

Smart Icing Systems for Aircraft Icing Safety

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Abstract

Ice accretion affects the performance and control of an aircraft and in extreme situations can lead to incidents and accidents. However, changes in performance and control are difficult to sense. As a result, the icing sensors currently in use sense primarily ice accretion, not the effect of the ice. No processed aircraft performance degradation information is available to the pilot. In this paper, the Smart Icing System research program is reviewed and progress towards its development reported. Such a system would sense ice accretion through traditional icing sensors and use modern system identification methods to estimate aircraft performance and control changes. This information would be used to automatically operate ice protection systems, provide aircraft envelope protection and, if icing was severe, adapt the flight controls. All of this would be properly communicated to and coordinated with the flight crew. In addition to describing the basic concept, this paper reviews the research conducted to date in three critical areas; aerodynamics and flight mechanics, aircraft control and identification, and human factors. In addition, the flight simulation development is reviewed, as well as the Twin Otter flight test program that is being conducted in cooperation with NASA Glenn Research Center.

1.0 Introduction

Recent icing accidents, such as the American Eagle roll upset near Roselawn, Indiana in October 1994, and the Com Air accident in January 1997 clearly show that

icing continues to be a serious safety concern. The development of safer, more reliable, and affordable aircraft must include better solutions for flight in icing and severe weather conditions.

Aircraft icing accidents are caused by the effect of ice accretion on the performance, stability and control of the aircraft. Accidents occur when aircraft are not properly protected against ice accretion either on the ground or inflight. This situation may result from an inadequate ice protection system, improper operation or failure to activate the system, or aircraft operation outside of the iced aircraft flight envelope.

Currently little, if any, information about the state of the aircraft in terms of performance, stability and control in icing conditions is available to the pilot. The ATR 72 digital flight data recorder, DFDR, recorded 96 distinct parameters including aileron position, roll attitude, and many other parameters relevant to the Roselawn accident. While a careful analysis of these data during the post-accident investigation was critical in determining the cause, none of this information was available to help the flight crew prevent the accident.

In most situations today, inflight aircraft icing is documented and evaluated based on the thickness of ice on the wing leading edge or on another surface (ice-evidence probe or other protuberance) that can easily be examined visually by the flight crew. The use of ice thickness is certainly convenient and there clearly is some relationship between ice thickness and aircraft performance and control. Unfortunately this relationship is complicated by the effect of ice shape, ice shedding and residual/intercycle ice, varying accretion rates on different

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components (which can change with icing conditions), IPS operations and irregularities, etc. These factors complicate the ice thickness to aircraft performance relationship to the point that it is too complex to be a useful and reliable measure of changes in performance and control. Therefore, while ice thickness and accretion rate measurements are still useful, they alone will not be sufficient to allow the development of a system to provide the pilot and automated systems with quantitative measurements of changes in aircraft performance and control in icing. In fact, even if a complete 3-D mapping of the ice accretion was available, current CFD methods could not accurately predict the performance and control changes to the desired accuracy.

Therefore, the approach taken in this research was to directly measure the effect of ice on aircraft performance and control in real time and use this information to perform safety-related functions. In this approach the entire aircraft is essentially an ice sensor, and these data are used to evaluate the effect of ice on the aircraft. This paper describes the concept and the research completed and currently underway to develop a new and innovative human-centered automated system, a smart icing system, which has the potential to improve aviation safety in icing conditions. Bragg et al.¹ presented preliminary research and outlined the research program in 1998. The purpose of this paper is to present a brief review of the concept and to summarize the current status and accomplishments since 1998 including future plans.

2.0 Approach

The Smart Icing System, SIS, is potentially a better way to manage the ice protection system and the operation of an aircraft in icing conditions where some degradation in performance and control can be anticipated. This safety system or concept is not intended to replace, but rather augment well-established icing safety procedures such as ice avoidance and pilot response.¹

The Smart Icing System is visualized schematically in Fig. 1 and the four primary functions explained in the list that follows.

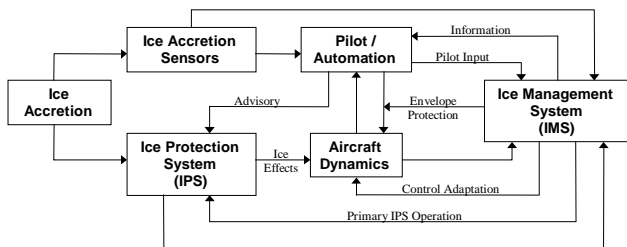


Fig. 1. Schematic of the functions performed by the Ice Management System

The aircraft is assumed to be equipped with a state-of-the-art Ice Protection System, IPS, but now an additional level of safety is available through the Ice Management System, IMS, depicted in Fig. 1.

The IMS is the computational or software center that gathers data, evaluates the data and determines the appropriate response, and communicates this to the pilot and automation.

The operation of the IMS can be summarized by the four functions:

1. Sense the presence of ice accretion and characterize its effect on aircraft performance, stability and control. Sense ice accretion and ice protection system performance.
2. Automatically activate and manage the ice protection systems, and provide the pilot with feedback on the system status and behavior of both the aircraft and the IPS.
3. If the performance degradation becomes significant, modify the aircraft flight envelope by use of the flight control system to avoid conditions where flight could potentially be uncontrollable. Notify the pilot of this action and its implications for the flight envelope.
4. Adapt the control system to maintain safe flight within the reduced flight envelope.

The fundamental principle behind the IMS is that the important effect of ice on an aircraft is its influence on the performance, stability and control of the aircraft system.

To accomplish these objectives, the IMS receives inputs from the traditional ice sensors, the IPS system, flight crew, the aircraft flight dynamics and other aircraft state information. The IMS controls the IPS much as a primary ice protection system does now; however, it has several other functions. The IMS analyzes the available information to determine the effect of the ice accretion on the aircraft performance, stability and control. All of this information is then used to provide flight envelope protection based on the actual, real-time ice accretion experienced by the aircraft. This could include angle of attack protection through the stick shaker as is commonly done today; however, the angle of attack for stick shaker would be a variable determined by the IMS. Other envelope protection features would be supplied through a digital flight control system. These might include maximum g loads, bank angles, control deflections, flap deflections, pitch and roll rates, among others.

Control adaptation could be added as an additional level of safety. Control adaptation, or reconfigurable controls, would modify the control laws to maintain acceptable flying qualities in the presence of the effects of the ice accretion. This adaptation would be most useful in emergency situations where, for some reason, the aircraft was allowed to accrete significant ice. Reconfiguring the

control laws would allow the pilot/automation to maintain control of the aircraft within some limited flight envelope. In severe icing this could be done until the icing conditions could be exited safely.

The new icing safety system proposed has been summarized in terms of the operation of a new Ice Management System. This approach assumes that regardless of the IPS, ice accretion can and will occur in some situations. Safety will be achieved in an ice tolerant aircraft if the pilot/aircraft system can continue to maintain the desired flight path with an acceptable safety margin, regardless of atmospheric icing conditions.

The research conducted to date has focused primarily on characterizing the effect of the ice on the aircraft in real time and examining the proper interaction of the system with the flight crew. The characterization research has been conducted through simulation. The effect of ice on the aircraft has been modeled and incorporated in six degree of freedom, 6 DoF, simulations where identification techniques have been developed. Neural networks have been explored as a means to take raw and processed sensor data to predict or characterize the icing effects on the aircraft performance and control. Human factors researchers are determining what information the flight crew need and when and in what format it can be most efficiently presented to them, which includes conducting research to develop cockpit displays of SIS-developed information. In support of these activities a piloted flight simulation capability is being developed to act as a system integrator for the various SIS displays and systems. The simulator will be used to develop, test, and demonstrate the technology. Flight testing is also being used to help develop the characterization methods and test the concepts. This research is briefly described below. More detail can be found in the many reports published by SIS researchers and referenced throughout the paper.

3.0 Current Research

To conduct this research several assumptions have been made about the aircraft and systems that will be available to a fully equipped SIS aircraft of the future. These assumptions include:

- Digital flight control system
- Glass cockpit
- All required sensors
- All required onboard processing power

It is anticipated that the SIS system when installed will be part of a larger onboard safety system. The overall system will protect the aircraft against terrain, actuator and other system failure, damaging turbulence and wind shear, and performance and control degradation due to ice, frost, etc. The costs of these systems,

including the certification process, are of concern and will undoubtedly affect the initial implementation. While this was recognized and addressed early in the research program,² it will not be discussed in this paper.

During this development period, Twin Otter dynamics have been used extensively because, as a result of NASA research programs, there exists excellent data on the aircraft with and without ice. However, it is not the intent to develop an SIS system for the Twin Otter. The simulations consider a modern aircraft with the attributes given above, but with the performance, stability and control parameters of the Twin Otter. This is not to say that concepts and components of the SIS could not be retrofitted to less sophisticated aircraft such as the Twin Otter, but full implementation requires a modern, digital aircraft.

In the following sections brief reviews of the research from the four groups: Aerodynamics and Flight Mechanics, Sensors and Controls, Human Factors, and Flight Simulation will be reviewed as well as the flight test research.

3.1 Aerodynamics and Flight Mechanics

In developing and simulating various SIS functions a 6 DoF computational flight dynamics capability has been developed. The model is based on the MATLAB Simulink software developed by Rauw called FDC.³ Extensive modifications were made to include sensor noise, nonlinear aerodynamics model capability, data filtering, hinge-moment modeling, improved gust modeling and atmospheric disturbance models.^{4,5} Significant effort has gone into the clean and iced aircraft stability and control models. The primary linear model was based on clean and iced aircraft flight data with a newly developed scaling method to generate icing effects models quickly for a wide range of icing conditions.

These models were critical to the development of the IMS and the flight simulation capability. Bragg et al.^{6,7} presented initial results on flight mechanics modeling. As part of the IMS development, these models were used for research on dynamic parameter estimation techniques that are an important part of the ice effects characterization function. Initial results of this research were reported by Schuchard et al.⁸

Ice effects model

The method was described in detail in previous papers^{4,6,7} and will only be reviewed here. The icing effects model is based on the following equation

$$C_{(A)iced} = (I + \eta_{ice} k'_{C_A}) C_{(A)}$$

where

$$k'_{CA} = \frac{\eta}{\eta_{ice}} k_{CA}$$

In this equation, η_{ice} is an icing severity parameter that represents the amount and severity of the icing encounter. η is an aircraft specific icing severity parameter and k_{CA} represents the relative effect ice has on a particular stability and control parameter $C_{(A)}$. Known Twin Otter data were used to establish values for k_{CA} . The term η_{ice} was developed based on the ratio of the drag rise on a NACA 0012 airfoil at the current icing cloud conditions to the drag rise experienced at a reference condition in the continuous maximum icing envelope. η is an aircraft specific η_{ice} calculated based on the aircraft velocity and wing MAC. The η_{ice} equation is a correlation based on airfoil data taken in the NASA Icing Research Tunnel. This correlation is a function of the amount of ice accreting and the freezing fraction that reflects the type of ice shape. Figure 2 shows η as a function of static temperature and LWC. The maximum between 20° and 30° corresponds to the large horns that accrete on airfoils just below freezing and result in large aerodynamic degradation. As LWC increases the temperature at which the horns form decreases.

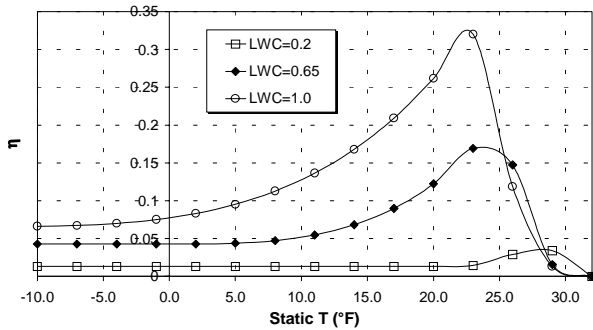


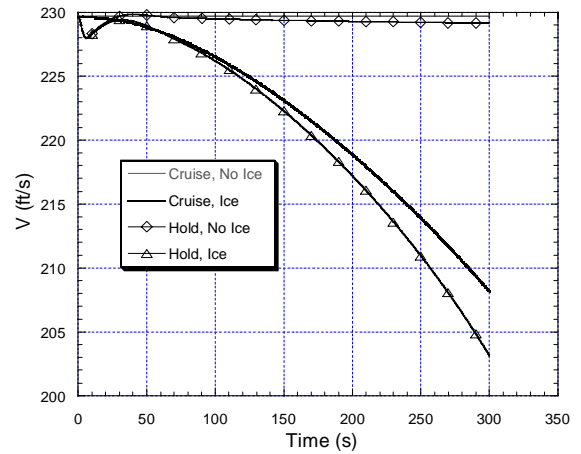
Fig. 2. Effect of static temperature on η for the Twin Otter at $V = 159$ Kts, $MVD = 20 \mu\text{m}$, $t = 5$ min.

Using the FDC computational tool, the effect of ice accretion on aircraft performance was studied to evaluate the time to identify ice due to performance changes, the use of hinge moment as an ice detector, performance in maneuvers, and many other topics.⁴⁻⁷ The code was also used extensively to train the neural nets used to perform the icing characterization.⁹

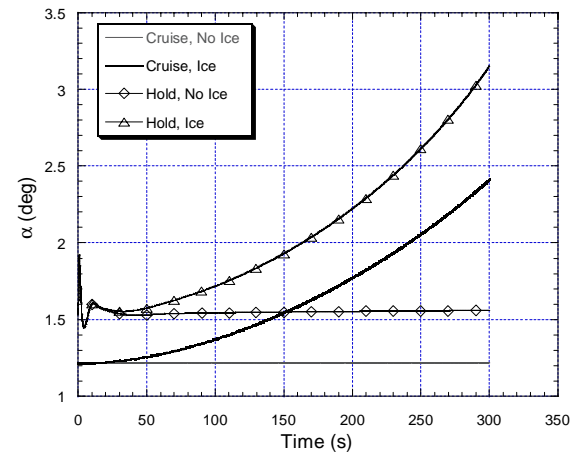
Results

As an example in Fig. 3 the degradation due to icing in a level standard rate turn is compared to that in steady, level rectilinear flight. Here the standard rate turn is intended to represent part of a holding pattern, but it could also be representative of maneuvering during climb out or landing approach. In both cases, the flight is level and at

constant power. Here the velocity has been matched at 230 ft/s and the altitude is 6560 ft. All of the other parameters for the Twin Otter are the same including η varying from 0 to 0.10 from 0 to 300 sec. The figure shows that the predicted velocity and angle of attack are more affected during the hold that cruise flight. This is due to the increased lift required in the hold and as a result larger power, angle of attack, and elevator deflection. For example the angle of attack after 300 seconds increases 1.2 deg for the cruise case and 1.6 deg for the hold.



a) Velocity vs time

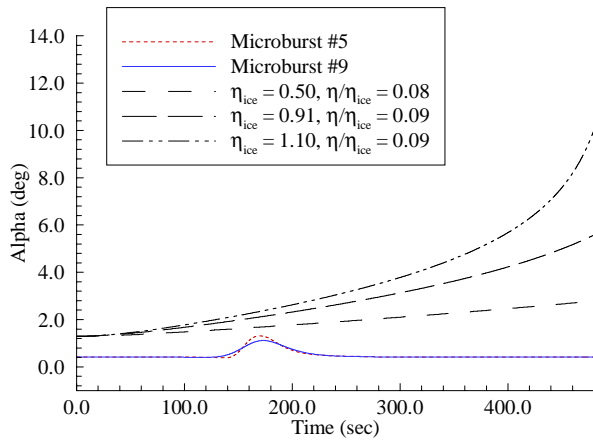


b) α vs time

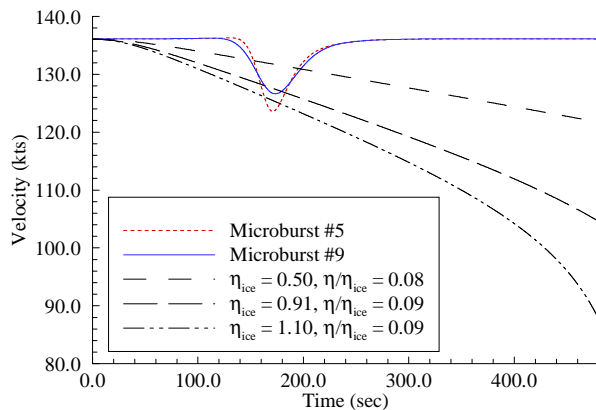
Fig. 3. Aircraft performance clean and iced ($\eta = 0$ to 0.10) in a holding turn and cruise. $V = 230$ ft/s and $h = 6560$ ft.

The iced flight modeling capability developed through the FDC code was also used to explore the effect of atmospheric disturbances and ice on an aircraft. The concern was that the characterization methods being developed might incorrectly identify as an icing encounter

some atmospheric disturbances that affect aircraft performance and control. Merret⁵ examined this issue in detail in his MS thesis where the effect of wind shear (microburst) and gravity waves were studied. Figure 4 shows the predicted response of the aircraft to two microbursts of different intensities and several different icing encounter intensities. In each case the aircraft is being simulated in an altitude-hold autopilot mode. Shown are the airspeed and angle of attack, however, elevator deflection behaves very similarly. The microburst has a very large and rapid effect on the aircraft with the rates of change of the velocity and angle of attack much larger than the initial icing effects. Not shown are the results that the autopilot could not hold altitude in the microburst, but was able to hold altitude for even the most severe icing encounter simulated.



a) Angle of attack for microbursts and icing



b) Velocity for microbursts and icing

Fig. 4. Comparison of the effect of microbursts and icing on aircraft parameters.

Simulation of the effect of gravity waves was not as straightforward. Gravity waves are not as well known as microbursts and were modeled as simple sinusoidal oscillations of the vertical velocity.⁵ For gravity waves of large wavelength, 8 -24 kilometers, the loss in aircraft performance due to the downdraft can resemble icing performance loss. However, control response differences may contribute to proper identification. More research on this will be needed before a characterization algorithm is completed.

Future research

Research is focusing on developing an envelope protection procedure based on the available or expected icing characterization information.¹⁰ This research includes the development of better nonlinear aerodynamic models to include stall and limited post-stall behavior. The current formulation is based on the concept that certain parameters, such as angle of attack, must be limited and that these limit values are strong functions of the current icing state that will be evaluated in situ during the flight. The concept includes determining in real time what control inputs will exceed these limits and notifying the pilot (or the automation) of these boundaries through hard or soft limits.

Flight testing

A joint University of Illinois – NASA Glenn flight test program is currently being conducted to develop and test the components of the Smart Icing System. The objective of this flight test was to evaluate the SIS identification and characterization methods using flight data from clear air and natural icing conditions.

The first phase of the flight test was conducted in March 2001 using the NASA Twin Otter research aircraft to provide initial flight test data.¹¹ A linear regression fit of the flight data to acquire stability and control derivatives showed many promising results. Significant changes in aircraft trim values and stability and control derivatives were observed due to ice accretion. The longitudinal derivatives, $C_{L\alpha}$ and $C_{m\alpha}$, were very sensitive to icing and showed particular promise as a means to characterize ice accretion effects. (This was also seen in the simulation results.) The effect of selectively deicing the aircraft component by component was also observed through the changes in the aircraft trim and stability and control derivatives.

Additional flight testing to gather more data in other icing conditions is planned for the current winter season. Data reduction is continuing to better understand the changes in identified parameters with ice accretion and the changes due to IPS operation. Future analysis will include using the data to aid in the development of the real-time algorithms to be used onboard an SIS-equipped

aircraft. Neural nets will be developed and tested using these data to tests and develop IMS models.

3.2 Sensors and Control

Icing Characterization Overview

In Schuchard et al.,⁸ a neural network that characterizes degradation of the aircraft flight dynamics based upon sensor data and parameter estimates was advocated for the core of the IMS. Neural networks are used because of their ability to extract information simultaneously from multiple data sources that depend on the desired information in a complex manner. It is already known¹² that a feed-forward neural network with at least one hidden layer is able to approximate any continuous function to an arbitrary level of accuracy on any bounded set given ideal training. Neural networks also have inherent parallel properties that provide a robust and fault-tolerant structure. Networks are practical for aircraft applications because, following initial training, they process information very rapidly.

The ultimate goal of the neural-network-based characterization is to provide not only a characterization of icing severity and location, but also to provide envelope protection information, IPS operation commands or cues, and perhaps even handling event recovery commands or cues. In proceeding toward this ultimate goal, Schuchard et al.⁸ began by applying neural networks to icing detection and classification during a normal operational maneuver modeled as an elevator doublet. In this limited scenario, neural networks were found to provide an accurate icing indication along with a less accurate, but still sufficient, classification of the icing severity. This study incorporated parameter identification of dimensional stability and control derivatives of longitudinal flight dynamics as the basis for characterizing the degradation of the flight dynamics due to icing, as captured by the icing severity factor η of Bragg et al.⁶ Several parameter identification techniques were evaluated in the context of icing characterization in Melody et al.,¹³ and of those algorithms considered, recursive H^∞ parameter identification technique was found to be most effective.

This initial neural network was generalized in Melody et al.⁹ to include the sensor fusion function of the IMS by incorporating, in simulation, information not taken advantage of in the previous work.⁸ Whereas environmental and ice probe measurements primarily provide information on the rate of ice accretion, increased hinge moments and steady-state effects provide information on icing degradation.⁶ Steady-state effects, as used here, are changes in trim conditions consistent with increased drag and decreased lift, characteristic of icing events during flight conditions with minimal aircraft accelerations (e.g., steady, level flight). While future

efforts will be made to incorporate traditional atmospheric and ice probe measurements, the focus here is to demonstrate the feasibility of the more novel aspects of the IMS approach.

Therefore, here the steady-state characterization and hinge moment sensing along with the parameter estimates are incorporated into the icing characterization. Furthermore, the extended characterization neural network of Melody et al.¹⁴ was applied to steady-level flight conditions, where the absence of excitation due to pilot input (e.g. elevator doublets) limits the effectiveness of parameter identification. One of the benefits of the recursive H^∞ parameter identification, demonstrated in Melody et al.,¹⁴ is that it can provide accurate parameter estimates even in the absence of pilot input so long as excitation is provided by turbulence, albeit at slower convergence rates. As with the initial neural network of Schuchard et al.,⁸ this extended neural network uses η as a measure of the degradation of flight dynamics, and it incorporates parameter identification of the dimensional derivatives of the longitudinal flight dynamics.

In this most recent work, the neural network characterization has been further generalized to include parameter identification of nondimensional derivatives of the full flight dynamics (i.e., longitudinal motion and lateral-directional motion). The parameter ID algorithm was modified to provide nondimensional derivatives so that the ID algorithm could be decoupled from trim estimation. Furthermore, consideration of lateral-directional motion along with the longitudinal motion was included so that the IMS may ultimately distinguish between longitudinal icing affects, e.g., tailplane stall, and lateral-directional icing affects, e.g., roll upset.

Neural network approach

As with the previous neural network results, we take the icing severity factor η as a measure of the degradation of the flight dynamics due to ice accretion. However, here we normalize η by the nominal icing condition that corresponds to the NASA Tailplane Icing Program simulated icing condition to produce $\bar{\eta}$.¹⁵ (In Bragg, et al.,⁶ this nominal icing condition corresponds to a value of $\eta = 0.0675$.) At present, the icing severity factor is the best measure of icing degradation available, and hence we adopt it. As in Melody et al.,⁹ we address icing encounters during periods of steady, level flight wherein the icing severity increases linearly over time from an initial clean condition.

A block diagram of the neural network is depicted in Fig. 5. In the upper left corner of the figure, the flight dynamics are subject to the unknown turbulence and measurement noise input. As discussed in Melody, et al.,^{13,14} these unknown exogenous signals fundamentally limit the accuracy of the parameter estimates, and hence must be included in any realistic simulation.

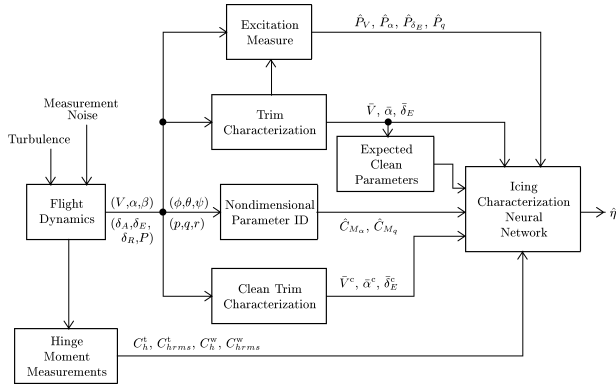


Fig. 5. Neural network block diagram.

From the flight dynamics we have measurements of the wing and tail hinge moments along with corresponding root-mean-square hinge moment measurements. The hinge-moment model is described in Pokhariyal, et al.¹⁶ From the flight dynamics, we also have measurements of total velocity V , angle of attack α , sideslip angle β , roll, pitch, and yaw rates (p, q, r) , roll, pitch, and yaw angles (ϕ, θ, ψ) , control signals for the elevator, rudder, and aileron, δ_E , δ_R , and δ_A , and engine power P . From these measurements we estimate the flight dynamics trim velocity \bar{V} , trim angle of attack $\bar{\alpha}$, and trim elevator angle $\bar{\delta}_E$ by lowpass filtering the corresponding measured signals at 1/30 Hz. The trim conditions are also used to calculate the expected clean stability and control derivatives against which the estimated stability and control derivatives from the parameter identification algorithm must be compared in order to ascertain icing degradation. Furthermore, expected clean-aircraft trim values must be calculated to provide a reference for interpreting the estimated trim values. Since the dynamic identification algorithm is expected to perform better under larger excitation and the steady-state characterization is expected to have better accuracy under smaller excitation, measures of excitation were calculated in order to aid the neural network in discriminating between dynamic parameter ID and steady-state characterization. As excitation measures we use an estimate of the dynamic portion of the power of the measured signals, denoted as \hat{P}_α , \hat{P}_V , \hat{P}_q , and \hat{P}_{δ_E} .

The excitation measures and all other input to the neural network are lowpass filtered by batch averaging each signal over the past 5 sec in order to reduce the effect of measurement noise. Finally, the neural network provides an estimate of the icing severity $\hat{\eta}$ at any given time instant t based only on the lowpass filtered input at that time t .

In order to be useful, the neural network must provide accurate icing characterizations over a broad range of trim conditions and turbulence intensity. Furthermore, the icing characterization network must accurately identify clean aircraft in order to avoid false alarms. The neural networks are applied in 600-sec simulations modeling a rich set of steady, level flight scenarios. Each simulation was run under the assumption of constant engine power, level flight, with ice accretion on both the wing and the tailplane, and at an altitude of 2,300 m. Simulations were performed with the aid of the FDC Matlab/Simulink toolbox as described in Bragg, et al.⁶ Furthermore, measurement noise consistent with Twin Otter instrument accuracy specifications, were incorporated as zero-mean, bandlimited white Gaussian noise. The simulations provided all measurement information at a 30-Hz sample rate.

As in Schuchard, et al.,⁸ we use a sigmoidal back-propagation neural network structure. Once the structure of a neural network is determined, the biases and weights of the nodes and connections, respectively, are determined via numerical optimization with respect to the least squares error between the known output and the network output from a suite of training data. In this case, the IMS network used three hidden layers of seven nodes, twelve nodes, and five nodes, respectively. Of the data available from the simulation cases described above, training data were obtained by sampling the measurements at 41-sec intervals from each of the cases. The network was trained using supervised learning with a back-propagation algorithm.

Network simulation results

Once the network was trained with the reduced data set, they were applied successively to each of the 230 simulation cases. The general accuracy of the neural network over the entire suite of simulation cases is measured by the root-mean-square $\bar{\eta}$ estimate error. The error distribution was estimated for each network over all simulation sample instants (i.e., 0 - 600 s at 30 Hz).

Although the icing severity estimate for the IMS neural network can have significant error at a given sample instant, Fig. 6 clearly indicates that these significant errors are rare in the set of all simulation sample instants. In fact, detailed study of all simulation cases for the IMS network, which are not included here for the sake of brevity, reveal that the cases appear almost perfect on visual inspection. The IMS network has a mean error of 7.2×10^{-6} , an error standard deviation of 9.8×10^{-5} , and an error of greater than 0.01 (i.e., 1% of the difference between a clean aircraft and a nominally iced aircraft) for only 0.31% of simulation time instants.

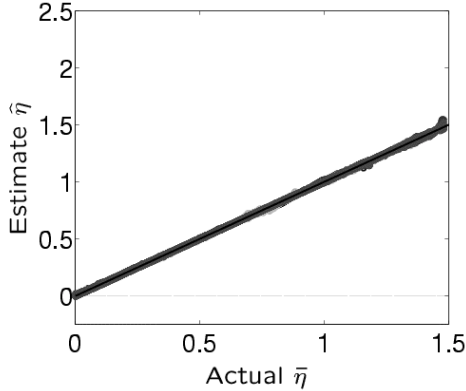


Fig. 6. Scatter plots of IMS neural network estimated $\bar{\eta}$ versus actual (instantaneous) $\bar{\eta}$ over all simulation runs. A perfect neural network would have all points lying on the depicted line of slope one.

Further analysis of these simulation results has demonstrated that the excellent performance of the IMS is primarily due to the accuracy of the hinge moment model, an accuracy that may not be available in practice. For this reason, a second IMS neural network was considered that excluded the hinge moment measurements altogether, in both the training and the simulation stages. This limited IMS network was simulated over the same set of scenarios as the full IMS network discussed above. The scatter plot corresponding to Fig. 6 for the case without hinge moment input, is depicted in Fig. 7. While the results for the limited IMS network are clearly degraded from those of the full IMS network, the results exhibit relatively large errors only very rarely, with an error of greater than 0.1 (i.e., 10% of the difference between a clean aircraft and a nominally iced aircraft) for only 0.1% of simulation time instants.

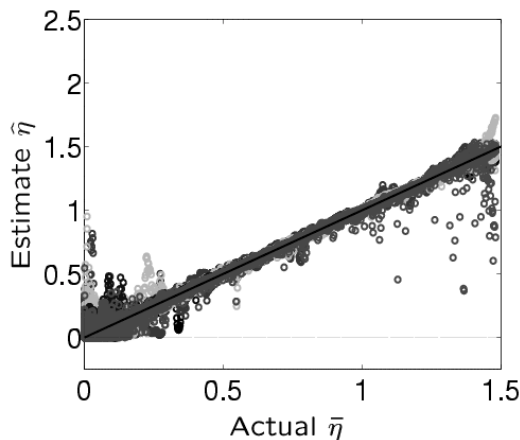


Fig. 7. Scatter plots of limited IMS neural network estimated $\bar{\eta}$ versus actual (instantaneous) $\bar{\eta}$ over all simulation runs. A perfect neural network would have all points lying on the depicted line of slope one.

Autopilot analysis

Many aircraft accidents and incidents have occurred due in part to the use of the autopilot that masks the effect of the ice on aircraft control from the pilots. Since the SIS is intended to communicate the effect of ice on aircraft control to the pilots, the autopilot would be used in icing. As a result a study is underway to examine the autopilot stability and performance under iced conditions. (This study is described in detail in Vikrant and Voulgaris.¹⁷) The autopilot analysis was done using the Flight Dynamics and Control (FDC) toolbox for MATLAB & Simulink with a pitch-attitude-hold autopilot structure. The behavior of various autopilot modes like the Pitch-Attitude-Hold (PAH), Altitude-Hold (ALH), Roll-Attitude-Hold (RAH) etc. was investigated through simulations.

It was seen that severely iced conditions could lead to aircraft stall and elevator saturation if the altitude-hold autopilot was engaged, especially at low flight velocities. The altitude in some cases could not be held just with the elevator and the ALH autopilot must also be able to use aircraft power to hold the altitude. Icing was also seen to cause severe degradation in the autopilot tracking response. Moreover, under iced conditions and in the control of the ALH autopilot it was found to be dangerous to issue a roll command because it could lead to the saturation of the elevator. Overall, it was noted that there was a need to adapt the current A/P structure to make it perform robustly to the icing conditions.

The effect of icing on the autopilot was examined from a theoretical point of view using quadratic stability analysis of the linearized Pitch-Attitude-Hold mode. The fact that the linearized PAH model was affinely dependent on the icing parameter, η , made the stability conditions reduce down to the feasibility of finite linear matrix inequalities. It was noted that the stability of the PAH did drop, but not very significantly, with increasing icing parameter value.

Currently work obtaining limits under icing conditions on the reference values issued to the autopilot is underway. This is being done by examining the peak-to-peak nominal performance of the PAH autopilot. Preliminary results have already been obtained and further investigation and analysis is being carried out.

3.3 Human Factors Research

The role of Human Factors Group in this project is to present the IMS-generated icing-related information to pilots in a meaningful and effective manner in order to support them in making decisions and selecting/executing actions under time pressure and uncertainty. The following sections will describe the conceptual design of the IMS interface and the CSE research activities that

were conducted to date as part of the overall Smart Icing Systems project.

Identification of Pilots' (Perceived) Information Requirements

The first step in any interface design is the identification of the information requirements of future users and the examination of the constraints under which these users must operate. To this end, a survey of regional carrier pilots was conducted. The survey served several purposes: a) identify pilots' perceived information requirements during actual or suspected in-flight icing encounters, b) learn about pilots' operational experience with, and their understanding of, icing conditions, and c) explore pilots' attitude towards highly autonomous control automation. With the assistance of the Airline Pilots' Association (ALPA), 6407 surveys were sent out to nine regional carriers.

In the context of this paper, it is possible only to present some of the main findings from the analysis of pilots' responses (n=386). First, we identified a number of gaps and misconceptions in pilots' knowledge and understanding of in-flight icing conditions. Information about gaps and misconceptions in pilots' understanding of in-flight icing can serve as important input for improvements of pilot training.

The vast majority of pilots in this survey (93%) indicated that visual checks for ice accretion are their primary means of ice detection and diagnosis. This reliance on visual cues is problematic because not all aircraft surfaces are visible to the pilot (e.g., the tail-plane of the aircraft) at all times (e.g., at night). Also, this approach requires that the pilot already has reason to suspect icing, which then triggers visual inspection of the aircraft. In the absence of such expectations, pilots may be surprised and experience difficulties as suggested by their descriptions of the worst icing encounters, which are characterized by a sudden onset and a rapid deterioration of aircraft performance. Visual icing cues can also mislead the pilot who needs to interpret them in light of the current flight context. A relatively small number of pilots mentioned that additional cues that alert them to possible icing include a loss of airspeed, the need for additional power to maintain airspeed and altitude, and unusual trim adjustments by the autopilot.

Overall, the survey results confirm the need for providing pilots with more effective and timely information as well as decision support in the context of icing conditions (for a detailed report on the survey results, see McGuirl et al.¹⁸). The following sections will describe our approach to achieving this goal and the various research activities that were conducted as part of this project.

A Decision Support System

As mentioned earlier, our goal is to support pilots in decision-making and action selection/execution under uncertainty. Figure 8 shows the various steps involved in the decision-making process and possible IMS functions that can serve to support the pilot during each phase.

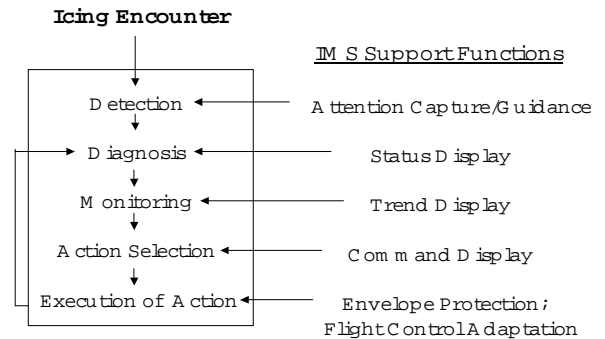


Fig. 8. IMS support functions.

The above support functions are implemented in the current IMS interface as shown in Fig. 9. The various functions and implementations will be discussed in more detail in the following sections. It is important to note that our main focus in this project is the conceptual design of the IMS interface rather than its specific implementation for a particular aircraft cockpit.

First, pilots need to be notified of the onset of, and significant changes in, icing conditions. In some cases, they may anticipate and look for visual signs of ice accretion. In other circumstances, however, their attention needs to be captured in a data-driven manner. This approach allows us to inform pilots about icing events as soon as possible, even before visual signs or performance decrements may be noticeable to the pilot. One way to achieve data-driven attention capture is the use of abrupt visual onsets. In particular, recent research by Nikolic and Sarter¹⁹ has shown that, in visually demanding highly dynamic environments such as the flight deck, it is most effective to use a visual alerting mechanism that extends horizontally across the pilot's forward field of view. In the IMS interface, a so-called "ambient strip" (see Fig. 9) fulfills this function. By extending the strip and drawing it around the affected system/parameter, we can go beyond alerting pilots to the fact that something has happened and also guide their attention to the specific problem.

Envelope Protection and Command Display:

Envelope protection indications
(e.g., bank angle and pitch limits)

Attention Capture:

Ambient strip



Attention Guidance:
Extended ambient strip

Trend Display:
Evolution of icing conditions over time

Status Display:
At-a-glance display of icing location

IMS Reliability Display:
Continuously updated IMS reliability

Fig. 9. Conceptual design of the IMS interface

Another way to support attention capture and guidance is to introduce multi-modal feedback. The rationale behind this approach is that, on most flight decks, pilots' visual attention is already highly taxed. Adding yet more visual information for the purpose of alerting pilots to the onset of icing condition and for indicating the nature and severity of the ice accretion is likely to overload pilots' visual attentional capacity. Instead, by distributing information across sensory channels (e.g., by providing both visual, auditory, and tactile feedback), it is possible to support time-sharing of tasks and parallel processing of information.^{20,21} In particular, a simulator study was conducted to test the effectiveness of vibrotactile cues for presenting pilots with information on the onset, location, and severity of icing. Using twenty-four pilots assigned to one of three experimental groups, possible cross-modal interference between this type of feedback and existing visual and auditory signals on the flight deck was examined. These results (for a more detailed report see McGuirl and Sarter¹⁸) suggest that the introduction of tactile cues, and thus the distribution of information across sensory channels, represents a promising approach to providing pilots with icing-related information.

Diagnosis and action selection

Once the pilot has noticed the presence of icing, he/she needs to diagnose its nature and select an appropriate response. Factors such as time pressure, few and ambiguous cues, or limited experience with certain icing conditions can make it difficult for pilots to perform these tasks successfully. Therefore, some form of decision support should be provided. One possible approach is to provide a status display that presents information about the icing situation but leaves the selection of the proper response to the crew.²² Another possibility is to introduce a command display that recommends appropriate actions and thus saves the crew the cognitive step from diagnosis to action selection. Both status and command displays involve benefits and disadvantages that need to be weighed carefully against one another. One of the biggest concerns with status and command displays, and with decision aids in general, is their potential for creating automation biases. Operators may show signs of excessive trust in, and reliance on, an automated decision support system. Experience with a system, or a negative attitude towards modern technologies, can lead to the opposite, but equally undesirable, effect: pilots may not

use the system-provided information or follow its recommendations when they should do so.²³⁻²⁶

We conducted a simulator study to examine the effectiveness and limitations of both forms of decision support in more detail in the context of icing. 27 commercial pilots were randomly assigned to one of three display conditions (baseline, status, and command). They were flying a total of 20 ILS approaches on a motion-based GAT 2 simulator that recreated the appropriate kinesthetic symptoms associated with an actual encounter of icing conditions (e.g., airframe or control buffet). They experienced eight wing ice scenarios, eight tail-plane ice scenarios, and four scenarios without any ice accretion. Pilots in the status and command conditions, but not those in the baseline condition, received information about the icing location or the appropriate response to the icing event, respectively. The overall reliability of the information was 70%.

Display condition and accuracy of the decision aid turned out to be the most influential, and often interacting, factors in this study. As expected, both status and command displays led to improved performance over the baseline condition when accurate information was presented. However, inaccurate information led to pilots' performance dropping below that of the of the baseline condition in both cases (see for example Fig. 10).

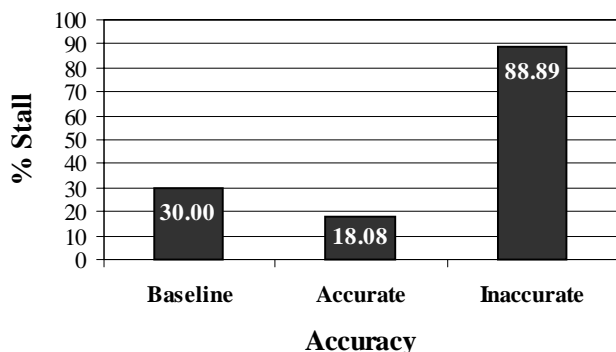


Fig. 10. Stall frequency as a function of accuracy

Overall, the findings from this study (for a more detailed report see Sarter and Schroeder²⁷) suggest the need for a context-sensitive choice between different forms of decision aids. Command displays may be preferable when pilots need to respond to an urgent problem (such as a stall) immediately, even at the risk of taking the wrong action in some cases. However, if the consequences of a wrong action are very severe, or if the circumstances allow the pilot more time for making a decision, a status display may be more effective as it leads to fewer errors in case of inaccurate information.

Future research

Our future research activities will focus on three areas: a) supporting trust calibration to avoid that pilots over rely on the decision support provided by the IMS, b) support long-term monitoring of icing conditions, and thus decision-making, by developing a trend display of icing severity, and c) refining the design of indications related to the envelope protection and control adaptation functions of the IMS.

3.4 Flight Simulation

Icing Encounter Flight Simulator

A key objective of the simulation effort is to combine the unique core technology elements of this SIS research into a piloted real-time flight simulator to provide a demonstration of the overall system and its components. In the process, systems engineering of the Icing Encounter Flight Simulator (IEFS) is being employed to update, integrate, test, validate and improve the functionality of the IMS and supporting individual elements. Specifically, one activity is to coordinate the development with the Human Factors group to provide simulator updates embodying their cockpit-display concepts for use in pilot experiments. Additional activity will involve using the simulator as a tool for engineering analysis to test the robustness and sensitivity of the overall SIS for particular flight scenarios being planned for demonstration. Feedback from all of these experiences will be used to improve the SIS.

A long list of general features of the IEFS includes: operation of SIS ID algorithms and neural nets, support for glass cockpit displays designed by the human factors group, flight in and out of icing conditions during day and night using the specialized iced aircraft models, realistic out-the-windows terrain and external aircraft views, flight in VFR and IMC conditions, real-time and batch-mode operation, flight-data-recording features and real-time playback, flight with and without autopilot operation, and finally flight with and without the aid of the SIS. All of these features are complete or under ongoing development.

In approaching the initial development of the IEFS, several factors were considered. First, given the level of complexity and limited time frame for this research, the creation of a new piloted real-time simulation code would not be feasible or economical, especially in light of the many simulation codes already in existence,²⁸ albeit most of them proprietary. Second, the envisioned simulation would ultimately involve several processor-intensive modules, among them the flight dynamics/aircraft model, out-the-window views, a glass cockpit display, and neural net icing characterization and associated IMS functions. Third, inexpensive PCs made them particularly attractive host computer systems, especially with the advantages of

Linux-based operating systems. As a result of these considerations, the IEFS has evolved to include chiefly a modified open-source flight simulator running as part of a component-based simulation with other modules in a networked environment using PC-client computers. These elements are discussed in greater detail.

The current IEFS main simulation module is based on the open-source Flight Gear Flight Simulator (FGFS) led by Curtis Olson of the Human Factors Research Lab at the University of Minnesota.²⁹ Over 50 developers from all over the world have contributed to its development. It is programmed using C/C++ and OpenGL, having more than 150,000 lines of code. Flight Gear adheres to the GNU General Public License (GPL), which gives permission for anybody to modify and redistribute the code without changing the copyright notice. The simulator is multi-platform and hence can be run on a range of computer systems including Windows NT, Windows 95/95/2000, Linux, BSD UNIX, SGI IRIX, SunOS and Macintosh. The pilot can run the simulator by providing input through the keyboard, the mouse or through a combination of a joystick, throttle and rudder pedals.

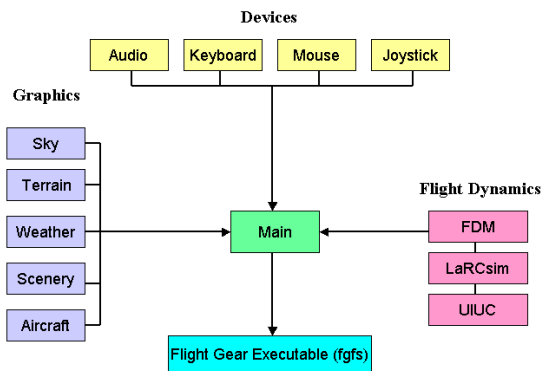


Fig. 11. Flight Gear code organization and location the UIUC aircraft-model addition to LaRCsim.

Of the various flight dynamics models implemented in FGFS, the current study uses the NASA Langley LaRCsim.³⁰ It implements the six degree of freedom rigid-body equations of motion solved using quaternions and requires user supplied routines for the aircraft model. In its original form, there are three aircraft models hard coded into FGFS.

To model the Twin Otter, a reconfigurable aircraft model was added to FGFS. This adapted code has been called UIUC-FGFS. The modifications are readily accomplished as the basic core FGFS code is extremely modular and takes advantage of the C/C++ programming language. Moreover, newer versions of FGFS available on the web include the most recent publicly available

UIUC modifications. Figure 11 shows the organization of the FGFS with the flight dynamics model (FDM) supported by the LaRCsim, which calls the UIUC aircraft model as shown. A keyword-based input file is used by the UIUC code to define all of the aircraft clean and iced parameters.³¹

FGFS includes scenery from all over the world for realistic out-the-window terrain views in addition to a HUD and instrument panel display. Owing to the input from several developers, the scenery views are being continually refined. For example, Fig. 12 shows a screen grab of the Twin Otter in flight above the San Jose International Airport based on aerial/satellite imagery. Additional views can be found on the Flight Gear website.²⁹



Fig. 12. Screen grab of the Twin Otter in flight over the San Jose International Airport (KSJC).

The IMS neural network native code is Matlab. In the current version of the UIUC-FGFS, this Matlab code was converted to C++ using a set of Matlab 6.0 APIs (Application Programming Interface). In future versions of the simulator, the computationally intensive IMS neural network will be run on a separate computer over the network.

As previously described, the Human Factors Group has developed a series of preliminary versions of the glass cockpit with IMS interfaces designed to help the pilots fly safely in icing conditions (see Fig. 12). These glass cockpits have been implemented using OpenGL graphics running as a separate process on another computer over the network. In particular, the current network version of the IEFS only includes the UIUC-FGFS and glass cockpit. UIUC-FGFS is used to transfer data to a socket on the client computer running the glass cockpit. The glass cockpit code then reads the sockets and updates the display.

Specifics regarding the system requirements and development environment are as follows. The platforms

used for development at UIUC are Redhat Linux 7.1 and Windows NT 4.0 PC machines running at 1.5 GHz with 3D accelerator graphics cards (GeForce 2 Ultra) with full OpenGL drivers to achieve smooth frame rates of nominally 30 Hz and higher. GNU utilities and others are used for development on both the Linux and Windows NT systems. Specifically, the GNU gcc compiler is used together with several libraries including Mesa/OpenGL, Perl, Automake, Autoconf, Make, Plib, and the C++ libraries provided by Matlab 6.0. To synchronize the development of UIUC-FGFS and to allow access to multiple developers, CVS (a version control system software) was used on a computer running Redhat Linux 7.1.

Icing scenarios

Two fictional icing encounters are being developed to demonstrate the IMS capabilities and benefits. The first involves airframe ice leading to tailplane stall of a generic turboprop commuter aircraft. A map view of the flight is shown in Fig. 13. In this fictional account, a myriad of conceivable factors put the pilots in the following situation on approach: (a) flight in an aircraft with a history of tailplane stalls related to airframe icing (b) erratic winds at destination, leading to a runway change and an unfamiliar, over-mountain approach (c) use of 45-deg flaps during approach phase, due to steep approach (d) high gross landing weight and forward CG due to full passenger and cargo load, placing aircraft near edge of certified flight envelope (e) low airspeed on final approach, due to spacing requirements for departing traffic (f) a distracting element, hydraulic pump failure. Tailplane stall occurs in this scenario.

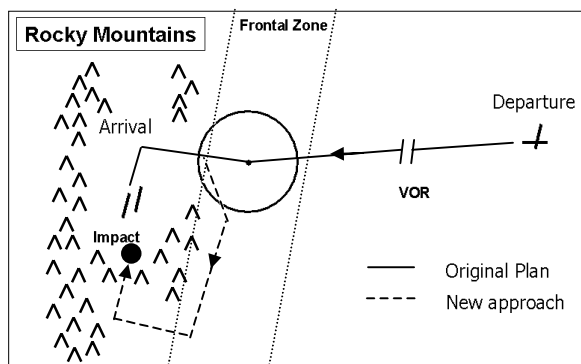


Fig. 13. Fictional flight plan and modified approach of a commuter aircraft flying in icing conditions that led to tailplane stall.

In this scenario, leading factors contributing to the failure can be categorized according to the three layers of defense: avoidance, the ice protection system, and then the pilots. With respect to avoidance, the descent occurred in icing conditions. PIREPs did not indicate significant icing over the destination. There was a tail de-ice boot

failure, and tail ice severity was not indicated by the nose-mounted ice-evidence probe. Ice detection procedures for this case were not adequately defined in the flight manual. Finally, the pilots were busy with last-minute approach changes, new charts, checklists, and hydraulic pump failure; hence, ice management was not the highest priority.

The future demonstration of the simulator will include the above scenario as well as one with the extra layer of protection provided by an onboard IMS. With the IMS, there are two possible interventions. First, icing effects characterization would alert pilots to tail icing severity and IPS failure during approach, overcoming the inadequate IPS and allowing for timely corrective action. Second, the envelope protection features would prevent pilots from placing aircraft in a steep descent configuration, eliminating high tail down-force and resulting tailplane stall. Both interventions would have prevented a crash. A roll-upset scenario is also under development for the simulator and SIS development.

Future Research

Work continues to implement the SIS components in the Icing Encounter Flight Simulator to be demonstrated through the icing scenarios under development. This includes integrating the non-linear Twin Otter model, refining and updating the IEFS glass cockpit and IMS functions, implementing new characterization methods and envelope protection, and adding features for the

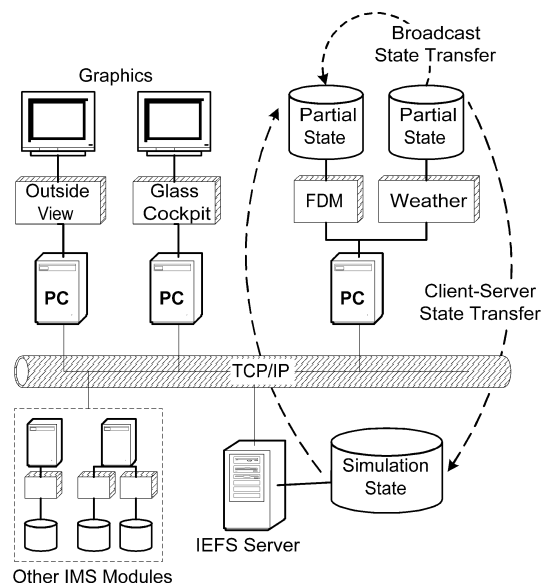


Fig. 14. Future expansion of the IEFS client-server layout showing a sample state transfer by two different methods: broadcast and client-server (dashed lines are abstractions and all communications ultimately use the TCP/IP network).

demonstration scenarios and human-factors pilot experiments.

In addition development of the networking aspects of the IEFS to improve overall simulator performance is ongoing. IEFS contains several processor-intensive modules, which include the flight dynamics model, an out-the-window display, the glass cockpit display, and the neural net icing characterization. While a modern Pentium-based PC is capable of executing one or two of these modules concurrently, a complete simulation requires the use of multiple processors for real-time execution of all modules. To this end, the next generation IEFS will run as a distributed simulation over many networked PCs, each handling one or more individual simulator components in parallel. The next-generation IEFS distributed model combines a client-server architecture with some peer-to-peer features for increased performance. As depicted in Fig. 14, a central server will maintain the master simulation state and communicates with each of the clients using the TCP/IP protocol in a networked environment. The clients, in turn, will host the simulator modules, with each module running in a separate process. One machine may host several module processes, although processor-intensive modules will be run on dedicated PCs for practical real-time execution. A prototype of this network-based system currently drives Microsoft Flight Simulator for out-the-window and external aircraft views, as shown in Fig. 15. Here, Flight Simulator's internal flight dynamics are bypassed while aircraft state is instead obtained from the IEFS server. A more detailed description of this work is available in Deters et al.³²



Fig. 15. An external view of the Twin Otter in Microsoft Flight Simulator, with the flight dynamics and aircraft state driven by the IEFS.

4.0 Conclusions

This paper reviewed the progress toward developing the technology for a smart icing system. Based on the research completed to date several conclusions can be drawn:

- A sophisticated 6 DoF simulation has been developed and used to study the effect ice accretion on aircraft performance and control.
- Large icing effects on aircraft have been documented and the effect of windshear found to differ significantly from an icing encounter. Gravity waves have more similar characteristics.
- Neural networks have been identified for use in analyzing the many sensor inputs for the system. Good results have been seen using stability and control derivatives and trim values to predict icing level.
- Pilot information needs have been identified along with the importance of accuracy in command display information.
- Multi-modal feedback shows promise in communicating icing information to pilots.
- Initial flight deck display concepts have been proposed and are being tested.
- Piloted flight simulation is under development using networked computing. SIS systems are being implemented and tested on realistic flight scenarios.

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