meshed with automated meshing in *Fluent* (Ozcer et al. 2019). The continuous maximum simulations were divided into fifteen steps, while the intermittent maximum simulations were divided into thirteen steps. More information on the simulation settings and a general overview of the results can be found in Lindner et al. (2023).

This work is part of a larger body of research on icing on unmanned aircraft. As such, it follows the methodology validated in previous publications. Specifically, Hann et al. (2020), who used the same methodology in the same range of Reynolds numbers, presented that the method accurately predicts the drag coefficient for clean and iced geometries.

The simulations were partially automated to cover a wide envelope of icing conditions with little manual input. First, a baseline simulation is generated, consisting of the multishot simulation and an additional airflow simulation of the final ice shape. A Bash script and a Python code are then used to copy the baseline simulation and replace the simulation settings with environmental conditions defined in a separate file. This reduces the setup work to preparing a single simulation and the condition matrix, even for many different conditions. A queuing system can be utilized to execute the batch of simulations on a high-performance computer, eliminating the need for additional manual input. Afterward, a Python code based on PyTecplot is used to automatically post-process all simulations. The entire workflow is visualized in Fig. 1.

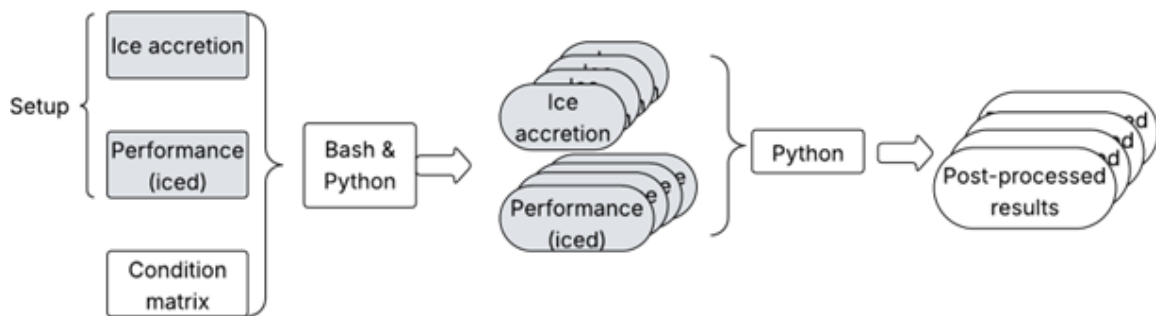


Fig. 1 The simulation workflow, including the automation. Manual processes are shown as rectangles, and *FENSAP-ICE* steps are shown in grey.

Existing analytical expression

Some existing drag predictions were mentioned in the previous sections, and all but two of them will be compared to the numerical results and will be described further. The omitted equations are the Gray equation and the correlation for glaze ice by Fleming and Lednicer. Gray's equation (Gray 1964) was shown to only provide good predictions within the range of parameters that was used to create it (Olsen et al. 1984). The Fleming and Lednicer correlation for glaze ice depends on two equations that are

documented insufficiently (Flemming and Lednicer 1985). Hence, both are excluded from this investigation.

The Bragg equation for the drag increase of rime ice shapes calculates the relative increase in drag compared to the clean drag coefficient:

$$\Delta c_d = 0.01 \left[15.8 \ln \left(\frac{k}{c} \right) + 28000 A_c E + I \right] \quad (1)$$

This expression considers the roughness height k , the chord length c , the accumulation parameter A_c , the total impingement efficiency E , and an airfoil-specific constant I (Bragg 1982).

The following equation for the increase in rime ice drag was introduced by Flemming and Lednicer (1985):

$$\Delta c_d = \left[0.158 \ln \left(\frac{k}{c} \right) + 175 \frac{u}{\rho_I c} E \cdot LWC \cdot t + 1.7 \right] \left[\frac{\alpha + 6}{10} \right] \left[1 - 8 \Delta c_d' \frac{u_{Helo}}{278} \right] c_{d, clean} \quad (2)$$

This equation, which was initially developed for helicopters, considers the speed u , the ice density ρ_I , the icing time t , the angle of attack (AoA) α , and the drag coefficient $c_{d, clean}$ of the clean airfoil. The additional parameters are the helicopter's forward speed u_{Helo} and the drag increase $\Delta c_d'$ if the forward speed is 0 m/s.

Han and Palacios (2013) developed the following correlation for the drag coefficient of an iced airfoil:

$$c_{d, icing} = \left(2.69 \beta_0 A_c Re_\delta + 3800 \frac{T_a}{273.15} + 9.65 (\alpha - 3.352)^2 - 3663 \right) \times 10^{-4} \quad (3)$$

This expression includes the stagnation point collection efficiency β_0 , the Reynolds number of a single droplet Re_δ , and the temperature T_a .

Bragg et al. (2000) also developed an equation for the drag increase caused by glaze ice accretions:

$$\Delta c_d = Z_1 (A_c E) g(n) \quad (4)$$

In this equation, Z_1 is a constant and g is a segmental function that depends linearly on the freezing fraction n and has a maximum at 0.2.

Development of new analytical expressions

New analytical expressions were developed during this study to match the simulated results for the UAV case. The development of analytical expressions consists of an equation baseline and the selection of parameters. CFD codes, such as FENSAP-ICE, provide the user with various parameters. Some of these parameters might be redundant or don't meaningfully affect the drag coefficient. The remaining, more critical, parameters can be found through analyzing the relationships between different parameters.

The equation structure should be based on the results and the combination of parameters. Hence, it will be presented in the results section. Analytical expressions typically contain multiple constants that are optimized to the data at hand. In this case, the parameters are fitted to the simulation results. This fitting process is performed in a Python script using the `curve_fit` function from the `scipy.optimize` library. The quality of all predictions is checked using the root mean square relative error (RMSRE):

$$RMSRE = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{x_i - \hat{x}_i}{x_i} \right)^2} \quad (5)$$

The RMSRE is based on the squared difference between the simulated drag increase x_i and the predicted drag increase $\hat{x}_i$ relative to the simulated value for all N datapoints. The Python script also provides the percentage of predictions within 10%, 20%, and 30% of the simulated values and the maximum difference between prediction and simulation.

Overfitting to the training dataset is a common problem in quantitative modeling (Hawkins 2004). One method of testing whether an equation was overfitted is cross-validation. The approach involves splitting the dataset into training and testing sets (Montesinos López et al. 2022). For this study, the dataset was randomly divided into one half for training and one half for verification using the random shuffle function of the NumPy library. This process was repeated 25 times, and the equation resulting in the lowest RMSRE values on the testing set was selected.

RESULTS:

The CFD simulations provide a drag increase for each environmental condition and each time step, which will subsequently be referred to as *data points*. Two exemplary simulated ice shapes are presented in Appendix B. For some cases at $-8\text{ }^{\circ}\text{C}$ and $-10\text{ }^{\circ}\text{C}$, data is only available for the final time steps. However, the dataset still comprises 1,798 data points that cover the entire temperature and droplet size ranges specified in the certification standards. The resulting drag increase for each data point is shown in Fig. 2. For a low ice mass, the drag rises by approximately 60% compared to the simulated drag coefficient of 0.008 for the clean airfoil. This is likely caused by the immediate flow transition that is assumed in the simulations and by the aerodynamic influence of roughness. Additionally, drag coefficients increase with the growth of ice mass. This is likely related to larger ice shapes that result in a more significant disruption of flow.

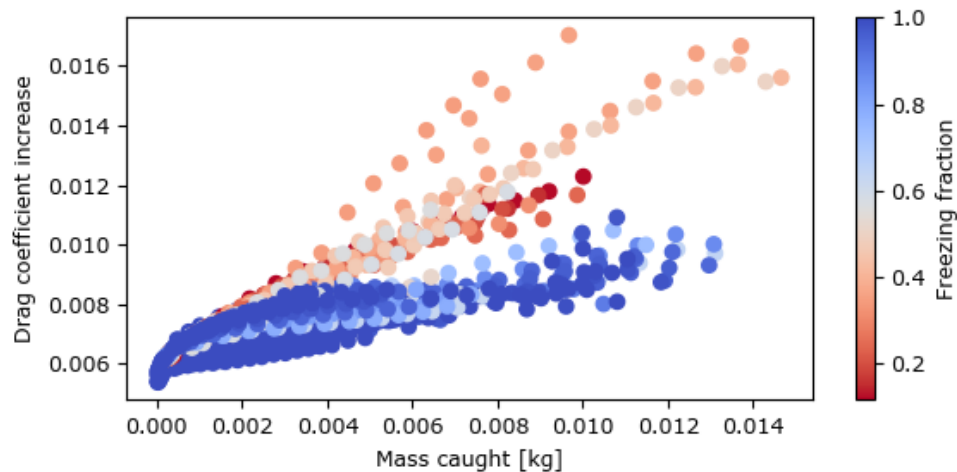


Fig. 2 The simulated increase in drag coefficient for different ice accretion times and icing conditions. The freezing fraction is the value measured at the stagnation point for the first time step.

Another characteristic is the difference between freezing fractions. Each data point in Fig. 2 is colored according to the freezing fraction in the stagnation point of the first time step, as calculated by FENSAP-ICE. This figure shows that data points can be grouped into clusters based on the freezing fraction, where

each cluster has a different gradient of the drag coefficient increase. One cluster represents the rime ice regime, characterized by large freezing fractions. Because rime ice shapes are more streamlined than glaze or mixed ice shapes, the drag increase is smaller for rime ice shapes than for other icing regimes. Ice shapes with intermediate freezing fractions yield the highest drag coefficients, likely due to the effect of ice horns.

Existing analytical expressions

The required input parameters to compare existing correlations with the numerical results were direct outputs of FENSAP-ICE, except for those described in Appendix C.

The Bragg equation in Eq. (1) predicts the relative increase in drag for rime ice cases. Although the freezing fraction range for rime ice can be defined more broadly, the correlation is only compared to simulated values with a freezing fraction of 1. The equation contains an airfoil-specific constant I that must be fitted to the dataset. The value required to match the simulated drag coefficient varies significantly across the data points, as shown in Fig. 3a. This indicates that the constants in Eq. (1) do not fit well for the UAV case. The average fitted airfoil-specific constant I across all cases is 100. When using this value, the predicted drag values differ significantly from the simulated drag, as shown in Fig. 3b. While all simulated values are in the order of 1, the range of predicted drag changes is from -0.5 to 4.5 . In addition to the wider range, the equation predicts some ice shapes with a negative relative drag change. In these cases, the iced drag would be reduced compared to the clean case. Thus, Bragg's equation in its current form does not work well for the considered UAV cases.

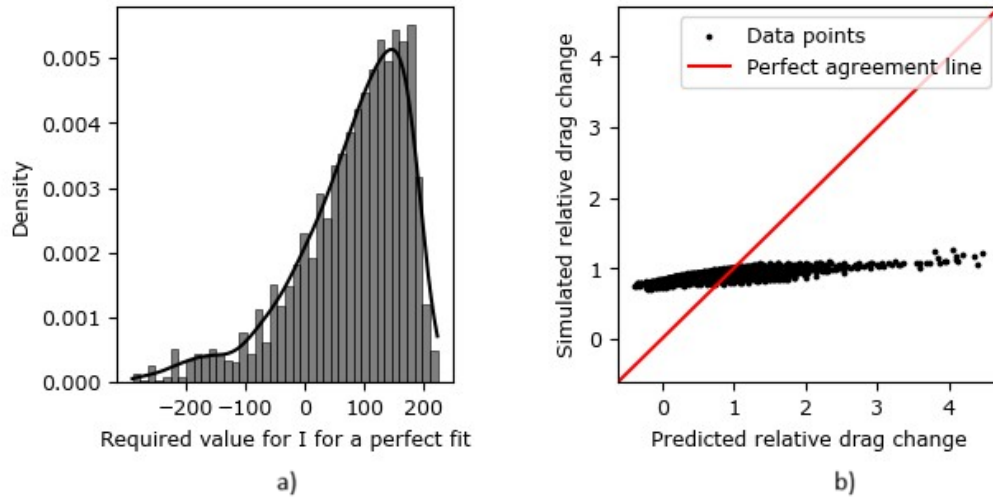


Fig. 3 Applying the Bragg equation to the simulated drag values: a) A histogram showing the distribution of required values for the airfoil constant I in Bragg's equation to match the simulated drag data exactly, b) The increase in drag coefficient predicted using Bragg's equation compared to the simulated values.

As mentioned earlier, the rime ice expression by Flemming and Lednicer that is presented in Eq. (2) was initially developed for helicopters. To use it for a fixed-wing case, the equation was analyzed for a forward velocity V_{Helo} of 0 m/s. Similarly to the Bragg equation, this equation typically predicts a larger spread in drag than the CFD simulation, as seen in Fig. 4. It represents an improvement over Eq. (1) because of the prediction of an increase in drag for all data points.

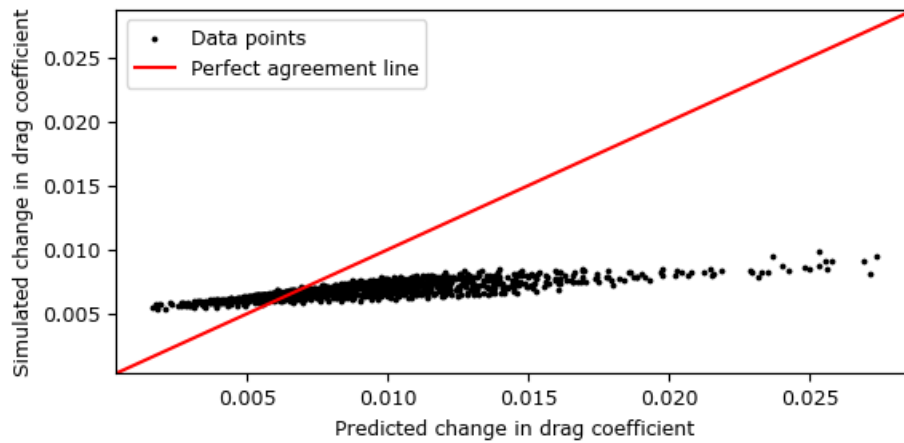


Fig. 4 The increase in drag coefficient predicted using Flemming's equation compared to the simulated values.

The comparison of the predictions for the increase in drag using Eq. (1) and Eq. (2) with the simulated results shows a greater increase in the predictions. This could indicate that the weight of the accumulation parameter is too large for the UAV dataset. When optimizing the parameter in front of the accumulation parameter and the constant offset to the UAV data, both analytical expressions show significantly better agreement with the simulated data, as illustrated in Fig. 5. The adjusted equations still show a larger spread than the simulated data but are within a good order of magnitude. The comparison of predicted and simulated drag values still shows systematic differences. These differences are likely related to a difference in the influence of roughness. This is further supported by the fact that in both adjusted equations

$$\Delta c_d = 0.01 \left[15.8 \ln\left(\frac{k}{c}\right) - 1357 A_c E + 186 \right] \quad (6)$$

and

$$\Delta c_d = \left[0.158 \ln\left(\frac{k}{c}\right) - 13 \frac{u}{\rho_l c} E \cdot LWC \cdot t + 1.9 \right] \left[\frac{\alpha + 6}{10} \right] \left[1 - 8 \Delta c_d' \frac{u_{Helo}}{278} \right] c_{d, clean} \quad (7)$$

the influence of accumulation has become negative.

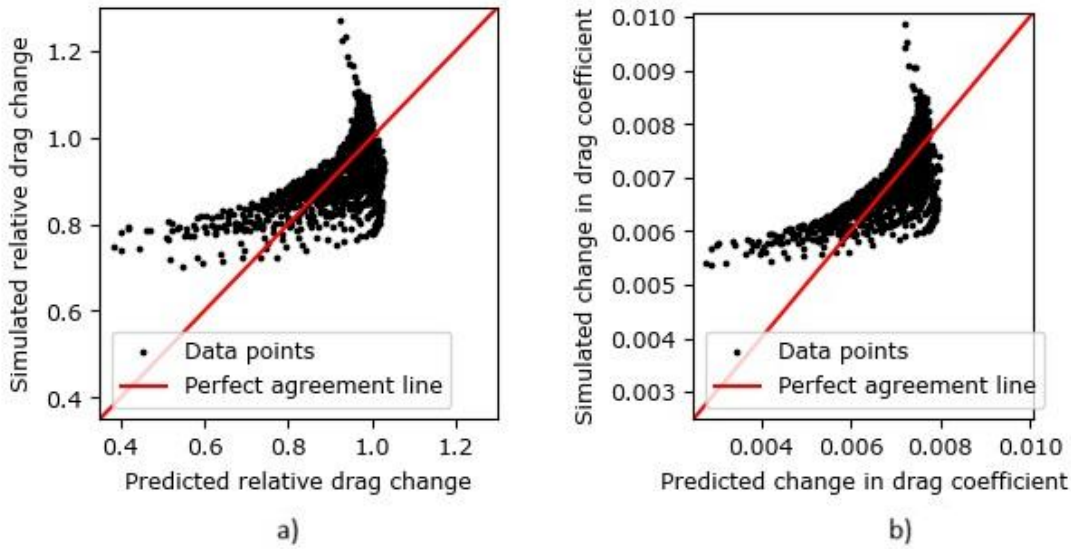


Fig. 5 The simulated drag increases compared to predictions with parameters adjusted to match the simulated data better: a) The comparison of the adjusted Bragg equation with the CFD results, b) The comparison of the adjusted Fleming and Lednicer equation with the CFD results.

The prediction in Eq. (3) developed by Han and Palacios can be used for all icing regimes. However, as shown in Fig. 6, the spread of predicted drag coefficients is almost ten times larger than in simulated drag coefficients. Additionally, the Han–Palacios correlation predicts negative drag coefficients in 42% of the cases and lower drag coefficients than the clean airfoil for another 10% of the data points.

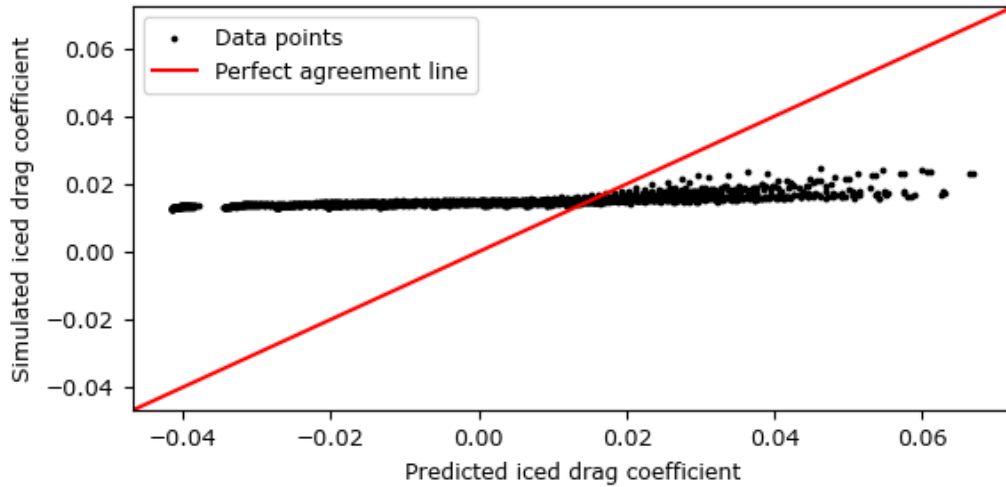


Fig. 6 The drag coefficient predicted using the correlation developed by Han and Palacios (2013) compared to the simulated values.

Equation (4) was developed by Bragg for glaze ice cases and uses a segmentally linear dependency on the freezing fraction with a maximum at 0.2. As shown in Fig. 7, the investigated data has a maximum in the region of freezing fractions in the stagnation point from 0.3 to 0.5. However, the data points cannot be described as segmentally linear. Thus, fitting a freezing fraction function to the dataset is unsuitable, and the correlation is not quantitatively compared in this study. Furthermore, developing a new prediction for the drag coefficient will not include a segmentally linear dependency on the freezing fraction but instead split the dataset into multiple clusters. A potential distribution of clusters can also be seen in Fig. 7.

In summary, the values predicted by existing analytical expressions and the simulated drag coefficients show a significant difference. Hence, new predictions are required that better capture low-Reynolds number cases, such as those in UAV applications.

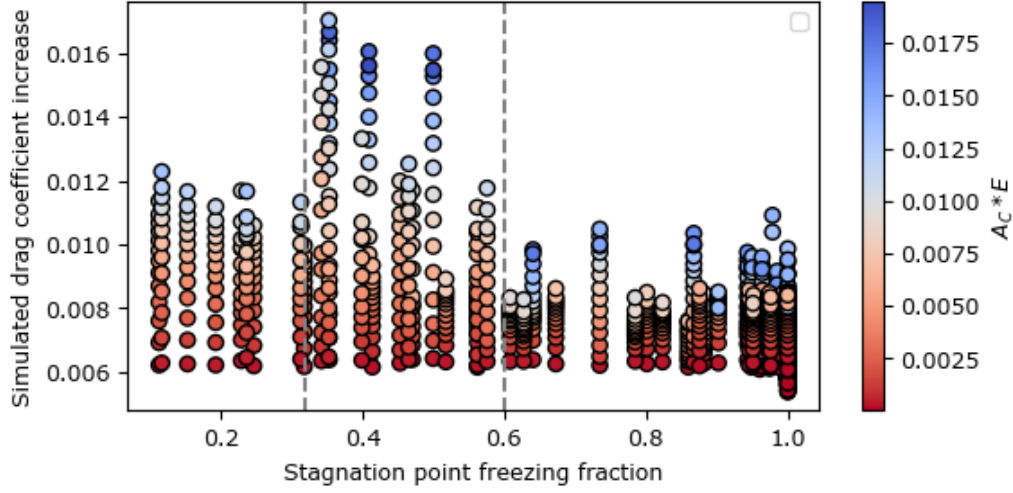


Fig. 7 The simulated drag increases for different accumulation levels and freezing fractions at the stagnation point of the clean airfoil. The vertical lines at 0.32 and 0.60 show clusters that are used in Eq. (11).

Development of new analytical expressions

Learning from existing equations, three different parameters are typically included. First, all expressions consider the amount of water impinging on the airfoil. Second, the predictions that capture the glaze shapes include the temperature or the freezing fraction as a quantification of the icing regime. Third, many existing expressions contain the ice roughness as a parameter. As described by McClain et al. (2019), the ice roughness can be estimated based on the freezing fraction and the amount of supercooled water accumulation on the airfoil. Hence, adding the roughness as a parameter to the expression is not expected to have a significant favorable influence and could lead to overfitting.

Based on initial findings and existing expressions, the following polynomial equation was chosen:

$$\Delta c_d = c_1 \prod v_n^{p_n} + c_2 \quad (8)$$

This equation includes the constants c_1 and c_2 and the powers p_n to the variables v_n . An equation of this type assumes that the input parameters influence each other and that the resulting increase in drag is not

simply a linear combination of the influence parameters. Additionally, this equation assumes an immediate rise in the drag coefficient, c_2 . Hence, this equation can only be used when ice has actually accreted on the wing, as it shows an increase in drag in all cases.

First, a single equation to cover all icing regimes was fit to the data:

$$\Delta c_d = 0.0364 m^{0.987} n^{-0.448} + 0.006205 \quad (9)$$

where m is the water mass that has impinged per meter span (in kg/m) and n is the freezing fraction at the stagnation point of the clean airfoil. Both values are outputs of FENSAP-ICE. As seen in Fig. 8, the equation can provide good predictions of the trend for the drag coefficients: 98.7% of the data points fall within 20% uncertainty of the simulated increase in drag coefficient, and the RMSRE is 7.4%. However, eight data points are underpredicted by more than 30%, with a maximum error of 44%. Additionally, a large spread exists for larger predicted drag coefficients. This is likely related to the significant influence of the icing regime on the drag coefficient.

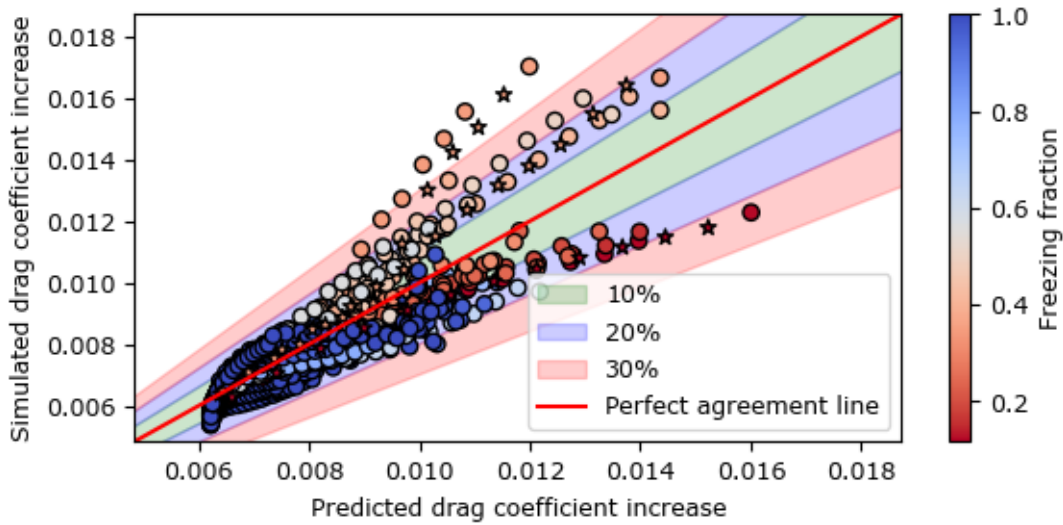


Fig. 8 The drag increases predicted using a one-part expression compared to the simulated values. The cases with a star will be used later.

A two-part equation was tested next to separate cases with low and high freezing fractions at the stagnation point of the clean airfoil. Different freezing fraction ranges were evaluated using the RMSRE metric. An optimum was found when dividing the cases into two groups, which are separated at a freezing fraction of 0.58. The resulting expression for glaze ice is:

$$\Delta c_d = 0.0780 m^{0.995} n^{0.062} + 0.006110 \quad (10a)$$

The resulting expression for rime ice is:

$$\Delta c_d = 0.0098 m^{0.498} n^{-0.101} + 0.005706 \quad (10b)$$

The step from the single equation to the two-part equation significantly improves prediction quality, as shown in Fig. 9. Except for two outliers, all data points are within 30% of the simulated drag coefficient, and 99.4% of data points are within 20% of the simulated value. The cases with higher predicted drag coefficients show a better match than those obtained when using the one-part equation. This trend is also reflected in the RMSRE, which has been reduced to 5.4%.

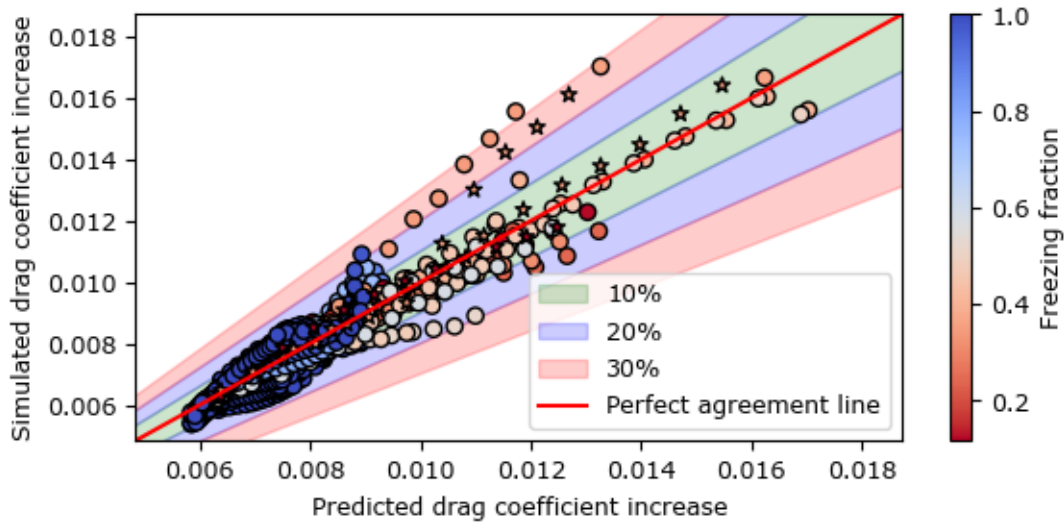


Fig. 9 The drag increase predicted using the two-part equation compared to the simulated values over the entire freezing fraction range. The cases with a star will be used later.

As was shown in Fig. 7, the data shows three different clusters when plotting the drag coefficients over the freezing fraction. Hence, a three-part equation is expected to show a considerable improvement. The first part predicts the drag increase for freezing fractions larger than 0.6:

$$\Delta c_d = 0.0091 m^{0.456} n^{-0.190} + 0.005584 \quad (11a)$$

The medium range for freezing fractions between 0.32 and 0.6 is predicted using the following equation:

$$\Delta c_d = 0.0351 m^{0.912} n^{-0.694} + 0.005897 \quad (11b)$$

The glaze ice region with freezing fractions below 0.32 is predicted using the following equation

$$\Delta c_d = 0.0205 m^{0.571} n^{-0.104} + 0.005285 \quad (11c)$$

The resulting prediction performs better, yielding an RMSRE of 5.1%. The maximum deviation of a data point is 23%, and only two data points are outside 20%, as seen in Fig. 10. Additionally, it is no longer possible to identify freezing fractions that are generally over- or underpredicted.

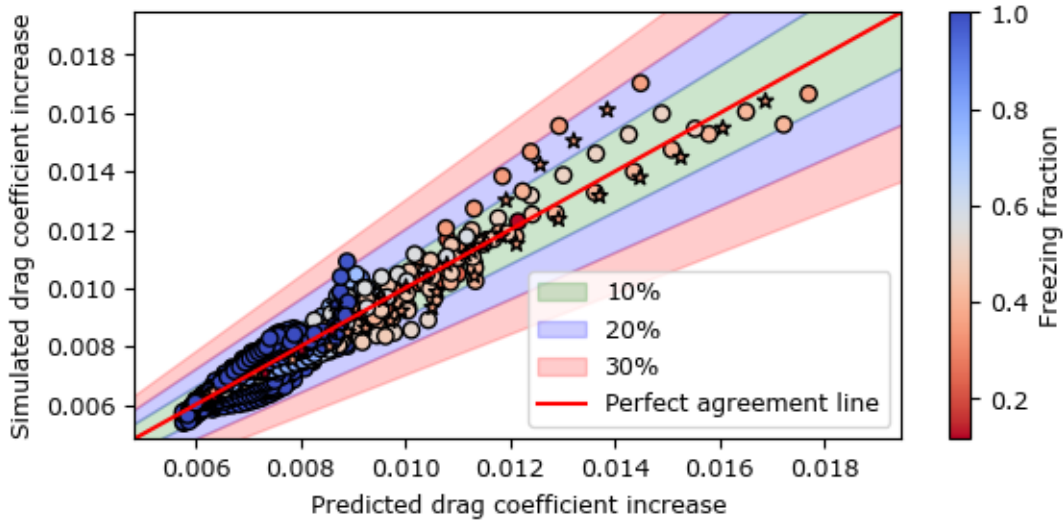


Fig. 10 The drag increase predicted using a three-part equation compared to the simulated values over the entire freezing fraction range. The cases with a star will be used later.

The expressions shown in the previous paragraphs present the best fit for the given parameter set. One way to improve predictions is by incorporating additional parameters, such as the stagnation point collection efficiency. Given the fixed airspeed, angle of attack, and chord length, the collection efficiency at the stagnation point is a direct measure of the droplet size. However, adding the collection efficiency could also result in overfitting to the dataset. Indeed, when including the collection efficiency in the three-part equation, the RMSRE is almost unchanged. This is also because the collection efficiency is already partially captured by the impinged mass parameter used for the analytical equations.

Extending the range of parameters

One problem with most expressions fitted to a dataset is that they are strictly valid only within the parameter range of the training set. This section discusses the accuracy of the new equations shown earlier when used on data outside the trained range, as long as the airfoil is the RG-15. The chord length, airspeed, and angle of attack were varied for two continuous maximum and two intermittent maximum cases. The parameter variations and conditions are shown in Table 1, and the results of the conditions are shown as stars in Fig. 8, Fig. 9, and Fig. 10. All results are from FENSAP-ICE simulations performed exactly as for the training dataset. This includes using the same angle of attack for ice accretion simulation and drag simulation in all cases.

Table 1: Overview of the parameter range for the extended simulations and the ambient conditions used. The parameter values in bold are the "standard values" used in this study.

Parameter / Condition	Values
Airspeed	20 m/s, 25 m/s , 30 m/s
Angle of attack	0°, 2°, 4°
Chord length	0.22 m, 0.27 m , 0.32 m
Continuous maximum case 1	T = −10 °C, MVD = 15 μm, LWC = 0.60 g/m ³
Continuous maximum case 2	T = −2 °C, MVD = 15 μm, LWC = 0.76 g/m ³
Intermittent maximum case 1	T = −6 °C, MVD = 20 μm, LWC = 2.35 g/m ³
Intermittent maximum case 2	T = −2 °C, MVD = 20 μm, LWC = 2.47 g/m ³

Using the three-part expression Eq. (11) results in a fair match but shows significant differences from the predicted values, as seen in Fig. 11. This is also highlighted by the RMSRE of 13.2% and the fact that 6.3% of the data points are outside 30%, with a maximum error of 96%.

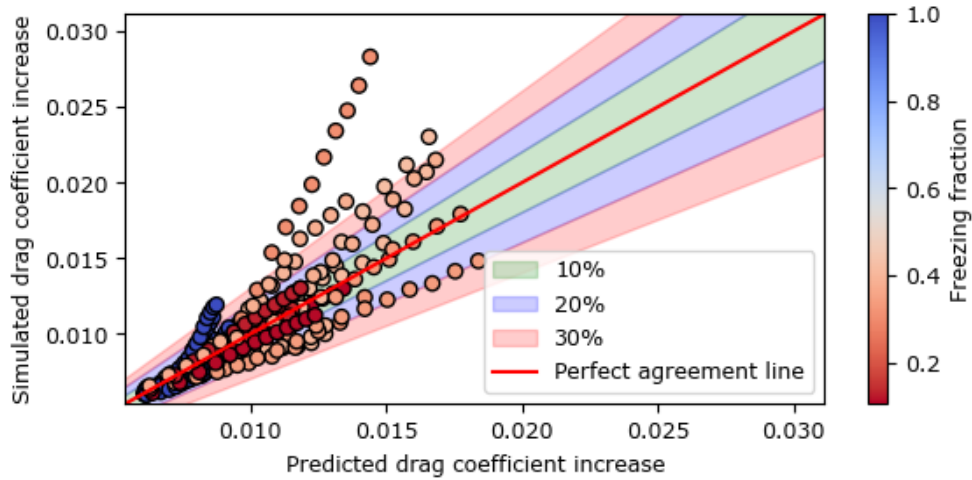


Fig. 11 The drag increase predicted using the three-part equation compared to the simulated drag increase for the extended parameter range.

The accuracy of the prediction can be improved significantly by implementing a few measures. First, one important finding of icing research is that the aerodynamics of an iced wing is almost independent of the Reynolds number (Kim and Bragg 1999). On the other hand, the Reynolds number influences the aerodynamic performance of a clean wing considerably. Thus, the absolute drag coefficient is much less sensitive to parameter variations than the increase in drag coefficient. Adding the clean drag coefficient to Equations (9), (10), and (11) to produce the absolute drag coefficient improves the prediction accuracy. However, the drag increase is almost constant for different angles of attack, at least those angles that are far from the stall angle. Thus, the baseline clean drag should depend on the angle of attack of the case at hand. Second, varying the chord length while still using the total impinged mass per meter span results in a worse prediction. This is because the same amount of ice on a smaller airfoil would result in a larger ice shape relative to the wing. A significant improvement in the prediction is possible when using a chord-

adjusted mass caught instead. Finally, the two-part equation resulted in lower errors than the three-part expression. This indicates that the freezing fraction clusters identified for the training data might occur at slightly different freezing fractions for other parameter ranges. It was decided not to search for better transition points for the expression because the new dataset is highly unbalanced regarding the conditions covered. Thus, any new results would be significantly biased.

Combining the changes results in two new equations: one for cases with a freezing fraction below 0.58:

$$c_d = 0.0780 \tilde{m}^{0.995} n^{0.062} + 0.006110 + c_{d, \text{clean}} \quad (12a)$$

and the other for cases where the freezing fraction is above 0.58:

$$c_d = 0.0098 \tilde{m}^{0.498} n^{-0.101} + 0.005706 + c_{d, \text{clean}} \quad (12b)$$

The chord-adjusted mass caught $\tilde{m}$ normalizes the mass caught per span to a chord length of 0.27 m. The clean drag coefficient $c_{d, \text{clean}}$ depends on the wing's angle of attack and is 0.0055 for an AoA of 0°, 0.006 for an AoA of 2°, and 0.0075 for an AoA of 4°.

Using the new chord- and angle-of-attack-adjusted two-part equation, the RMSRE for the extended range cases is reduced to 7.6%. None of the extended cases is outside 30% error (the maximum is 28%). Although 6.4% of the cases are outside 20% prediction accuracy, this is a significant improvement over the previous version, as seen in Fig. 12. It should also be highlighted that, except for the step from the three-part equation to the two-part equation, no change would affect the results for the training dataset.

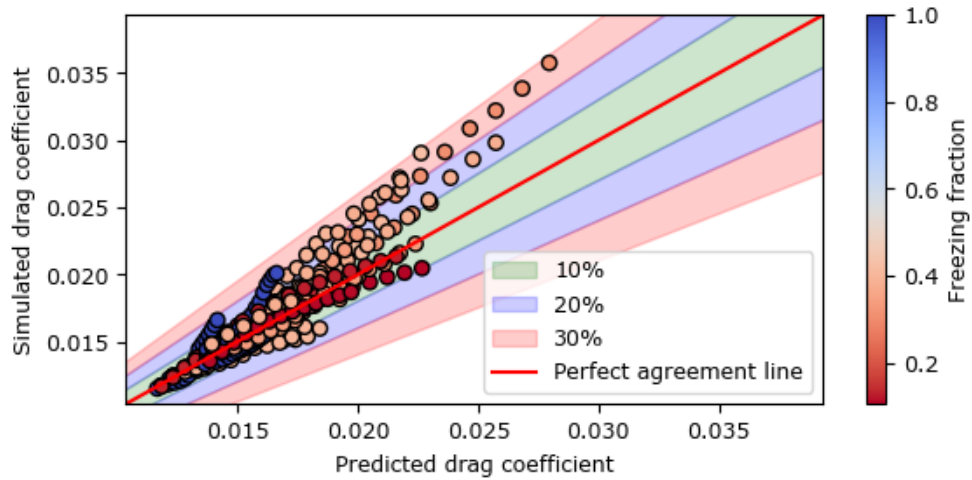


Fig. 12 The drag increase predicted using the adjusted two-part equation compared to the simulated drag increase for the extended parameter range.

Real-life applications

The previous sections concerned the development of drag equations for flight through icing conditions, assuming all relevant parameters are known. This is typically true for CFD simulations because they provide the user with numerous parameters that can be utilized to develop correlations. However, some parameters might not be available when using the prediction in flight. This is because common aircraft are only equipped with limited sensing capabilities regarding icing. While some parameters can be estimated from others that are measured more often, some situations require simplified approaches. This section will present approaches to dealing with different scenarios in which sensors provide information regarding some parameters (but not all).

Scenario 1: All parameters can be estimated:

In the first scenario, a sufficient amount of data is available to calculate both parameters required for the prediction. The first parameter is the mass caught per meter span m . Ideally, the aircraft would have a

sensor that can estimate the impinging mass on the wings. For example, if measurements of the LWC and the droplet size are available, the mass caught can be calculated as

$$m = LWC \cdot u \cdot h \cdot t \cdot E \quad (13)$$

where h is the projected vertical airfoil height at the flight angle of attack; t is the accretion time; and E is the total collection efficiency of the wing, which depends mainly on the airspeed and droplet size. Contrary to the local collection efficiency mentioned before, the total collection efficiency describes the overall percentage of droplets impinging on the wing. The LWC can, for example, be measured using a hot-wire approach and the MVD measured using a spectrometer probe (Sand et al. 1984). MVD probes are not common on aircraft, but when using multiple sensors along the wing chord, it is often possible to estimate the MVD.

The second parameter is the freezing fraction. A simplified heat balance of the following form:

$$q_c + q_e + q_w = q_k + q_f \quad (14)$$

is required to calculate the freezing fraction (Anderson 2004). The terms in this expression are convective heat, evaporative heat, sensible heat, kinetic heat, and latent heat of freezing, respectively. A more detailed explanation of how to calculate each term and the freezing fraction is provided in Appendix D. To use these equations, the ambient temperature and pressure, the airspeed, the impinging mass rate, and the radius of the leading edge of the airfoil must be known. In addition, certain thermal material properties of air and water are required, but these parameters can be calculated using the given flight conditions.

When using the calculated input values instead of those provided by the numerical simulations, the three-part equation still accurately predicts the drag increase, as seen in Fig. 13. The RMSRE remains at 5.1%, with only eight data points exceeding 20% accuracy and a maximum offset of 28%.

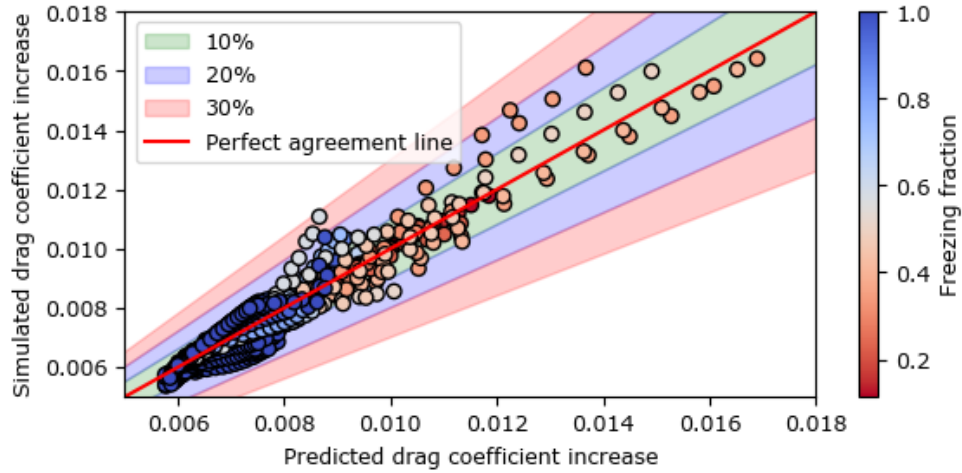


Fig. 13 The drag increase predicted using the three-part equation with calculated input values compared to the simulated drag increase.

Scenario 2: No information on droplet size:

As explained before, an aircraft might have a sensor estimating the ice mass impinged, for example, based on thermal or capacitive measurements. Information on the droplet size or collection efficiency is less common. However, depending on the airfoil and airspeed, the potential spread in collection efficiencies may not be significant. The analyzed dataset showed a collection efficiency at the stagnation point of 0.59 when using a MVD of 15 μm and 0.71 when using a MVD of 50 μm . Using the average of 0.65 for the three-part equation results in an RMSRE of 5.3%. As can be seen in Fig. 14, one data point is underpredicted by more than 30%. The drag increase is generally predicted well, although the prediction is slightly worse than with known collection efficiency.

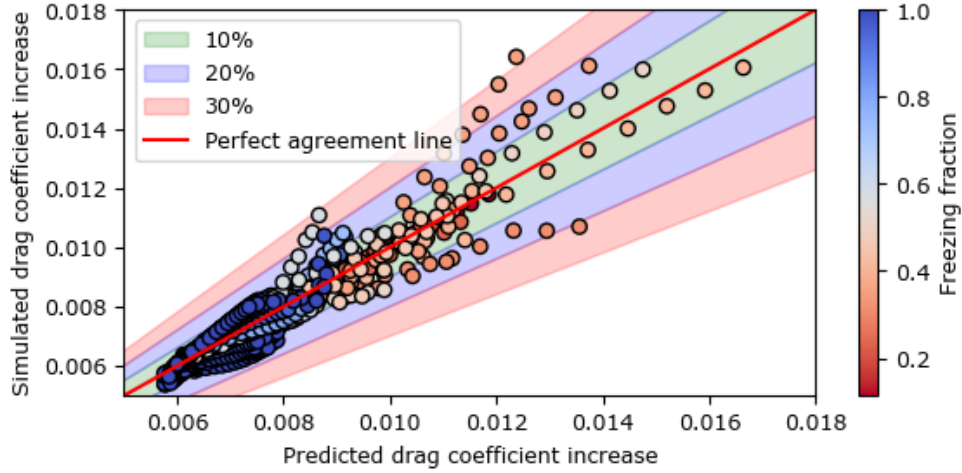


Fig. 14 The drag increase predicted using the three-part equation with calculated input values and average collection efficiency compared to the simulated drag increase.

Scenario 3: The only icing-related information is the LWC:

Depending on the aircraft and the installed sensors, there may be no estimate of the actual amount of ice accretion on the wing. The only available information might be the amount of water in the air, i.e., the LWC that can be estimated using a hot-wire approach. Thus, neither the mass caught nor the freezing fraction can be calculated. This is particularly problematic because the percentage of droplets impinging on the wing depends significantly on the droplet size. The total collection efficiency on the wing can vary from 0.19 for 15- μm droplets to 0.66 for 50- μm droplets. Instead, the drag increase may be estimated based on the LWC, ambient temperature T_a , and accretion time t . When developing a one-part equation based on a polynomial approach, the following expression can be used:

$$\Delta c_d = 0.0289 \left(\frac{LWC}{1000} \right)^{0.730} (273.15\text{K} - T_a)^{-0.449} t^{0.603} + 0.006313 \quad (15)$$

This expression yields an RMSRE of 8.0%. As shown in Fig. 15, the fit is slightly worse than for the ideal predictions. Only 81.6% of the data points are within 10% accuracy, and the maximum offset is 61%. The equation especially underpredicts the largest drag coefficients, highlighting the importance of good sensor data for obtaining accurate prediction.

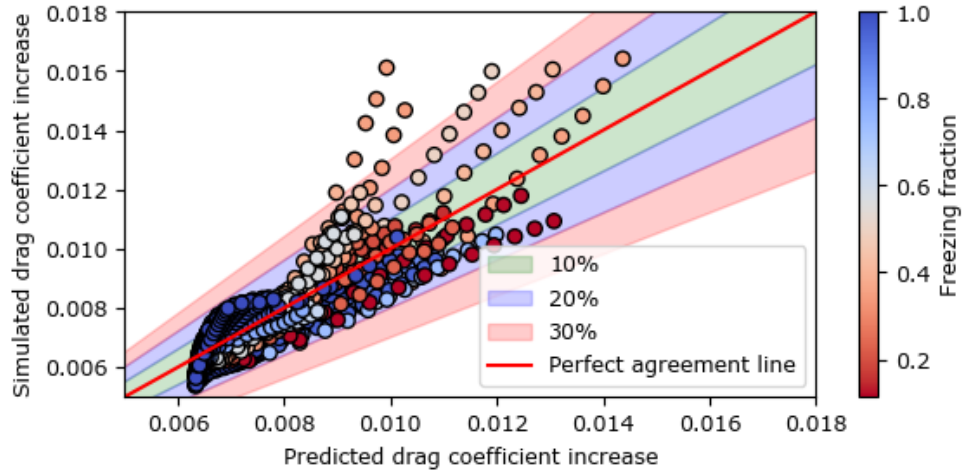


Fig. 15 The drag increase predicted using a one-part equation with limited input values compared to the simulated drag increase.

DISCUSSION:

Analytical expressions for the drag increase caused by ice accretions on a wing can be faster and simpler than numerical simulations or experiments. However, all existing predictions have been developed for the large Reynolds numbers of manned applications or helicopter rotor blades with Reynolds numbers typically between 1,500,000 and 15,000,000. This study examines the usability of existing correlations for simulated drag increases for small UAVs with a Reynolds number of 450,000. Additionally, a new expression based on the simulation results is developed, and its potential real-life applications are presented.

Several shortcomings of the simulations must be considered in data analysis. First, icing CFD codes are primarily verified for manned applications and may perform worse for low-Reynolds number applications, such as UAV flights (Hann 2022). Research in recent years has shown that FENSAP-ICE can also produce reasonable results for UAV icing cases (Frey et al. 2024; Hann 2019; Hann et al. 2020; Hann and Johansen 2021). However, most of these studies focus on the ice accretion, not the aerodynamic performance. One simplification in this study is that the flow is assumed to be fully turbulent as soon as ice accretion begins.

It is realistic that the airflow starts transitioning already after short ice accretion times because of the surface roughness of the ice (Kerho and Bragg 1997). Nevertheless, the simulations might overpredict the drag coefficient of time steps with little accreted ice mass. Another influence parameter is the surface roughness, which can significantly influence the drag coefficient (Bragg et al. 2005). However, the aerodynamic influence of surface roughness can be different in reality and in CFD simulations, also depending on the selected turbulence model (Wallisch et al. 2024). While the droplets were simulated using a single size for each condition, real clouds contain droplets of different sizes (Cober et al. 1995). Using real droplet size distributions is likely to change impingement limits but has only a minor influence on the mass caught and the mass impinging at the stagnation point, and it therefore has an insignificant effect on the predictions developed in this study. In general, experiments are necessary to verify the numerical results because the combined uncertainty of predicting ice shapes, their roughness, and the corresponding drag is significant.

The comparison of the existing expressions with the simulated drag coefficients shows a significant error. This error could be related to general differences between manned and unmanned applications. For example, small unmanned aircraft with a low Reynolds number typically experience laminar flow over longer distances. Additionally, the different sizes and velocities influence the collection efficiency and the aerodynamic influence of ice shapes (Hann and Johansen 2021; Szilder and McIlwain 2011, 2012). Finally, the datasets for the existing correlations were based on experiments with airfoils with a maximum thickness of 12 to 15%. The maximum thickness of the RG-15 airfoil used for this study is only 9%. This could result in differences in collection efficiency and ice shapes (Politovich 2000). However, some differences may also be seen between FENSAP-ICE results and the results of experimental tests. Several existing analytical expressions were based on results of Shin and Bond (1992). Simulating some of their cases with FENSAP-ICE resulted in similar ice shapes, but drag increases about 50% below those reported

in the publication. Nevertheless, the comparison demonstrated the need for a new analytical expression to account for the increase in drag on a small-scale UAV wing.

New predictions were developed based on polynomial equations. Three different equations for the different freezing fraction regimes resulted in the best agreement between the predicted and simulated drag increases. That matches the findings from the raw data of three different freezing fraction clusters. The polynomial equations based on the mass caught on the wing and the freezing fraction predicted all data points within 23% of the simulated drag increase. This is a significantly better agreement than those obtained when using existing correlations (Han and Palacios 2013). However, the data in the dataset limits the usability of the new prediction. First, all drag increases are simulated for a single combination of airfoil, chord size, angle of attack, and airspeed. Hence, the expression is strictly only applicable for this parameter combination. However, additional cases with a chord length, angle of attack, or airspeed outside the training data were predicted fairly well with the newly developed equations. Particularly after adjusting the expressions based on knowledge about icing physics and aerodynamics, the adjusted two-part prediction could predict the drag coefficient with an average error of only 7.6%. This highlights the usability of the developed expressions, even when used slightly outside the training set range, provided that the RG-15 remains the airfoil.

Nevertheless, an expanded dataset is required to utilize the prediction for a broader range of parameters. First, all simulations in this study were done with the RG-15 airfoil. Thus, the predictions are limited to this airfoil. Ideally, an expanded dataset would also contain information about the drag increase in cases where the aircraft flies at a different angle of attack than the one at which the ice accreted. These cases would be particularly interesting because of the need for the angle of attack to be increased in order to maintain lift when ice accumulation occurs. In addition, the dataset only considered standard ice shapes on a wing without an ice protection system. If the prediction was used for wings with a thermal ice protection system, intercycle ice shapes would be more representative. These intercycle ice shapes might

result in larger drag coefficients, especially in the early stages of ice accretion (Wallisch and Hann 2023). An additional interesting data expansion would be to consider supercooled large droplets that are significantly larger than the droplets investigated in this study. Supercooled large droplets result in more impingement, but they could also present different physical challenges, such as bouncing and droplet split-up. Finally, the drag is not the only important parameter for determining icing severity or planning missions and IPS operations. The loss of lift and stall angle might be more critical in some cases. Developing analytical expressions also for these parameters would combine this study into an even more helpful tool.

The usability of the three-part drag increase prediction in real-life applications depends on the available measurements. If the mass caught on the wing can be estimated, all required parameters for the full correlation can be calculated. This could be achieved by having an LWC sensor and an MVD sensor or an MVD estimate from a sensor array. If the mass caught can be estimated, but no information on the droplet size is available, using an averaged value can still accurately predict the drag increase. Only one data point was outside a 30% accuracy of the simulated drag increase. When only the LWC but not the impinging mass is known, a prediction based on the LWC and the temperature can be used, which still predicts 81.6% of the data points within 10% error, but also has outliers as far as 61% from the simulated values.

SUMMARY:

Knowing the performance degradation caused by ice accretion on a small-scale UAV wing can be valuable information for mission planning and the operation of an ice protection system. Analytical expressions are a cheap and quick alternative to CFD simulations and experiments. However, all existing correlations were fitted to manned applications with larger Reynolds numbers in a typical range between 1,500,000 and 15,000,000.

This study compared existing drag increase predictions to simulated drag increases for a small UAV wing with a Reynolds number of 450,000. The predictions were inaccurate, with many cases predicted to produce negative drag and a modeled spread in drag increase up to ten times as large as the simulated spread. This inaccuracy appears to be caused by the existing predictions overestimating the influence of roughness and the accumulation parameter on drag. A new analytical expression was developed using the CFD results as an alternative. The prediction was split into three equations for different freezing fraction regimes, and the mass caught by the wing and the freezing fraction were used as parameters. The developed prediction for the RG-15 airfoil at 25 m/s, for a 0.27-m chord at an angle of attack of 4° is the expression presented in Eq. (11). Using this equation, all data points within the dataset can be predicted within 23% uncertainty and an average error of 5%. This is a significant improvement compared to existing predictions. Even when the parameters are slightly outside those used to train the equation, the average error can be kept at 8%, as long as the wing has the RG-15 airfoil. For these cases outside the training dataset, the recommended prediction method presented in Eq. (12) is adjusted to the chord length.

Since the new analytical expression was based solely on CFD results, experimental verification of the dataset is necessary. Additionally, in the next step, the data used for the expression should be broadened to include even more variation in airfoil selection, chord length, airspeed, and angle of attack, and it could potentially include supercooled large droplets. This would increase the confidence in the prediction, which might currently be overfitted to the dataset. Finally, repeating this process to develop correlations for the decrease in lift coefficient and stall angle would provide additional useful information.

APPENDIXES:

Appendix A: Icing conditions

Table 2 and Table 3 contain the icing conditions that were selected from the certification guidelines to be analyzed in this study.

Table 2: The simulated combinations of ambient temperature, MVD, and LWC (in g/m³) for continuous maximum conditions.

	15 µm	20 µm	25 µm	30 µm	35 µm	40 µm
−2 °C	0.76	0.60	0.46	0.35	0.24	0.14
−4 °C	0.72	0.55	0.42	0.32	0.22	0.13
−6 °C	0.68	0.51	0.38	0.28	0.20	0.12
−8 °C	0.64	0.47	0.34	0.25	0.18	0.11
−10 °C	0.60	0.44	0.31	0.22	0.15	0.10
−15 °C	0.45	0.32	0.23	0.17	0.12	0.08
−20 °C	0.30	0.21	0.15	0.11	0.08	0.06
−25 °C	0.25	0.17	0.12	0.09	0.06	0.05
−30 °C	0.20	0.14	0.10	0.07	0.05	0.04

Table 3: The simulated combinations of ambient temperature, MVD, and LWC (in g/m³) for intermittent maximum conditions.

	15 µm	20 µm	25 µm	30 µm	35 µm	40 µm	45 µm	50 µm
−2 °C	2.81	2.47	1.70	1.27	0.95	0.71	0.53	0.38
−4 °C	2.74	2.41	1.64	1.21	0.89	0.66	0.50	0.36
−6 °C	2.66	2.35	1.58	1.15	0.83	0.61	0.46	0.34
−8 °C	2.58	2.29	1.52	1.09	0.77	0.56	0.42	0.32
−10 °C	2.50	2.23	1.46	1.03	0.71	0.51	0.39	0.30
−15 °C	2.21	1.97	1.31	0.92	0.64	0.45	0.33	0.24
−20 °C	1.92	1.71	1.15	0.82	0.57	0.39	0.27	0.18
−25 °C	1.52	1.35	0.93	0.67	0.47	0.32	0.22	0.14
−30 °C	1.11	0.99	0.71	0.51	0.36	0.25	0.16	0.10
−35 °C	0.68	0.60	0.43	0.30	0.22	0.15	0.11	0.07
−40 °C	0.25	0.21	0.15	0.10	0.07	0.06	0.05	0.05

Appendix B: Simulated ice shapes

Exemplary ice shapes, including the intermediate results, are shown in Fig. 16 and Fig. 17.

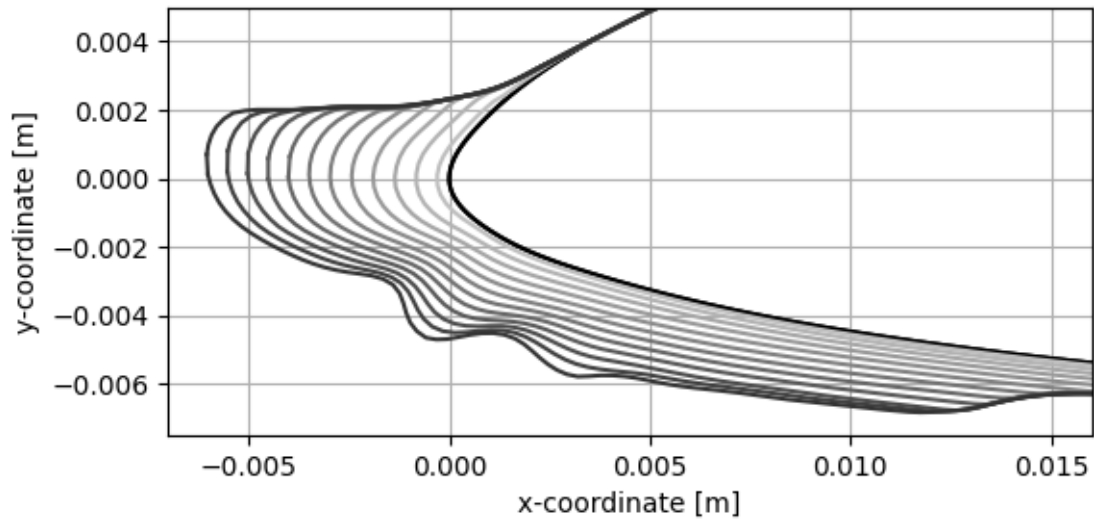


Fig. 16 The growth of the ice shape under -8°C , $20\text{ }\mu\text{m}$ MVD, and 2.29 g/m^3 LWC. Each line represents one shot of the simulation, and the time between lines is 16 s.

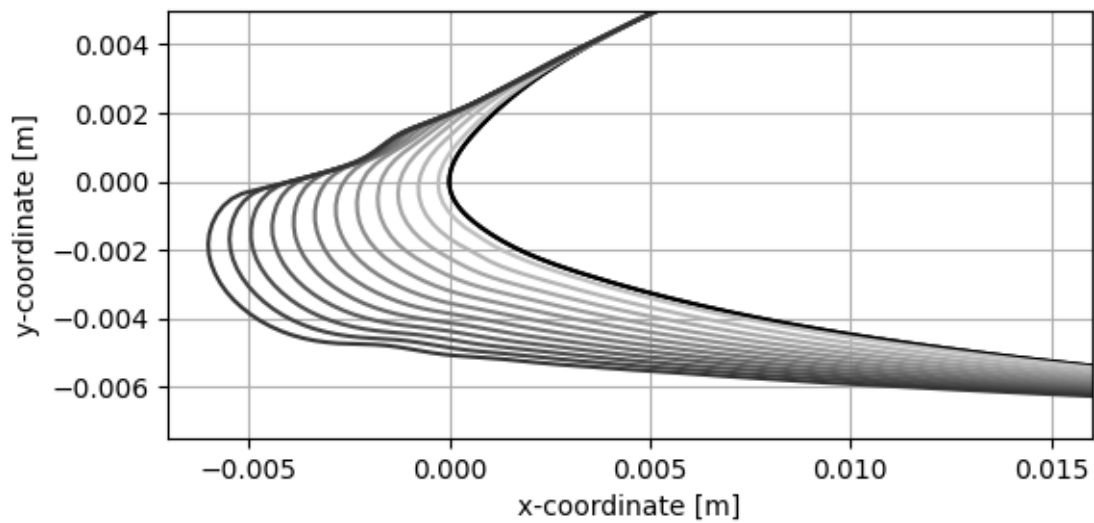


Fig. 17 The growth of the ice shape under -15°C , $20\text{ }\mu\text{m}$ MVD, and 1.97 g/m^3 LWC. Each line represents one shot of the simulation, and the time between lines is 16 s.

Appendix C: Calculation of required input parameters

Three input parameters for the existing correlations are not direct outputs of FENSAP-ICE. The accumulation parameter depends on the liquid water content, the airspeed, the accretion time, the ice density, and a characteristic length l :

$$A_c = \frac{LWC \, u \, t}{\rho_l l} \quad (A1)$$

Eq. (3) uses the leading edge diameter of the airfoil as the characteristic length, while Eq. (1) uses the chord length.

The total collection efficiency is calculated based on the impinged mass, the projected airfoil height, the LWC, the airspeed, and the time:

$$E = \frac{m}{h \, LWC \, u \, t} \quad (A2)$$

Finally, the calculation of the Reynolds number based on the droplet diameter requires the airspeed, the droplet diameter δ , the air density, and the dynamic viscosity of air:

$$Re_\delta = \frac{u \delta \rho_a}{\mu_a} \quad (A3)$$

Appendix D: Calculation of the freezing fraction

Unless marked otherwise, all equations are taken from Anderson (2004).

The convective heat flux

$$q_c = h_c (T_s - T_{bl}) \quad (A4)$$

depends on the local heat transfer coefficient h_c , the surface temperature T_s , and the boundary layer temperature T_{bl} . The surface temperature will be 0 °C except for cases with a freezing fraction of 1.

Because these cases are not particularly interesting, the surface temperature will be assumed to be 0 °C.

The boundary layer temperature can be calculated as

$$T_{bl} = T_a + \frac{ru^2}{2c_{p,a}} \quad (A5)$$

depending on the static ambient temperature T_a , the recovery factor r , the airspeed u , and the specific heat at constant pressure of air $c_{p,a}$. Because this analysis is limited to the stagnation point, the recovery factor is 1.

The heat transfer coefficient h_c at the stagnation point depends on the Nusselt number at the stagnation point

$$Nu = \frac{h_c d}{k_a} \quad (A6)$$

as well as a characteristic length d and the thermal conductivity of air k_a . For this case, the characteristic length is chosen to be twice the airfoil leading edge radius. The Nusselt number at the stagnation point

$$Nu = 0.81 Re_r^{0.5} Pr^{0.4} \quad (A7)$$

depends on the Reynolds number Re_r for the leading edge radius and the Prandtl number Pr of air (Kays and Crawford 1993). The second term in the heat balance Eq. (14) is the evaporative heat flux

$$q_e = \dot{m}_e \Lambda_v \quad (A8)$$

which depends on the latent heat of vaporization Λ_v and the evaporative mass flux

$$\dot{m}_e = h_G \frac{(p_{ww} - p_w)}{p_{st}} \quad (A9)$$

This equation depends on the gas-phase mass transfer coefficient h_G , the vapor pressure of water over liquid water p_{ww} , the vapor pressure of water in the atmosphere p_w , and the static air pressure p_{st} . The vapor pressure over water is taken as the saturation pressure at the surface's assumed temperature

of 0 °C, and the vapor pressure in the atmosphere can be calculated based on the air temperature. The gas-phase mass transfer coefficient

$$h_G = \frac{h_c}{c_{p,a}} \left(\frac{Pr}{Sc} \right)^{0.67} \quad (\text{A10})$$

depends on the heat transfer coefficient and fluid properties like the Schmidt number (Sc):

$$Sc = \frac{\mu_a}{\rho_a D_v} \quad (\text{A11})$$

The dynamic viscosity μ_a , the air density ρ_a , and the mass diffusivity can be calculated based on the temperature and pressure (Sutherland 1893).

The heat flux required to heat the droplets from the ambient temperature T_a to the freezing temperature $T_f = 0$ °C

$$q_w = \dot{m} c_{p,ws} (T_f - T_a) \quad (\text{A12})$$

depends on the specific heat of water $c_{p,ws}$ on the model surface. Because the stagnation point is the most important position along the chord, the mass impingement rate $\dot{m}$ should be taken at this position.

The kinetic heat flux added to the surface by the impinging droplets is:

$$q_k = \dot{m} \frac{u^2}{2} \quad (\text{A13})$$

The remaining term is the latent heat released by freezing water

$$q_f = \dot{m} n \Lambda_f \quad (\text{A14})$$

which contains the freezing fraction n and the latent heat of freezing Λ_f . By re-arranging the terms in the latent heat equation (A14), the freezing fraction can be calculated. While the result of the equation can be greater than 1, the maximum physical freezing fraction is 1. Higher values highlight that more water could be frozen than has impinged.

DATA AVAILABILITY STATEMENT:

All data generated or used during the study are available in a DataverseNO online repository (DOI: 10.18710/QK4XH3) in accordance with funder data retention policies. All code generated or used during the study is available in a Git online repository (https://git.ntnu.no/joachw/Drag_prediction_public) in accordance with funder data retention policies.

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NOTATION LIST:

The following symbols are used in this paper:

A_C	= Accumulation parameter, [-]
c	= Chord length, [m]
C_d	= Drag coefficient, [-]
$C_{d, clean}$	= Drag coefficient of the clean airfoil, [-]
$c_{p,a}$	= Specific heat of air for constant pressure, [$\text{J kg}^{-1} \text{K}^{-1}$]
$c_{p,ws}$	= Specific heat of water for constant pressure, [$\text{J kg}^{-1} \text{K}^{-1}$]
c_1, c_2	= Constants, [-]

D_v	= Diffusivity of water vapor in air, [$\text{m}^2 \text{s}^{-1}$]
d	= Twice the airfoil leading edge radius, [m]
E	= Total collection efficiency, [-]
g	= Segmentally linear function, [-]
h	= Projected airfoil height, [m]
h_c	= Heat transfer coefficient, [$\text{W m}^{-2} \text{K}^{-1}$]
h_G	= Mass transfer coefficient, [$\text{kg m}^{-2} \text{s}^{-1}$]
I	= Airfoil-specific constant, [-]
k	= Roughness height, [m]
k_a	= Conductivity of air, [$\text{W m}^{-1} \text{K}^{-1}$]
LWC	= Liquid water content, [kg m^{-3}]
l	= Characteristic length, [m]
m	= Impinging mass per meter span, [kg m^{-1}]
$\dot{m}$	= Impinging mass rate, [$\text{kg m}^{-2} \text{s}^{-1}$]
$\tilde{m}$	= Chord-adjusted mass caught per meter span, [kg m^{-1}]
$\dot{m}_e$	= Evaporative mass flux, [$\text{kg m}^{-2} \text{s}^{-1}$]
N	= Number of data points, [-]
Nu	= Nusselt number, [-]
n	= Freezing fraction, [-]
Pr	= Prandtl number, [-]
p_n	= Power to the variable v_n , [-]
p_{st}	= Static air pressure, [Pa]
p_w	= Water vapor pressure in the atmosphere, [Pa]
p_{ww}	= Water vapor pressure over liquid water, [Pa]
q_c	= Convective heat flux, [W m^{-2}]
q_e	= Evaporative heat flux, [W m^{-2}]
q_f	= Flux of latent heat release, [W m^{-2}]
q_k	= Kinetic heat flux, [W m^{-2}]
q_w	= Sensible heat flux, [W m^{-2}]
Re_r	= Reynolds number based on the leading edge radius, [-]
Re_δ	= Reynolds number based on the droplet diameter, [-]
$RMSRE$	= Root mean square relative error, [-]
r	= Recovery factor, [-]
Sc	= Schmidt number, [-]
T_a	= Static ambient temperature, [K]
T_{bl}	= Boundary layer temperature, [K]
T_f	= Freezing temperature, [K]
T_s	= Surface temperature, [K]
t	= Ice accretion time, [s]
u	= Airspeed, [m s^{-1}]
u_{Helo}	= Helicopter forward flight speed, [m s^{-1}]
v_n	= Variables, [-]
x_i	= Simulated value, [-]
$\hat{x}_i$	= Predicted value, [-]
Z_l	= Constant, [-]
α	= Angle of attack, [$^\circ$]
β_0	= Collection efficiency at stagnation point, [-]
δ	= Median volumetric droplet diameter, [m]
Δ_f	= Latent heat of freezing, [J kg^{-1}]
Δ_v	= Latent heat of vaporization, [J kg^{-1}]
μ_a	= Dynamic air viscosity, [$\text{kg m}^{-1} \text{s}^{-1}$]
ρ_a	= Air density, [kg m^{-3}]
ρ_I	= Ice density, [kg m^{-3}]
$\Delta c_d'$	= Increase in drag coefficient in hover, [-]

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