Icing Characterization

Smart Icing Systems Review, May 28, 2003

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* presenting

Icing Characterization Outline

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- Icing characterization overview
- Icing characterization design
- Icing characterization validation in simulation
- Identification validation on flight test data
Icing Characterization Objective and Approach

Objective: Provide a real-time estimate of the degradation of the flight dynamics due to icing.

Approach:
- Icing matters to the extent that it affects the flight dynamics.
- Effect of icing on flight dynamics is captured by parameter $\chi$.
- By observing behavior of dynamics, can infer the value of $\chi$ ⇒ Parameter Identification (ID)
- From estimated parameter $\hat{\chi}(t)$, characterize icing effects.
- Icing characterization will also incorporate
  - aerodynamic sensors
  - steady-state characterization
  - hinge moment sensing
  ⇒ Sensor Fusion
Icing Characterization Contributions

Icing characterization design:

- Detailed block diagram along with algorithmic descriptions
- Sufficient detail for simulation using simulated measurements
- Only longitudinal icing degradation is addressed
- Two novel aspects
  - real-time $H^\infty$ ID of flight dynamics
  - neural-network based sensor fusion
Objective (refined): Given all pertinent information, provide a real-time estimate of the degradation of the flight dynamics due to icing over the range of normal flight conditions.

Information:
- Flight dynamics measurements
- A/C trim estimates
- S/C derivative estimates
- Hinge moment measurements
- Ice probe measurements
- External temperature measurements

Variations in flight conditions:
- Icing type, location, and severity
- Trim velocity, pitch angle, pitch rate, and AOA
- Turbulence level
- Altitude
- Flight modes: climb, cruise, descent, landing, holding pattern, heading change

Icing Characterization Detailed Block Diagram
Neural Networks Overview

- NN are layered networks of interconnected nodes. Nodes \( \Rightarrow \) activation functions, lines \( \Rightarrow \) weights, multiple lines are summed.

- Weighted sum of inputs to node plus a bias are input to activation function. Sigmoidal activation functions are used.

- Sigmoidal activation functions generalize discrete switching.

- For a given structure (\# of layers and nodes) training refers to numerical optimization of biases and weights based on a suite of training cases.

- NN are general enough to recognize complex nonlinear relationships, such as between our sensor information and icing.

Parameter ID of Flight Dynamics

- \( \chi := (C_{X_0}, C_{m_0}, C_m, C_m, C_m\delta_E) \)
  are parameters to identify and convert flight dynamics to

\[
\begin{align*}
\dot{x} &= A(x, u)\chi + b(x, u) + d_p \\
y &= x + d_m
\end{align*}
\]

where

- \( x = (V, \alpha, \beta, p, q, r, \phi, \theta, \psi) \) state
- \( u = (\delta_E, \delta_R, \delta_A, T) \) input
- \( y \) measured output
- \( d_p \) state disturbance (i.e., turbulence)
- \( d_m \) measurement noise

- \( d_p(t) \) represents unknown excitation of the flight dynamics, e.g., turbulence, modeling error

- \( d_m(t) \) represents inaccuracies in the measurement, e.g., sensor precision

- system excitation is necessary for identification

- unknown exogenous signals \( d_m(t) \) and \( d_p(t) \) limit accuracy of estimated parameter
$H^\infty$ Parameter Identification

- $H^\infty$ generally refers to an algorithm/controller that achieves guaranteed performance in the presence of unknown harmful input
  $\Rightarrow$ “worst-case performance”

- $H^\infty$ does not require statistical descriptions of unknown quantities

![Diagram](image)

- Given pilot input, think of ID as a system with turbulence and measurement noise as unknown input, and parameter estimate error as output. Would like to have estimate error go to zero regardless of input.

- $H^\infty$ ID provides a worst-case gain $\gamma$ from unknown input to error.

- $H^\infty$ ID algorithm is recursive hence depends on an initial estimate.

- $H^\infty$ ID algorithm is robust to model uncertainties, and can be used for time-varying and nonlinear systems as well

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$H^\infty$ ID in the Icing Context

**Objective:** Estimate aircraft stability and control parameters over time, based on noisy measurements of the flight-dynamics state and knowledge of control input, sufficiently well to aid in icing characterization

**Functional requirements:**
- Test input cannot be introduced, normal operational maneuvers must suffice
- Identification must perform well in all phases of flight

**Performance requirements:**
- **High excitation** from control input: fast parameter convergence is necessary in order to provide pilot with icing characterization before triggering a handling event
- **Low excitation:** trim characterization alone should provide useful icing characterization, hence parameter estimates must only be minimally well-behaved
- **Moderate excitation** due to turbulence: accurate parameters are needed, but slower parameter convergence is acceptable

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Validation in simulation:

- Real-time $H^\infty$ ID of flight dynamics
  - useful for icing characterization in absence of turbulence
  - (colored-noise) turbulence substantially reduces effectiveness
- Neural-network based sensor fusion
  - accurate for broad range of flight conditions with hinge moment measurements
  - still useful without hinge moment measurements, but performance degraded significantly by turbulence in this case

$H^\infty$ Validation Simulations: Turbulence-Free

2 minute icing encounter: $\eta$ varies from 0 to 1
no turbulence; 5-s, 5° elevator doublet at 60 s, initial velocity of 70 m/s
five simulations, each with different noise realizations, are plotted

⇒ minimally well-behaved before doublet at 60 s; fast convergence with doublet
2 minute icing encounter: \( \eta \) varies from 0 to 1
0.2 \( g \) turbulence; 5-s, 5° elevator doublet at 60 s, initial velocity of 70 m/s
ten simulations, each with different noise realizations, are plotted

\[ \text{Estimate } \bar{C}_{m_u} \]

\[ \text{Estimate } \bar{C}_{m_u} \]

\[ \Rightarrow \text{very erratic before doublet at 60 s; some convergence with doublet but then again erratic} \]

Sensor-Fusion Validation: Simulated Conditions

Each simulation corresponds to a five minute icing encounter, with constant ice
accretion rate to a prespecified final value over that period. All simulation data is
provided as measurements over time sampled at 30 Hz, and with additive, white-
Gaussian, measurement noise of appropriate intensity. Performance testing uses
different data than training set.

Sensor Information:
- Flight dynamics measurements (FDC): translational velocity \( (\alpha, \beta, V) \), rotational velocity \( (p, q, r) \), orientation \( (\phi, \theta, \gamma) \), control input \( (\delta_a, \delta_E, \delta_r, T) \), and altitude \( h \)
- A/C trim estimates: \( (\bar{V}, \bar{\alpha}, \bar{\delta}_E) \)
- Parameter identification: nondim'\( \bar{S}/C \) estimates \( \bar{\chi} \)
- Hinge moment measurements: wing \( (C_{h}^{W}, C_{hrms}^{W}) \), tail \( (C_{h}^{T}, C_{hrms}^{T}) \)
- Excitation measures: \( \bar{P}_{V}, \bar{P}_{\alpha}, \bar{P}_{\delta_a}, \bar{P}_{q} \)

Variations in flight conditions:
- Pitch-Attitude Hold autopilot
- Tail-only icing
- Final icing severity: \( \bar{\eta}_{f} \in \{0, 0.375, 0.75, 1.125, 1.5\} \)
- Initial trim velocity: \( \bar{V} \in \{60, 65, 70, 75, 80\} \) m/s
- Altitude: \( h \in \{1000, 3000\} \) m
- Turbulence level: \( \sigma_{\text{turb}} \in \{0, 0.075, 0.15, 0.225, 0.3\} \) \( g \)
- elevator doublet input: either none or three randomly-placed elevator doublets
  of random amplitude \( \in [2, 10] \) degrees
Full IMS Neural Network

Scatter plot for turbulent and turbulence-free cases

⇒ Estimate \( \bar{\eta} \) is accurate to within 0.1 for 98.16% of time instants
But, is hinge moment model too optimistic?

Limited IMS Neural Network:
trained on turbulence-free data

⇒ fairly good performance for turbulence-free cases
poor performance for turbulent cases
## Sensor-Fusion Validation Summary

<table>
<thead>
<tr>
<th>Neural Network</th>
<th>Testing Data Set</th>
<th>Mean Error</th>
<th>Standard Deviation</th>
<th>Large Error Probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>full sensor-fusion network</td>
<td>full set</td>
<td>0.0093</td>
<td>0.0728</td>
<td>&gt; 0.05 for 4.34%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>&gt; 0.1 for 1.84%</td>
</tr>
<tr>
<td>limited network:</td>
<td>full set</td>
<td>0.1545</td>
<td>0.6091</td>
<td>&gt; 0.1 for 52.86%</td>
</tr>
<tr>
<td>turb-free training set</td>
<td>turb-free set</td>
<td>0.0388</td>
<td>0.1820</td>
<td>&gt; 0.1 for 18.77%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>&gt; 0.2 for 8.59%</td>
</tr>
<tr>
<td>limited network:</td>
<td>full set</td>
<td>0.0733</td>
<td>0.1425</td>
<td>&gt; 0.1 for 40.28%</td>
</tr>
<tr>
<td>full training set</td>
<td>turb-free set</td>
<td>0.0698</td>
<td>0.1344</td>
<td>&gt; 0.1 for 32.53%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>&gt; 0.2 for 13.27%</td>
</tr>
</tbody>
</table>

## Icing Characterization Contributions (cont’d)

### Validation of real-time $H^\infty$ ID on selected flight test data:

- $H^\infty$ ID applied to flight test data in post-flight simulations
- Simulations mimic real-time implementation
- $H^\infty$ ID estimates of pitching moment derivatives compare favorably with SIDPAC linear regression estimates
- At present $H^\infty$ ID does not incorporate translational acceleration measurements $\Rightarrow$ it does not yield useful lift derivative estimates, while SIDPAC does
2001 Flight 010223f2, from 20:30:50 to 20:31:10

![Graphs and data tables here]

### SIDPAC $H^\infty$ Final Value Difference

<table>
<thead>
<tr>
<th></th>
<th>SIDPAC</th>
<th>$H^\infty$ Final Value</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{m_a}$</td>
<td>-0.0263</td>
<td>-0.0274</td>
<td>4.46%</td>
</tr>
<tr>
<td>$C_{m_q}$</td>
<td>-35.93</td>
<td>-41.01</td>
<td>14.12%</td>
</tr>
<tr>
<td>$C_{m_{de}}$</td>
<td>-0.0316</td>
<td>-0.0340</td>
<td>7.56%</td>
</tr>
</tbody>
</table>

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### $H^\infty$ ID Flight Test Validation: Icing Flight

2001 Flight 010302f2, from 17:55:45 to 17:56:04

![Graphs and data tables here]

### SIDPAC $H^\infty$ Final Value Difference

<table>
<thead>
<tr>
<th></th>
<th>SIDPAC</th>
<th>$H^\infty$ Final Value</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{m_a}$</td>
<td>-0.0284</td>
<td>-0.0308</td>
<td>8.37%</td>
</tr>
<tr>
<td>$C_{m_q}$</td>
<td>-35.78</td>
<td>-39.92</td>
<td>11.56%</td>
</tr>
<tr>
<td>$C_{m_{de}}$</td>
<td>-0.0315</td>
<td>-0.0335</td>
<td>6.34%</td>
</tr>
</tbody>
</table>

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Aircraft Characterization Using Flight Test Data

Edward Whalen
University of Illinois at Urbana-Champaign
Goals of Research

- Establish a baseline, clean aircraft from flight test data in clear air
- Identify the changes in trim and stability and control derivatives as a result of the onset of icing, IPS activation, selective deicing, etc.
- Identify which of these parameters are the best indicators of icing
- Investigate the correlation between icing severity, as measured by $\eta$, and the magnitude of the changes in both trim and stability and control derivatives
- Aid in the development and evaluation of real-time identification methods for use with the SIS system
Program Summary

- Two test periods – February and March in 2001 and 2002
- 2001 – Collected data across test matrix in both clear air and icing conditions and established a baseline aircraft
- 11 icing flights and 22 clear air flights
- 2002 – Focused on elevator doublet data collection in icing conditions
- 12 icing flights 3 clear air flights
The Twin Otter

- DeHavilland DHC-6
- High-wing, twin-engine commuter class aircraft
- Max Gross Weight: 11,000 pounds
- Cruise Speed: 130 KIAS
- Fully instrumented to collect aerodynamic, performance, icing and atmospheric data.
Flight Test Cases

<table>
<thead>
<tr>
<th>Case</th>
<th>Icing Flight</th>
<th>Doublet Mag.</th>
<th>Test Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Clear Air</td>
<td>0.25g</td>
<td>Baseline</td>
</tr>
<tr>
<td>1.2</td>
<td>Clear Air</td>
<td>0.10 to 0.50</td>
<td>Vary doublet magnitude</td>
</tr>
<tr>
<td>1.3</td>
<td>Clear Air</td>
<td>None</td>
<td>Standard maneuvers</td>
</tr>
<tr>
<td>1.4</td>
<td>Clear Air</td>
<td>None</td>
<td>Clear air turbulence</td>
</tr>
<tr>
<td>2.1</td>
<td>Icing</td>
<td>0.25g</td>
<td>Doublets during ice accretion</td>
</tr>
<tr>
<td>2.2</td>
<td>Icing</td>
<td>0.25g</td>
<td>Doublets with selective deicing</td>
</tr>
<tr>
<td>2.3</td>
<td>Icing</td>
<td>0.25g</td>
<td>Doublets with intercycle icing</td>
</tr>
<tr>
<td>2.4</td>
<td>Icing</td>
<td>None</td>
<td>Intercycle icing</td>
</tr>
<tr>
<td>2.5</td>
<td>Icing</td>
<td>None</td>
<td>Standard maneuvers</td>
</tr>
</tbody>
</table>
Data Reduction

• Individual doublets and doublet sets extracted from raw data.
• Filter used to remove nose-boom oscillations.
• Data corrected for instrument offsets and angular rate contributions to velocities, aerodynamic parameters recalculated from data
• Doublet data passed to SIDPAC step-wise regression scheme to calculate S&C values.
• Trim state extracted immediately before doublets using time average.
Step-wise Regression Model

Lift:

\[ C_L = C_{L0} + C_{L\alpha} \cdot (\alpha - \alpha_0) + C_{Lq} \cdot (q - q_0) \cdot \frac{c}{2 \cdot V} + C_{L\delta e} \cdot (\delta e - \delta e_0) \]

Pitching Moment:

\[ C_M = C_{M0} + C_{M\alpha} \cdot (\alpha - \alpha_0) + C_{Mq} \cdot (q - q_0) \cdot \frac{c}{2 \cdot V} + C_{M\delta e} \cdot (\delta e - \delta e_0) \]

Rolling Moment:

\[ C_l = C_{l0} + C_{l\delta a} \cdot (\delta a - \delta a_0) + C_{l\delta r} \cdot (\delta r - \delta r_0) + C_{l\beta} \cdot (\beta - \beta_0) + \ldots \]

\[ C_{lp} \cdot (p - p_0) \cdot \frac{b}{2 \cdot V} + C_{lr} \cdot (r - r_0) \cdot \frac{b}{2 \cdot V} \]

Yawing Moment:

\[ C_n = C_{n0} + C_{n\delta a} \cdot (\delta a - \delta a_0) + C_{n\delta r} \cdot (\delta r - \delta r_0) + C_{n\beta} \cdot (\beta - \beta_0) + \ldots \]

\[ C_{np} \cdot (p - p_0) \cdot \frac{b}{2 \cdot V} + C_{nr} \cdot (r - r_0) \cdot \frac{b}{2 \cdot V} \]
Clean Aircraft Results

“Illinois” results were obtained from an average of 37 doublets executed at approximately 0° angle of attack. All parameters were estimated using a step-wise regression technique.

<table>
<thead>
<tr>
<th>Derivative</th>
<th>NASA TM 4099 (deg⁻¹)</th>
<th>AIAA 93-0398 (deg⁻¹)</th>
<th>Illinois (deg⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{L\alpha}$</td>
<td>0.1003</td>
<td></td>
<td>0.1072</td>
</tr>
<tr>
<td>$C_{Lq}$</td>
<td>0.3498</td>
<td></td>
<td>0.3517</td>
</tr>
<tr>
<td>$C_{L\Delta e}$</td>
<td>0.0118</td>
<td></td>
<td>0.0118</td>
</tr>
<tr>
<td>$C_{M\alpha}$</td>
<td>-0.0229</td>
<td>-0.0258</td>
<td>-0.0266</td>
</tr>
<tr>
<td>$C_{Mde}$</td>
<td>-0.031</td>
<td>-0.0305</td>
<td>-0.0299</td>
</tr>
<tr>
<td>$C_{Mq}$</td>
<td>-0.611</td>
<td>-0.65</td>
<td>-0.5653</td>
</tr>
<tr>
<td>$C_{n\beta}$</td>
<td>0.00136</td>
<td></td>
<td>0.0015</td>
</tr>
<tr>
<td>$C_{nr}$</td>
<td>-0.0031</td>
<td></td>
<td>-0.0035</td>
</tr>
<tr>
<td>$C_{n\Delta e}$</td>
<td>-0.00218</td>
<td></td>
<td>-0.0023</td>
</tr>
</tbody>
</table>
Typical Icing Flight

* Assumes $\eta$ returns to zero after each deicing
Atmospheric Turbulence

Estimated $\alpha$ Scaling Factor vs. $C_{L_a}$ (1/deg)

Clean Flight Data
Iced Flight Data
Parasite Drag

\[ R^2 = 0.7883 \]
IPS Activation: Automatic Boot Cycle

Deicing Boots on Three-Minute Automatic Cycle

![Graph showing boot activation times and corresponding temperatures.](image)
IPS Activation: Automatic Boot Cycle

- Change in parasite drag due to ice accretion on unprotected portions of the airplane

![Graph showing change in parasite drag over time](image)
IPS Activation: Selective Deicing

Variation of $C_{L\alpha}$ during IPS activation

- Deice Wings
- Deice Horizontal Stabilizer
- Deice Vertical Stabilizer, Struts and Landing Gear
- Fully Iced
IPS Activation: Selective Deicing
Conclusions

• $C_{L\alpha}$ and $C_{M\alpha}$ clearly indicate the effects of icing on the aircraft.

• Turbulence has a significant effect on the accuracy of the parameter identification.

• The parameter $\eta$ is an excellent indicator of the severity of the ice accretion, as seen through its correlation with the parasite drag.

• The effect of IPS operation is visible in both the stability parameters and the parasite drag including: selective deicing, standard deicing boot cycles and full deicing.

• Characterizing icing through identifying $C_{L\alpha}$, $C_{M\alpha}$ and $C_{D0}$ shows promise for use in the SIS system.