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İSTANBUL TECHNICAL UNIVERSITY ★ INSTITUTE OF SCIENCE AND TECHNOLOGY

**AIRCRAFT ICING DETECTION, IDENTIFICATION
AND RECONFIGURABLE CONTROL BASED ON
KALMAN FILTERING AND NEURAL NETWORKS**

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**KALMAN FİLTRESİ VE YAPAY SİNİR AĞLARI İLE
UÇAK BUZLANMALARININ TESPİTİ, TEŞHİSİ VE
YENİDEN ŞEKİLLENDİRİLEBİLİR KONTROL**

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PREFACE

The risks of the iced aerodynamic surfaces of the flying aircraft have been known since the beginning of the first flights. Until last years, as a solution for this event, the icing conditions ahead flight route are estimated from radars or other environmental sensors, hence flight paths are changed, or, if it exists, anti-icing/de-icing systems are used. Unfortunately, the increasing number of vital accidents in result of this event, insufficiency of the existing systems, increasing air traffic, and need of flight in every weather condition lead to look for new means. Since this subject directly affects to flight safety, civil aviation authorities and aircraft manufacturers have given special attention. Looking at the reasons of the accidents in Turkey and worldwide having recently happened, I have seen the accidents of one military helicopter in 1996, one THY Boeing 737 aircraft in 1998 and two military aircraft (CASA) in 2001 are directly or indirectly related to icing. I could not see an academic work on this subject in Turkey up to now.

With this work, a new method to detect and identify aircraft wing icing occurrences from aircraft dynamic motion variations has been developed. Moreover, a new icing tolerant flight control system has been designed.

I thank my supervisors Prof. Dr. Çingiz HACIYEV and Assist. Prof. Dr. Fikret ÇALIŞKAN, who have given me their helps during my PhD works. I am thankful to the management of my company Turkish Airlines, Inc., which has supported to my study. I thank my friends who have given their supports. I am especially thankful to my wife and two sons, who have been so patient, so self-sacrificing and so encouraging along my study at day and night indeed.

I am dedicating this thesis to my mother and father, who gave their spiritual supports to me, and I have always felt them with me, although they were far from me.

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Rahmi AYKAN

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ABBREVIATIONS

AAA	: Advanced Aircraft Analysis, the software of ROSKAM Aviation
AFCS	: Automatic Flight Control System
AIMS	: Aircraft Icing Performance Monitoring System
AOA	: Angle of Attack
ASDIS	: Airspeed Directional Indicator System
BFGS	: Broyden, Fletcher, Goldfarb, and Shanno
BP	: Back propagation
BTUKS	: Buzlanma toleranslı uçuş kontrol sistemi (ITFCS)
CG	: Conjugate Gradient
DIDS	: Dynamic Icing Detection System
EASA	: European Aviation Safety Agency
EKF	: Extended Kalman Filter
FAA	: Federal Aviation Authority
FAR	: Federal Aviation Regulations
FDF	: Failure Detection Filter
FDI	: Fault detection and isolation
FDR	: Flight Data Recorder
FIR	: Finite Impulse Response
FL	: Fuzzy logic
FTFCS	: Fault Tolerant Flight Control Systems
GDM	: Gradient Descent with Momentum
GLR	: Generalized Likelihood Ratio
GN	: Gauss-Newton
IDI	: Innovative Dynamics, Inc.
IPS	: Ice Protection Systems
ITFCS	: Icing Tolerant Flight Control Systems
JAA	: Joint Aviation Authority
JAR	: Joint Aviation Regulations
KF	: Kalman Filter
KFID	: Kalman Filter Icing Detection
LMA	: Levenberg-Marquardt Algorithm
LMS	: Least Mean Squares
LQG	: Linear Quadratic Regulator
ML	: Maximum Likelihood
MSE	: Mean square error
NASA	: National Aeronautics and Space Administration
NN	: Neural Network
NNII	: Neural Network Icing Identification
NTSB	: National Transportation Safety Board
OSS	: One Step Secant
OUKS	: Otomatik Uçuş Kontrol Sistemi (AFCS)
RBP	: Resilient Back propagation
SCG	: Scaled Conjugate Gradient
SOLA	: System for Onboard Lift Analysis
SOM	: Self Organizing Map

SPR	: Sequential Probability Ratio
SRFCS	: Self Repairing Flight Control System
SIS	: Smart Icing System
THK	: Turkish Air Forces – Türk Hava Kuvvetleri
THY	: Türk Hava Yolları – Turkish Airlines
VLR	: Variable Learning Rate
YSA	: Yapay sinir ağı (NN)



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NOMENCLATURE

a	: output of a neuron
a_{ij}	: i -th row j -th column of A , $A(i,j)$. icing parameters: a_{12} , a_{22} , a_{23} , a_{32} , a_{33}
$\mathbf{a}$	: output vector of NN
$\mathbf{A}$	: aircraft dynamic matrix in state space representation
$\mathbf{A}_1$	: the matrix which is multiplier of the state vector in state space representation of aircraft flight equations with the coefficient of the state derivative
$\overline{\mathbf{A}}$	: modified $\mathbf{A}_1$, $\overline{\mathbf{A}} = (\mathbf{T}_1)^{-1} \mathbf{A}_1$
$\hat{\mathbf{A}}$	: estimated system matrix via NN
$\mathbf{A}$	: a positive definite random matrix, $\mathbf{A} = (N - 1) \hat{\mathbf{S}}$
b	: a bias of a neuron
$\mathbf{b}$	: bias vector of NN
B	: innovation statistics
$\mathbf{B}$	: aircraft control matrix
$\mathbf{B}_1$	: the matrix which is multiplier of the control vector in state space representation of aircraft flight equations with the coefficient of the state derivative
$\overline{\mathbf{B}}$	: modified $\mathbf{B}_1$, $\overline{\mathbf{B}} = (\mathbf{T}_1)^{-1} \mathbf{B}_1$
$\mathbf{c}$	: icing parameters' vector-simulated
$\hat{\mathbf{c}}$	: icing parameters' vector-estimated
$\bar{c}$	: wing mean aerodynamic chord
C_d	: drag coefficient of airfoil
C_D	: drag coefficient of aircraft
C_{D_α}	: stability derivative of drag coefficient with respect to AOA
C_l	: lift coefficient of airfoil
C_L	: lift coefficient of aircraft
C_{L_α}	: stability derivative of lift coefficient with respect to AOA
C_{L_q}	: stability derivative of lift coefficient with respect to pitch rate
C_m	: pitching moment coefficient of airfoil
C_M	: pitching moment coefficient of aircraft
C_{M_α}	: stability derivative of pitching moment coefficient with respect to AOA
C_{M_q}	: stability derivative of pitching moment coefficient with respect to pitch rate
D	: drag of airfoil
$\mathbf{D}_u$	: covariance matrix of control input error
$\mathbf{e}$	: network error
E	: expected value operator
E	: mean square error (MSE) of NN
f	: transfer function or activation function of NN
$\mathbf{F}$	: nonlinear system matrix of flight equations

g	: gravity acceleration
g_{ij}	: elements of g
g	: gradient matrix of NN weights' changes
G	: transfer matrix of system disturbance
G₁	: the matrix which consists of the nonlinear terms in state space representation of aircraft flight equations with the coefficient of the state derivative
$\bar{G}$	: modified G₁ , $\bar{G}(\mathbf{x}) = (\mathbf{T}_1)^{-1} \mathbf{G}_1(\mathbf{x})$
G_X	: gravitational force in axis X
G_Y	: gravitational force in axis Y
G_Z	: gravitational force in axis Z
h	: nonlinear measurement matrix of flight equations, general form
h_X	: angular moment per axis X
h_Y	: angular moment per axis Y
h_Z	: angular moment per axis Z
H	: linear measurement matrix of flight equations
H	: Hessian matrix of network
I_{XX}	: inertial moment per axis X
I_{YY}	: inertial moment per axis Y
I_{ZZ}	: inertial moment per axis Z
I_{XZ}	: inertial moment per plane X-Z
I_i	: modified inertial terms, i=1,2,...,6
I_{9x9}	: unit matrix with 9 rows and 9 columns
J	: performance function (index) for LQG design
J	: Jacobian matrix of MSE and NN weight
k	: discretization instant, iteration
k_C	: relative icing effect on parameter C
K	: Kalman filtering gain, $\mathbf{K}(k) = \mathbf{P}^-(k) \mathbf{H}^T(k) (\mathbf{R}(k) + \mathbf{H}(k) \mathbf{P}^-(k) \mathbf{H}^T(k))^{-1}$
K	: control gain-simulated
$\hat{K}$	: reconfigurable control gain
K⁽¹⁾	: the multiplier of prediction when calculating current estimate
l	: total moment per axis X, perturbed
L	: total moment per axis X
L_u	: stability derivative, $L_u = \frac{1}{I_{xx}} \frac{\partial L}{\partial u}$
L	: lift of airfoil
m	: aircraft mass
m_{pm}	: total moment per axis Y, perturbed
M	: total moment per axis Y
M_q	: stability derivative, $M_q = \frac{1}{I_{yy}} \frac{\partial M}{\partial q}$
M_u	: stability derivative, $M_u = \frac{1}{I_{yy}} \frac{\partial M}{\partial u}$
M_α	: stability derivative, $M_\alpha = \frac{1}{I_{yy}} \frac{\partial M}{\partial \alpha}$
M_{δ_E}	: control derivative, $M_{\delta_E} = \frac{1}{I_{yy}} \frac{\partial M}{\partial \delta_E}$
M	: aerodynamic moment of airfoil
M	: covariance matrix of extrapolation error

n	: total moment per axis Z, perturbed
n	: net input to a transfer function of a neuron
N	: total moment per axis Z
N	: number of experiments in KF innovation sequence
N_u	: stability derivative, $N_u = \frac{1}{I_{zz}} \frac{\partial N}{\partial u}$
N_o	: number of network outputs
p	: roll rate, perturbed
p	: an input of a neuron
$\mathbf{p}$	: input vector of NN
P	: angular velocity in axis X, roll rate
P	: probability
$\mathbf{P}$	: covariance matrix of estimation error, $\mathbf{P}(k) = E[(\tilde{\mathbf{x}}(k)) (\tilde{\mathbf{x}}(k))^T]$
$\mathbf{P}_\Delta$	: covariance of normalized innovation sequence
q	: pitch rate, perturbed
$\bar{q}$	: dynamic pressure
Q	: angular velocity in axis Y, pitch rate
$\mathbf{Q}$	: covariance matrix of system disturbance
$\mathbf{Q}_c$	: semi-positive definite symmetric weighting matrix of states at J
r	: yaw rate, perturbed
$\hat{r}_{ij}$	: the elements of matrix $\hat{\mathbf{R}}_0$
R	: angular velocity in axis Z, yaw rate
$\mathbf{R}$	: covariance matrix of control input error
$\mathbf{R}_c$	: positive definite symmetric weighting matrix of controls at J
$R_{\tilde{\Delta}(k)\tilde{\Delta}(k-j)}$	: auto-correlation function of $\tilde{\Delta}$
$\hat{\mathbf{R}}_0$	: estimate of the covariance matrix of the innovation sequence
s	: dimension of innovation sequence
S	: reference wing area
$\mathbf{S}$	: solution matrix of Riccati equation
$\hat{\mathbf{S}}$	: sample covariance matrix
t	: time
$\mathbf{t}$	: network targets
$\mathbf{T}_1$	: the matrix which is multiplier of the derivative of the state vector in state space representation of aircraft flight equations
u	: forward velocity - x-direction
$\mathbf{u}$	: aircraft control vector
$\mathbf{u}_r$	: aircraft control vector - reconfiguration
U	: translational speed in direction of the axis X
U_1	: trimmed total aircraft speed
$\mathbf{x}$	: state vector
$\hat{\mathbf{x}}$	: state vector estimated by KF, a posteriori estimate, or current estimate
$\hat{\mathbf{x}}^-$	: a a priori estimate of state, or prediction
$\tilde{\mathbf{x}}$	: state estimation error, $\tilde{\mathbf{x}}(k) = \mathbf{x}(k) - \hat{\mathbf{x}}(k)$
$\mathbf{x}$	: search direction of the NN learning process
x	: aerodynamical / thrust force in axis X, perturbed
X	: aerodynamical / thrust force in axis X
X_u	: stability derivative, $X_u = \frac{1}{m} \frac{\partial X}{\partial u}$

X_α	: stability derivative, $X_\alpha = \frac{1}{m} \frac{\partial X}{\partial \alpha}$
χ^2	: The statistic of Chi-squared distribution
v	: side velocity perturbation, y-direction
$\mathbf{v}$	: measurement disturbance (noise) vector
$\bar{\mathbf{v}}$	: mean vector of measurement noises
V	: translational speed in direction of the axis Y
V_T	: total aircraft speed
w	: translational speed in direction of the axis Z, perturbed
w	: weight of a neuron per an input
w_{ij}	: correlation coefficients
w_{ij}	: elements of NN weight matrix, $\mathbf{W}$
$\mathbf{w}$	: system disturbance (noise) vector
$\bar{\mathbf{w}}$	: mean vector of system noises
W	: translational speed in direction of the axis Z
$W(A)$	: Wishart distribution
$\mathbf{W}$	: NN weights' matrix
$\mathbf{y}$	: measurements' vector
$\hat{\mathbf{y}}$	: measurement estimate or prediction, $\hat{\mathbf{y}}(k) = \mathbf{H}(k) \hat{\mathbf{x}}^-(k)$
$\tilde{\mathbf{y}}$	: measurement error or innovation, $\tilde{\mathbf{y}}(k) = \mathbf{y}(k) - \hat{\mathbf{y}}(k)$
y	: aerodynamical / thrust force in axis Y, perturbed
Y	: aerodynamical / thrust force in axis Y
Y_u	: stability derivative, $Y_u = \frac{1}{m} \frac{\partial Y}{\partial u}$
z	: aerodynamical / thrust force in axis Z, perturbed
Z	: aerodynamical / thrust force in axis Z
Z_q	: stability derivative, $Z_q = \frac{1}{m} \frac{\partial Z}{\partial q}$
Z_u	: stability derivative, $Z_u = \frac{1}{m} \frac{\partial Z}{\partial u}$
Z_α	: stability derivative, $Z_\alpha = \frac{1}{m} \frac{\partial Z}{\partial \alpha}$
α	: angle of attack, perturbed
α_T	: angle of attack
α_l	: learning rate of NN
α	: level of significance of a distribution
β	: side-slip angle, perturbed
β_T	: side-slip angle, total or trim
β_u	: parameter of CG learning methods
$\Gamma[\cdot]$	: gamma function
$\sigma_{w_{ij}}^2$	: variance of w_{ij}
δ	: Kronecker symbol
δ_A	: aileron deflection
δ_C	: canard deflection
δ_E	: elevator deflection
δ_F	: flap deflection
δ_{FL}	: left flap deflection
δ_{FR}	: right flap deflection
δ_H	: horizontal stabilizer deflection
δ_{HL}	: left stabilizer deflection

δ_{HR}	: right stabilizer deflection
δ_R	: rudder deflection
Δ	: innovation sequence, $\Delta(k) = \tilde{y}(k) = y(k) - H(k) \hat{x}^-(k)$
$\tilde{\Delta}$	: normalized innovation sequence, $\tilde{\Delta}(k) = [H(k) P^-(k) H^T(k) + R(k)]^{-1/2} \Delta(k)$
$\bar{\Delta}$	: mean value of $\tilde{\Delta}$
η	: aircraft specific icing severity parameter,
η_{ice}	: icing severity parameter based on NACA 0012 airfoil drag rise ratio
θ	: pitch or elevation angle perturbation
Θ	: pitch or elevation angle
π_k	: one-dimensional statistics of the sequence
$\chi^2_{\alpha, Ns}$	: chi-square distribution, α -level of significance and Ns measurements
ρ	: air density
ρ_{rs}	: correlation coefficient statistics of $\tilde{\Delta}(k)$, r and s are two components of the normalized innovation sequence
ψ	: yaw or azimuth angle perturbation
Ψ	: yaw or azimuth angle
ϕ	: roll or bank angle perturbation
Φ	: roll or bank angle
Φ	: system transfer matrix
μ	: training speed parameter of LM algorithm

Subscripts:

e	: estimated values of KF
1	: trim values of dynamic characteristics

Superscripts:

T	: transpose of a vector or matrix
$-$	: priori value

AIRCRAFT ICING DETECTION, IDENTIFICATION AND RECONFIGURABLE CONTROL BASED ON KALMAN FILTERING AND NEURAL NETWORKS

SUMMARY

The recent improvements and research on aviation have focused on the subject of aircraft safe flight even in the severe weather conditions. As one type of such weather conditions, aircraft icing has been found considerably negative effect on the aircraft flight performance. Particularly, upon a fatal accident in 1997, icing was announced as a top subject by NASA, and then several researches have begun on icing detection and protection systems. The risks of the aircraft icing encountered during flight at freezing temperatures and humid air have been known early 1900s. In addition, ice may occur on wings, control surfaces, horizontal and vertical stabilizers, fuselage nose, landing gear doors, engine intakes, fuselage air data ports and sensors and drain system outputs. Aircraft icing is important for economical reasons as well as aviation safety since most of the existing anti-icing systems on modern aircraft are related to aircraft fuel consumption. Icing effects to the aircraft systems or to the motion depend on the ice location. This study only examines wing icing occurrences. Icing during grounding of aircraft is not in the scope of this study.

Although some modern aircraft have sensors to detect icing, they can give only indication of the possibility of icing occurrence, but they cannot provide any information about degraded performance. Detailed information about icing for pilots/autopilots cannot be produced by the existing systems. With the improved ice detection, identification and control system, regardless atmospheric icing conditions, military and commercial aircraft can fly along their predetermined paths in acceptable safety margins by taking reasonable measures against it. This work aims at the detection and identification of airframe icing based on statistical properties of aircraft dynamics and reconfigurable control protecting aircraft from hazardous icing conditions. A new detection and control system is proposed so called Icing Tolerant Flight Control System (ITFCS). Its block diagram is shown in Figure 1.

Icing in aerodynamic surfaces decreases the aerodynamic quality of aircraft: aircraft weight and drag increase, lift decreases, and the affectivity of angle of attack and pitch angle. According to the experimental studies about airfoil in the literature aircraft icing model is represented by five stability derivatives. In parallel to the past studies, it is assumed that, within 2 minutes, drag increases 400%, and lift decreases 60%.

Icing presence is detected by Kalman filtering (KF) innovation process approach by monitoring statistical changes of aircraft states. Innovation process is defined as the difference between actual system output and estimated output based on mathematical model and priori information. Chi-square distribution property of the normalized innovation process is used for the selection of threshold.

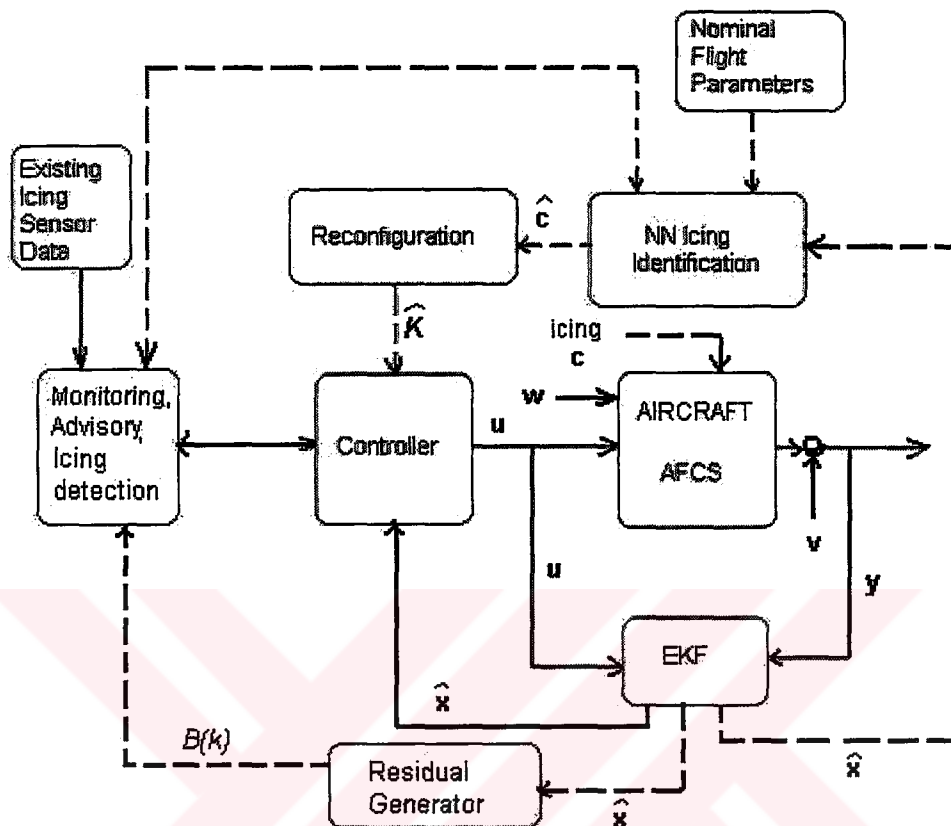


Figure 1. Block diagram of proposed Icing Tolerant Flight Control System (ITFCS)

A feed forward neural network (NN) structure having 1 hidden layer is embodied such that its inputs are the aircraft estimated states, and its outputs are icing parameters. The necessary training and validation set for the NN model of the iced aircraft are obtained from the simulations, which are performed for various possible icing conditions around flight conditions at ice detection time. In order to decrease noise effects on the states and to increase training performance of the NN, the estimated states by the KF are used. A suitable NN model of the iced aircraft is obtained by using system identification methods and learning algorithms. The Levenberg-Marquardt backpropagation training algorithm is used since it is faster and more accurate in several tests.

This trained NN model finds new values of the icing parameters by taking real flight data. These parameters are used for the automatic control of the aircraft that has lost its controllability due to icing. Although aircraft dynamic matrix is changed by icing conditions, existing control algorithm uses outputs of the aircraft and constant gain. However, in this condition, the gain is not optimal anymore. Even the simulations have showed that if the aircraft continues the flight with the existing controller, there would be a catastrophe. In this work, a new controller is designed in terms of the parameters found by the trained NN model.

The method is applied to multi input multi output nonlinear unstable F16 military and linear A340 commercial aircraft models. These models are assumed to be affected by wing icing occurrences in different levels accumulating within 7 minutes. The aircraft is stabilized by a linear quadratic optimal controller. In addition, the controller ensures the mechanical limits of the control surface deflections.

As an approximation, the accumulation of ice is represented with the linearly varying certain parameters of the aircraft models. Hence, the necessary training and testing data for the neural network models of the aircraft are obtained from the simulations. Training batch time is taken 30 s such that aircraft control system should be reconfigured within this time and the model parameters should not be so different from the existing trim conditions. The states and measurements are assumed to have certain level white noises. In order to decrease measurement noises or estimate non-measurable states all states are filtered through Kalman filter. The control inputs of the flight control system are automatically obtained from linear regulator such that the control deflections are to be within their mechanical limits. Hence, training set having vectors of 9 states as inputs and 5 parameters as outputs are produced by artificially varying parameters in the interval of 0.03 s. On the other hand, the each element of training set has one (9x1) input vector and one (5x1) output vector.

Icing at the same level on F16 and A340 aircraft is detected by the KF innovation approach within 3 and 1 min., respectively, without additional physical sensors. Icing parameters of the aircraft which lost their controls have been found through NN models with acceptable accuracy. As the flight control system is reconfigured based upon the new parameters found from NN models, it has been shown in simulations that the aircraft could safely fly in severe icing conditions. In the result of various tests, the selections of 1 hidden layer and 10 neurons have improved the performance of NN models such as computation speed, convergence speed, instant error, resultant error and minimum square error. Relative errors of the estimated icing parameters have been maintained in acceptable margins such as %5-7.

In order to find the icing parameters from the evaluation of flight data, the effects of icing should not be hidden under the noise effects. Fortunately, Kalman filtering decreases the noise effects in considerable levels.

Aircraft icing is a multi-discipline subject of the specialist on aerodynamics, flight mechanics, flight performance, etc. Although the works on icing till now have been managed by NASA, NATO and a few universities, they are not enough and airframe icing is still an open subject to research.

The proposed method for icing may be applied to other problems: Deformations or missing of the parts such as winglet, fairings, aerodynamic panels, elevator, rudder, aileron, spoiler, flap and slat, or one or more engine out conditions. These types of damages are not so uncommon. These could result from not only the external events such as lightening strike and gust but also faults in manufacturing maintenance and pilots.

The methods proposed in this work can be used for aircraft accident investigations, improvement of aircraft flight performance by manufacturers or operators such that it provides how flight data can be processed.

KALMAN FİLTRESİ VE YAPAY SINIR AĞLARI İLE UÇAK BUZLANMALARININ TESPİTİ, TEŞHİSİ VE YENİDEN ŞEKİLLENDİRİLEBİLİR KONTROL

ÖZET

Havacılıktaki son gelişmeler ve araştırmalar uçakların kötü hava şartlarında da güvenli bir şekilde uçuşması konusunda yoğunlaşmıştır. Özellikle 1997 yılında ölümcül bir kaza üzerine NASA tarafından öncelikli bir konu olarak ilan edildikten hemen sonra uçaklarda buzlanma tespiti ve önleyici sistemler ile ilgili birçok çalışma başlatılmıştır. Havada, sıfırın altında sıcaklıklardaki nemli ortamlarda kanatlarda meydana gelen buzlanmanın uçuş performansına olumsuz etkisi eskiden beri bilinmektedir. Buzlanma uçaklarda kanatlarda meydana gelebildiği gibi kuyruk ve kontrol yüzeylerinde, burunda, iniş takımı kapaklarında, motor kaportaları giriş kısımlarında, sensörlerde ve tahliye sistemlerinde meydana gelebilir. Uçaklarda buzlanma, havacılık emniyetini ilgilendirdiği kadar mevcut buz önleyici ve çözücü sistemlerin uçak yakıtına etkisi olduğundan ekonomik açıdan da önemlidir. Buzlanma, oluştuğu yere göre uçak sistemlerini ve/veya hareketini etkiler. Bu çalışmada sadece kanat buzlanmaları göz önüne alınmıştır. Uçakların yerde beklemesi sırasında meydana gelen buzlanmalar da bu çalışmanın dışındadır.

Uçuş buzlanmasının tespiti için gelişmiş bazı uçaklarda sensörler kullanılsa da bunlar sadece buzlanmanın oluşma ihtimali hakkında bilgi verir, fakat buzlanmadan dolayı uçağın performansının ne kadar azaldığı ile ilgili bilgi vermez. Mevcut sistemler pilota buzlanma ile ilgili detaylı bilgi verememektedir. Gelişmiş bir buzlanma tespit, izleme ve kontrol sistemi ile atmosferik buzlanma şartları ne olursa olsun gerekli önlemler alınarak askeri ve sivil uçakların kabul edilebilir emniyet sınırları içinde istenilen uçuş yörüngesinin devam ettirmesi sağlanabilir. Bu çalışma ile uçak dinamiklerinin istatistiksel karakteristiklerine göre uçak buzlanmalarının tespit ve teşhis edilmesi ve uçağı tehlikeli buzlanma şartlarından koruyan Buzlanma Toleranslı Uçuş Kontrol Sistemi (BTUKS) adını verdiğimiz yeni bir kontrol sisteminin dizayn edilmesi amaçlanmıştır. Önerilen kontrol sisteminin blok diyagramı Şekil 1’de gösterilmiştir.

Aerodinamik yüzeylerde meydana gelen buzlanma uçağın aerodinamik kalitesini azaltır: Uçağın ağırlığı artar, sürükleme artar, taşıma düşer. Kanat profilleri üzerinde literatürde yapılan deneysel çalışmalar baz alınarak uçağın buzlanma modeli en çok etkilenen beş adet kararlılık türevlerinin değiştirilmesi ile temsil edilmiştir. Yapılan çalışmalara paralel olarak kanat buzlanmasından dolayı uçaktaki sürüklemenin 2 dk içinde %400 arttığı ve taşımanın %60 azaldığı varsayılmıştır.

Uçağın dinamik karakteristiklerinin Kalman filtresi inovasyon prosesindeki istatistiksel değişiklikleri izlenerek buzlanmanın olup olmadığı tespit edilmiştir. Inovasyon prosesi gerçek sistemin çıkışı ile matematiksel modele ve önceki çıkış bilgilerine dayalı tahmin edilen çıkış arasındaki fark olarak tanımlanır. Normalleştirilmiş inovasyon prosesinin Chi-square dağılım özelliği kullanılarak eşik değeri hesaplanmış ve buzlanma tespit edilmiştir.

Önerilen metot çok girişli ve çok çıkışlı doğrusal olmayan kararsız F16 savaş uçağı modeline ve doğrusal kararlı A340 yolcu uçağı modeline uygulanmıştır. Bu modellerin 7 dk. lık zaman içinde gelişen çeşitli seviyelerde kanat buzlanmalarına maruz kaldığı varsayıldı. Uçak bir lineer kuadratik optimal kontrolör ile kararlı hale getirilmiştir. Ayrıca kontrolör kontrol yüzeylerindeki sapma miktarlarını mekanik limitler içinde tutmuştur.

Buzlanmanın gelişmesi parametrelerin bir yaklaşımla lineer olarak değiştirilmesi ile temsil edilmiştir. Böylece ağıın eğitimi ve testi için gerekli bilgi kümesi oluşturulmuştur. Ağıın eğitimi için geçen süre buzlanma için kontrol sisteminin yeniden şekillendirilmesi ve model parametrelerinin denge şartlarından çok uzaklaşmaması gerektiği süreye uygun olarak 30 sn olarak seçilmiştir. Modelin durumlarının ve ölçümlerin kabul edilebilen seviyelerde gürültülü olduğu varsayılmıştır. Ölçüm değerlerinde bu gürültülerin etkisini azaltmak veya ölçülemeyen durumları tahmin etmek amacıyla bütün durumlar Kalman filtresi ile filtrelenmiştir. Kontrol girişleri doğrusal regülatör ile kontrol elemanların mekanik kapasitesi ölçüsünde otomatik olarak elde edilmiştir. Böylece buzlanmadan etkilenen parametreler 0.03 sn zaman aralıklı değiştirilerek 9 durum girişi ve 5 parametre çıkışı olan bir bilgi kümesi elde edilmiştir. Bilgi kümesinin herbir elemanı (9x1) durum vektörü ve (5x1) buzlanma parametre vektöründen oluşmaktadır.

İlave bir bir sensör kullanmadan F16 ve A340 uçağında oluşan buzlanma KF inovasyon süreci ile 3 ve 1 dk içinde tespit edilebilmiştir. Aşırı buzlanma şartlarında kontrolü kaybolan F16 uçağının buzlanma parametreleri yapay sinir ağları ile yeteri doğrulukta bulunmuştur. Eğitilmiş yapay sinir ağlarının bulduğu parametrelere göre uçuş kontrol algoritması yeniden şekillendirildiğinde uçakların aşırı buzlanma şartlarında bile güvenli uçabileceği simülasyonlar sonucunda anlaşılmıştır. Değişik denemeler sonucunda bir gizli katmanlı toplam 10 nörona sahip bir yapay sinir ağ yapısının YSA modelinin performansı açısından (işlem hızı, yakınsama hızı, anlık hata ve toplam hata, minimum karesel hata) yeterince uygun olduğu görülmüştür. Kestirilen buzlanma parametrelerinin bağıl hatalarının %5-7 gibi kabul edilebilir limitler içinde olduğu görülmüştür.

Buzlanma parametrelerinin tespit edilebilmesi için buzlanma etkisi ölçüm veya model gürültüleri içinde kaybolmaması gerekir. Kalman Filtresi gürültülerin etkisini azaltmıştır.

Uçaklardaki buzlanma aerodinamik, uçuş mekaniği ve performansı gibi değişik konularda uzmanların ortak bir çalışması olması gerekir. Şimdiye kadar yapılan uluslararası kapsamlı çalışmalara bakıldığında tamamı NASA, NATO veya üniversiteler tarafından desteklenmiş ve özel gruplar kurulmuştur. Buna rağmen yapılan çalışmalar yeterli değildir ve buzlanma konusu hala açık bir konudur.

Buzlanma problemini çözmek için önerilen metod başka problemleri çözmek için de kullanılabilir: Uçağın winglet, fairing, aerodinamik panel gibi herhangi bir yapısal elemanında, veya elevatör, düşey dümen, eleron, spoyler, flap ve slat gibi kontrol yüzeylerinde meydana gelen deformasyonlar veya tamamen kopması, veya çok motorlu uçağın herhangi bir motorunun devre dışı kaldığı durumlarda bu metodun etkili olacağı söylenebilir. Bu şekildeki arızalar az karşılaşılan olaylar değildir. Bu arızalar yıldırım çarpması, sağnak gibi dış olaylardan olabileceği gibi bakım, montaj ve pilot hatalarından da kaynaklanabilir. Ayrıca bu çalışma; uçak kaza-kırım incelemelerinde veya uçağın kullanıcısı olarak performansının iyileştirilmesi amacıyla yapılacak çalışmalarda gerçek uçuş bilgilerinin işlenip kullanılmasına olanak sağlayan bir uygulama olabilir.

1. INTRODUCTION

The safety and cost saving are the most important issues in the air transportation. Current aviation research and development has begun to focus more upon creating aircraft that are safe and reliable during severe weather conditions. Aerodynamical changes of the airframe in flight must be determined in early phase of the changes such that pilot or autopilot should take the most important remedial actions to get rid of a disaster. Broken movable surfaces (flap, slat, elevator, tap, etc), lightning strike damages, icing at the leading edge of wing or empennage can be regarded as structural changes in aircraft.

Without knowing the aerodynamical changes in certain dimensions, aircraft performance and cost saving cannot be calculated and maintained successfully. Several repairs (patches) are externally embodied on airframe. Sometimes this may be in large sizes. These modifications affect aircraft performance.

The recent improvements and research on aviation have focused on the subject of aircraft safe flight even in the severe weather conditions. As one type of such weather conditions, icing has been found to have considerably negative effect on the aircraft flight performance. Furthermore, this phenomenon has resulted in several fatal accidents.

The risks of the aircraft icing encountered during flight at freezing temperatures and humid air have been known early 1900s. Although it has been seen that icing could be hazardous at every flight phase, take-off and landing have been affected most importantly.

On the other hand, especially for commercial aircraft, safety, revenue, schedules and comfort must be maintained at highest possible levels. Aircraft icing is important for economical reasons as well as aviation safety since most of the existing anti-icing systems on modern aircraft are related to aircraft fuel consumption. As long as an airplane flies with an iced wing or empennage, fuel consumption increases in parallel.

Icing effects on aircraft systems or motion depend upon the location of icing. Ice may occur on wings, control surfaces, horizontal and vertical stabilizers, fuselage nose, landing gear doors, engine intakes, fuselage air data ports and sensors and drain system outputs. This study examines only the wing icing occurrences. Icing during grounding of aircraft is out of the scope of this study.

With the improved ice detection, identification and control system, regardless of icing conditions, military and commercial aircraft can fly along their predetermined paths in acceptable safety margins by taking reasonable measures against it. This work aims at the detection and identification of airframe icing based on the statistical properties of aircraft dynamics and reconfigurable control protecting aircraft from hazardous icing conditions.

1.1 Icing Phenomenon and Effects

Icing primarily occurs on the leading edge of wing, tail, and engine. It can be formed inside engine, which may cause engine failure. It may be on the some other protuberances such as measurement probes and drains. Probes and drains are electrically heated by the bleed hot air. Most aircraft does not have any de-icing system on horizontal and vertical tail.

Aircraft icing was documented and evaluated based on standard airfoils. The use of ice thickness may be helpful and there is an obvious relationship between ice thickness and aircraft performance and control. Unfortunately this relationship is complicated by the effect of icing type, ice shedding and residual, varying accretion rates on different components, flight envelope operations and irregularities, etc.

In-flight icing can significantly change the flight performance, stability and control. An ice ridge can lead to reduced lift, increased drag, change in moments and a loss in control effectiveness. In addition, the existing ice protection system in the most common aircraft uses engine hot air. This attributes to decrease in the engine performance. With the use of bleed hot air, fuel consumption is increasing, and maximum engine power is decreasing.

1.2 Icing Accidents

As the measure of aviation safety, the causes of the aircraft accidents and incidents are to be clarified and then be eliminated completely. Aircraft icing is a large area of concern due to the detrimental effects of accumulated ice upon aerodynamic

performance. Small amounts of ice can have an extreme impact upon aircraft dynamics and consequently, icing has been one of the most visible causes of severe accidents. Most icing-related accidents occur as a result of ice accretion affecting the performance and stability of an aircraft by altering the shape of its aerodynamic surfaces. Other icing incidents include engine failure and propeller ice, but this work will focus only on the effects of airframe icing.

Icing was determined to be the factor in 803 aircraft accidents that has occurred between 1975 and 1988 according to National Transportation Safety board (NTSB) reports. Nearly half of these accidents resulted in fatalities. Commercial accidents such as Air Florida Boeing 737 at Washington in 1982 and the American Eagle ATR-72 crash in Indiana, which killed 68 people in October 1994, have also led to national recognition of icing problems. In response to the abundance of aircraft icing accidents, NASA and the President's Commission on Aviation Safety and Security developed an aviation safety research plan that placed a high national priority upon icing protection and prevention. NASA established an icing research group in 1997 [1-2]. FAA, JAA, and newly founded EASA have issued special regulations (FAR and JAR Part 25) in order to maintain flight safety in icing conditions.

Additionally, it is unclear how many icing related accidents have occurred in the other countries. Most accidents having unknown reasons may be due to icing. In Turkey, in 2001 two CASA accidents were firstly claimed that the reason would have been icing. In 1996, Turkish Air Forces (THK) accident carrying org Eşref Bitlis was considered to happen as a result of aircraft icing. In 1998, a Turkish Airline accident occurred in severe weather conditions, probably due to icing. These claims show that more research is needed in this area.

1.3 Solutions against Icing

There are currently two main approaches that deal with the dangers of ice accretion. First, pilots are given complete weather information before and during flights in order to avoid potential icing conditions. Second, aircraft are thoroughly deiced before take-off and then operate an ice protection system (IPS) to accomplish in-flight ice removal. Such a system exist in a modern aircraft Airbus A340 as shown in Figure 1.1. An IPS functions in either an advisory or primary capacity. Advisory systems rely upon the flight crew to activate ice protection devices based upon data received from icing and environmental sensors. On most classical aircraft, icing sensors are not available and pilots determine the level of ice accretion by visual inspection of

the wings and control surfaces. This type of visual ice detection is inadequate because pilots usually cannot see all of the wing or any of the tail. Current ice protection equipment consists mainly of devices that bleed hot engine exhaust onto the wings to prevent icing or inflatable boots that break off accumulated ice.

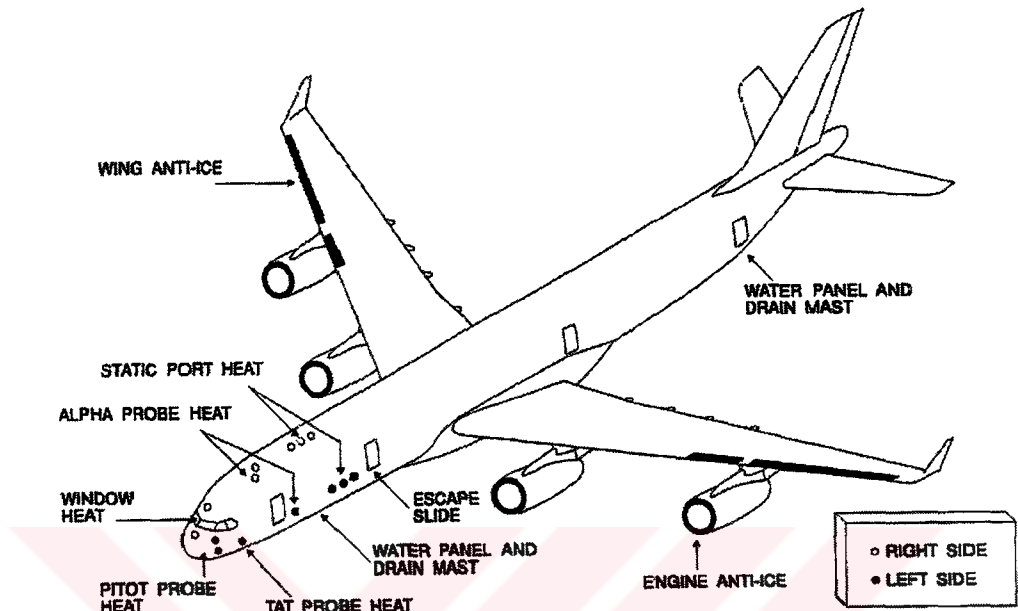


Figure 1.1 Solutions on Airbus A340-300 for icing at different locations

Changes in performance and control due to aircraft icing are difficult to detect. The existing icing sensors in commonly used only give an indication about possible icing. They do not show the degraded performance of an aircraft flight performance.

After the real reason of some fatal accidents and incidents was found to be due to icing in late 1980s, an intensive research started on aircraft icing in early 1990s. There are several systems under development that will monitor, and possibly predict, degraded aerodynamic performance due to airfoil contamination such as ice, by detecting the presence and extent of separated flow. One such sensing device is the Aircraft Icing Performance Monitoring System, AIMS, developed at Innovative Dynamics, Inc. (IDI). Another system formerly owned by the Jet Electronics and Technology, Incorporated (a unit of BFGoodrich Aerospace) and now under development, a stall warning and contamination advisory system. A third contamination detection product is due to System for Onboard Lift Analysis / Airspeed Directional Indicator System, SOLA / ASDIS.

Due to the numerous icing related accidents the envelope protection systems aboard some aircraft have been modified to account for the performance

degradation due to ice accretion. For instance, the ATR 72 SPS operates in conjunction with the IPS to reduce the AOA limit from 18.1 degrees to a predetermined value of 11.2 degrees in icing conditions [3].

1.4 Literature Review

In order to correctly detect, classify and control the aircraft icing, during last fifteen years many investigations have been conducted. NASA has performed several flight test for in-flight icing of the aircraft DHC-6 Twin Otter since 1986 [1-4]. Very useful data were obtained about the effects of aircraft icing to aircraft stability and control in early 1990 [4]. As soon as aircraft icing was announced as a prior issue on 1997, NASA established a team called Icing Research Group. The scientists from Illinois University have investigated aircraft icing from several different viewpoints and proposed a Smart Icing System (SIS) [5-6]. SIS is the most recent conceptual system for in-flight icing. Basically the concept is to measure in flight the effect of the ice on performance and control and to use this information in a human-centered autonomous system to control the Ice Protection Systems (IPS), perform envelope protection, and, if icing is severe, adopt the flight controls. All of this would be properly communicated to and coordinated with the flight crew. Such a system would sense ice accretion through traditional icing sensors and use modern system identification methods to estimate aircraft performance and control changes.

A method for ice detection on tail of an experimental aircraft was developed. The decrease of elevator effectiveness was used as a failure detection filter (FDF) [7]. In another application, a state estimator as a type of Luenberger Observer was used instead of FDF [8]. These studies showed that icing detection via statistical error analysis of states was more effective than online parameter estimation. With NASA support, the effects of tail icing were examined experimentally and analytically, and provided useful data [9]. A method for flight envelope protection was proposed in terms of icing factors by identifying icing characterization [10]. H-infinity algorithm was applied to icing identification problem. It was claimed that proposed method was better than least square estimation methods and Extended Kalman Filter (EKF) methods [11-12].

A method for tail icing detection and classification via neural networks was proposed in [13]. Two special icing parameters were defined: icing severity parameter (η_{ice}) representing the amount and severity of the icing, and relative icing effect parameter

(k_{C_A}) to the particular stability and control derivative. These parameters were estimated via neural networks under the several elevator control inputs [13].

Atmospheric disturbances such as microbursts, windshear and gravity waves were taken into consideration in [3]. Their effects on aircraft performance and control were compared to those of icing. Stability and control derivatives based upon the flight dynamics model have been calculated for the NASA DH-6 Twin Otter based on flight data. A system for flight envelope was developed, using parameter prediction algorithms based on available sensor data and control surface deflection. The system utilized the functional dependence of the equation of motion and the envelope limits on the aircraft state. The idea of a dynamic envelope was considered. A dynamic trim condition was defined as any dynamic flight condition that a pilot is likely to sustain over several seconds in order to maneuver the aircraft. It was also proposed that it may be possible to identify changes due to icing without control inputs (doublets) if sufficient turbulence is present to excite the aircraft dynamics [3].

A method detecting icing via neural networks and Kohonen Self Organizing Maps (SOMs) was proposed. By observing neural network connection weights' changes, the iced and clean aircraft parametric models were developed via SOMs. The dependency of the level of atmospheric turbulences and elevator input signal to icing identification were presented. Aircraft stability and control derivatives were modified to account for artificial tail ice and its effects on response to elevator inputs. It was shown that the effects of atmospheric turbulence could be differentiated from the effects of ice given sufficiently large elevator inputs. In calm air, the method was shown to work perfectly, requiring very small control inputs. However, as the turbulence intensity was increased, the magnitude of the required control input increased as well. With reasonable levels of turbulence, encountered in most operational environments, the method was shown to accurately identify airframe icing approximately 75% of the time. This level of identification was achieved with reasonably small elevator deflections and without subjecting the passengers and the airframe to undue load factors. This approach is shown to be capable of acting in an advisory role for the flight crew [14].

With respect to identification of degradation in aerodynamic parameters and characteristics of flight dynamics due to aircraft icing, Dynamic Icing Detection System (DIDS) was proposed [15]. Hinge moment sensors were used in order to detect icing on control surfaces via a neural network model which estimates stability and control derivatives [16-18]. A neural network algorithm was developed to

estimate stability and control derivatives by an *H-infinity* parameter identification algorithm during a longitudinal maneuver in the *absence of pilot input* when poor excitation of the flight dynamics limits the accuracy of parameter estimates. In order to improve this accuracy, the neural network integrates steady-state characterization and hinge moment sensing with parameter estimates [18].

Icing formation on airframe may be considered as a variety of fault disrupting the original aerodynamic shape of wing and hence air flow around. From this point of view, airframe icing can be regarded as a structural fault detection and identification problem. Kalman filter (KF), neural network (NN), fuzzy logic (FL) and hybrid systems have been known useful means for the solution of this kind of problems in aerospace applications. Hajiyeve and Çalışkan [19] presented new sensor / actuator fault detection and isolation (FDI) method based on Kalman filter innovation approach. Bucak, Çalışkan and Gürleyen [20] offered a method based on neural networks to find the new elements of the system state and control matrices after fault occurs. The elements of these matrices were expressed as the connection weights of the network.

Structural faults are commonly known cracking, delaminating, debonding, misuse, loosening fasteners which cause a change in the dynamic responses of a structure. A general methodology was presented for structural fault detection based on monitoring the static and dynamic responses of a structure or a machine in [21].

In order to accurately apply neural network methods to airframe icing, gathering in-flight icing data is very important. Some specific real data from a 12-month pilot program of icing event data gathering was provided in [22]. Federal Aviation Rules / Joint Aviation Rules (FAR/JAR) Part 25 Appendix C including the flight restrictions under icing conditions were criticized according to the obtained data.

Icing identification techniques were presented from several view points in [23-28]. The techniques were applied to nonlinear F16 Fighter model and linear Airbus A340 model.

1.5 Results from the Past Studies

Some in-flight anti-icing systems proposed in the recent research have used the intentionally varied elevator deflections to detect icing. Therefore, these systems submitted the inconvenience of the passenger in some degrees as well. On the other hand some other aircraft use inflatable boots that break off accumulated ice.

This is not good in the point of maintainability. It also degrades the aerodynamic smoothness of the surface.

Systems utilizing information from the existing icing sensors are required to automatically activate anti-icing/de-icing devices. The flight crew should be awared updates concerning icing protection system (IPS) status and should manually override the system.

Aircraft icing problem can be considered as a fault detection and classification problem. Detection involves only determining whether ice of any amount has accumulated upon the aircraft. Classification refers to determining both the type and severity of icing.

The ice detection and classification must be able to be performed accurately over variations in external inputs (turbulences, etc.), internal inputs (elevator doublet, icing severity, etc), and trim point changes. Due to mistrim caused by the ice contamination, the pilot may over-rotate the aircraft resulting in wing stall and loss of longitudinal and lateral control. In the past researches, this part of the problem has been considered as icing characterization. After icing characterization, flight adaptation must be provided. Flight adaptation calls for flight envelope and in-flight anti-icing and de-icing.

In order to ensure the safety of an aircraft during icing conditions, existing conventional envelope protection systems need to be modified to smarter versions, which would update the envelope limits in real-time depending on the aircraft state and icing severity.

In order to determine the limits for safe flight in icing conditions, minimum speed, maximum AOA, maximum bank angle, maximum control deflections and their change rates must be considered. Certain critical parameters must be chosen in order to formulate the proposed envelope protection scheme. Aerodynamically, the aircraft should be protected from wing stall, horizontal tail stall, roll upset and loss of longitudinal and lateral control. The most critical parameters are angle of attack, pitch rate and roll angle. Boundaries need to be defined for these parameters as functions of ice accretion, aerodynamic parameters, and stability and control derivatives.

1.6 Objective of the Work

Our study aims to correctly detect and identify wing icing on A340 and F16 aircraft by observing the changes of five stability derivatives within the shortest time possible, and then to redesign the existing control systems with new parameters. Hence, an improved wing ice detection and protection system will be developed. Furthermore, the efficiency of the proposed method for a commercial and a military aircraft will be discussed.

In order to train NN models, some data are required. Past studies used experimental data for one specific aircraft. In this thesis simulated data will be applied to parametric iced models.

This research will present a new icing tolerant automatic flight control system by optimizing existing ice protection systems in order to improve the flight performance and safety, by minimizing the use of engine heat air, by minimizing missed ice detection and false alarms, and by optimizing the inputs of ice detection systems. A neural network model will be used for icing identification since the iced models cannot be represented by a few parameters. Parameter estimates and environmental sensor data will be used in the new system.

Since ice accretion is expected to occur over a period of a few minutes, we will reasonably assume that the parameters are linearly changed as in the experimental results.

After icing problem is solved, several aircraft failures showing similar effects to icing will be easily examined in the same way. This study has also many other objectives: to collect and evaluate all the icing-related studies which have been done up to now, to propose a method for how Kalman filter can be used as an icing sensor, and how NN can help the identification process.

Generally recent studies have examined the linear and non-linear longitudinal dynamics. However, it is known that asymmetric icing affects the lateral dynamics as well. In addition, many assumptions were predetermined in past studies such that icing may have not been represented in a few parameters, hence the changes of these parameters resulted from icing may be lost under model uncertainties. Therefore, this research will take into account longitudinal and lateral states and controls as well as their stability and control derivatives, and five stability parameters will be assumed to be affected by icing.

1.7 Scope of the Work

Chapter 2 will explain the basics of the flight mechanics and control. General flight dynamics equations will be described. Linear and nonlinear models of the investigated aircraft, F16 and A340, will be obtained. Stability and control derivatives will be identified for these aircraft.

Chapter 3 will give detailed information on the case study: Aircraft icing. Icing event and its effects to aircraft flight dynamics will be explained. In-flight icing detection and identification techniques will be presented. Five stability derivatives mostly affected by icing will be defined.

Chapter 4 will propose a new icing detection system based on Kalman filter. The derivation of equations of KF and EKF will be presented. Innovation approach will be explained for icing detection on F16 and A340 aircraft.

Chapter 5 will propose a new icing identification method based on NN. The structure of NN and the selected training algorithm will be described.

Chapter 6 will explain the new icing tolerant flight control system (ITFCS) by combining the method for icing detection in Chapter 4 and the method for icing identification in Chapter 5. A new controller design will be given.

Chapter 7 will include the simulation results for F16 and A340 aircraft about the application of new proposed methods.

Finally, in Chapter 8, conclusions and future studies will be presented and discussed.

In Appendix A, computer program is given in a floppy disk, and in Appendix B, more simulation graphs are illustrated.

2. MATHEMATICAL MODEL OF THE AIRCRAFT FLIGHT DYNAMICS

An aircraft designer has a mental model of the type of aircraft that is needed, uses physical models to gather wind-tunnel data, and designs with mathematical models that incorporate the experimental data. A mathematical model based on the laws of physics often suggests what experimental data should be taken, and the model may then undergo considerable adjustment in order to fit the data. This is called as an iterative process. A model is built according to purposes of the work with limitations. Some of the limitations of the models involve uncertainty in the values of their parameters. Later, this uncertainty is mathematically added in complete design. The mathematical model is used, in conjunction with computer simulation, to evaluate the performance of the prototype aircraft and hence improve the design. It can also be used to derive training simulations, to reconstruct the flight conditions involved in accidents, and to study the effects of modifications to the design. Furthermore, other mathematical models are used in all aspects of the aircraft design (e.g., structural models for studying stress distribution and predicting fatigue life).

In aerospace industry it is necessary for a wide range of specialists to work together; thus flight control engineers must work with the aerodynamicists as well as with structural and propulsion engineers. This is becoming increasingly important as designers seek to widen aircraft performance envelopes by integrating many parts of the whole design process.

In order to create an aircraft model, firstly equations of aircraft general motion should be formed according to objectives of study and aircraft type. The equations obtained from Newton's Law are nonlinear and difficult to solve.

Secondly, aircraft equations are linearized around trim conditions in the common method. These linear equations include stability and control derivatives that are the multipliers of the model states. In the case that these parameters are specified certainly, the underlying aircraft's model is obviously known. Aircraft manufacturers or designers cannot give these detailed parameters on which all the design objectives are based. Aircraft's geometry, weight, maneuverability, performance, controllability and stability are represented inside these parameters. From thrust characteristics to aerodynamic efficiency all properties are carried out in them.

In this study, two types of aircraft are used for simulations: Linear Airbus A340-300, and nonlinear F16 Fighter. The linear Airbus A340 model is considered based on the data in [29-30], and its parameters are found at one special cruise condition by the methods in the literature [31]. The flight of aircraft TC-JDM in Turkish Airlines, flying at 30000 feet height over South Asia on 30 March 2003, is chosen for modeling. From take-off to landing all flight data of 2.5-hour flight are downloaded from Flight Data Recorder (FDR) or commonly known as Black Box. By using these flight data, stability and control derivatives are calculated with the procedures described in [31-33]. F16 Fighter model are taken from Lyshevski's book [34].

The equations of aircraft motion are basically obtained from Newton's Second Law. This law expresses the conservation of both linear and angular momentum. It yields that rates of changes in the linear and angular momentum correspond to applied total force and moment, respectively. In the early phases of a study in terms of the objectives the change of the total mass of the airplane is assumed as constant with time. This assumption is typically restricted only for the time histories of 60 s [31].

Second assumption is that the subject airplane is rigid. Third is that the mass distribution is constant with time. For instance, the effects of fuel motions are negligible.

2.1 Flight Axes, Angles, Forces and Moments

In order to express the aircraft equations of motion, the coordinate system to be used has to be chosen suitable to the aims of study. Though, a motion of body in earth can be defined with earth or other reference axis system, the definition of its motion in air is not so easy. Therefore, several coordinate systems are used to specify the aircraft motion in terms of the study's objectives.

Figure 2.1 shows earth axes system and aircraft axes system, which are commonly used in flight mechanics and control. In $X'Y'Z'$ earth axis system, the origin is the center of gravity of earth, X' is parallel to earth and points north, Y' is parallel to earth and points east and Z' is perpendicular to earth. Hence, right hand side rule is valid. In XYZ body axis system, the origin is the center of gravity of the aircraft, X points forward, Y points starboard (right) wing, and Z points down. These two axis systems specify the aircraft attitude with the help of Euler angles, ψ azimuth or yaw angle, Θ pitch or elevation angle, and Φ bank or roll angle. In the definition of an aircraft motion, the direction of the aircraft nose in terms of the total velocity vector

has to be specified. For that reason, angle of attack α in pitch position and sideslip angle β in azimuthal position are used. This axis system, called the stability axis system $X_S Y_S Z_S$, is chosen such that only the X-axis coincides with the velocity vector, V_T . Hence, there is only angle of attack between two axis systems.

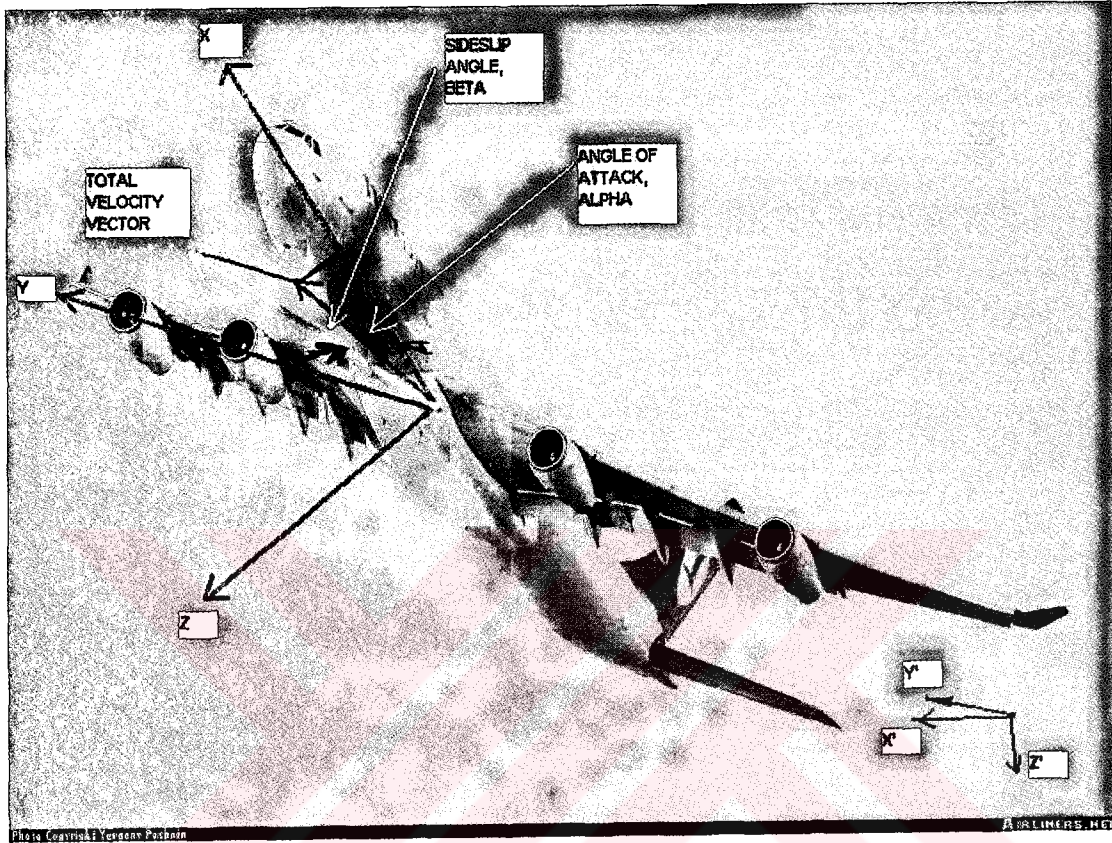


Figure 2.1 Coordinate Systems and Angles

The external forces and moments applied to an aircraft come from gravitational effects, aerodynamic characteristics of the aircraft and the thrust supplied by power systems. Aerodynamic forces are commonly known as the components of lift and drag. The reader who wants to have more information on these subjects may apply to [31, 33, 35-36].

Forces and moments produced by airfoil are represented by lift (L), drag (D) and pitching moment (M). As commonly known, these are described per unit span as

$$L = \bar{q} \bar{c} C_l \quad (2.1a)$$

$$D = \bar{q} \bar{c} C_d \quad (2.1b)$$

$$M = \bar{q} \bar{c}^2 C_m \quad (2.1c)$$

where $\bar{q}$ is dynamic pressure, $\bar{c}$ is mean chord length, and C_l, C_d, C_m are the coefficients depending on airfoil type and angle of attack. Dynamic pressure is written as

$$\bar{q} = \frac{1}{2} \rho V_T^2 \quad (2.2)$$

where ρ is air density (1.225 kg/m³ at sea level), and V_T is free-stream airspeed.

2.2 General Nonlinear Aircraft Flight Dynamics Equations

Let the components of the velocities of the translational motion be shown as U, V , and W . Similarly, let h_x, h_y, h_z show the angular moments, and L, M, N show the total moments in the directions of X, Y, Z , respectively. P, Q, R indicate the roll rate, pitch rate and yaw rate, respectively. Let X, Y, Z and G_x, G_y , and G_z denote aerodynamical/thrust forces and gravitational forces, respectively. Φ, Θ, Ψ denote Euler angles in the directions of X, Y, Z , respectively. For more information, the reader may look at [33]. For this research, aircraft assumed a rigid body, which means that inertial effects are constant.

As provided in more detailed in [31, 36], the following general aircraft flight equations are set from Newton's second rule and angular orientation relationships in terms of the representations and the assumption defined above.

Force balance:

$$\begin{aligned} \dot{U} &= -QW + RV - g \sin \Theta + (X/m) \\ \dot{V} &= -RU + PW + g \sin \Phi \cos \Theta + (Y/m) \\ \dot{W} &= -PV + QU + g \cos \Phi \cos \Theta + (Z/m) \end{aligned} \quad (2.3a)$$

Moment balance:

$$\begin{aligned} \dot{P} - \dot{P}_1 &= -QR I_5 + PQ I_1 + (L/I_{xx}) \\ \dot{Q} &= -PR I_3 - (P^2 - R^2) I_6 + (M/I_{yy}) \\ \dot{R} - \dot{R}_2 &= -PQ I_4 - QR I_2 + (N/I_{zz}) \end{aligned} \quad (2.3b)$$

Angular orientation relationships:

$$\begin{aligned} \dot{\Phi} &= P + Q \sin \Phi \tan \Theta + R \cos \Phi \tan \Theta \\ \dot{\Theta} &= Q \cos \Phi - R \sin \Phi \\ \dot{\Psi} &= (Q \sin \Phi + R \cos \Phi) \sec \Theta \end{aligned} \quad (2.3c)$$

l_i ($i = 1, 2, \dots, 6$) denotes the modified inertial terms as follows:

$$\begin{aligned} l_1 &= l_{xz} / l_{xx} & l_2 &= l_{xz} / l_{zz} & l_3 &= (l_{xx} - l_{xz}) / l_{yy} \\ l_4 &= (l_{yy} - l_{xx}) / l_{zz} & l_5 &= (l_{zz} - l_{yy}) / l_{xx} & l_6 &= l_{xz} / l_{yy} \end{aligned} \quad (2.4)$$

Instead of V and W , the use of angle of attack (α) and sideslip angle (β) in the equations is more common. In this case, using the relationships, $\alpha = \arctan (W/U)$ and $\beta = \arctan (V/U)$, or approximately $\alpha = W/U$ and $\beta = V/U$, the equations may be modified. As it can be seen in the equation set (2.3), in the general case, without any further assumptions, aircraft equations are nonlinear. Such equations cannot be solved analytically and would require numerical solution methods. Such nonlinear solutions are useful in certain applications such as airplane simulators, accident investigations (break off flap, slat, control surfaces, etc) and the analysis of airplane response to large disturbances, for instance, severe icing.

2.3 Linearization of Equations

General aircraft motion can be considered as the summation of two motions: a mean motion representing trim or equilibrium conditions, and a dynamic motion regarding small perturbations about the mean motion. Thus, every motion variable ($U, V, W, P, Q, R, \Phi, \Theta, \Psi, X, Y, Z, \alpha, \beta$) is separable into two components. The letters with subscript “1” such as “ U_1 ” and the lower case letters without subscripts such as “ u ” denote trim conditions and perturbations, respectively. These relationships may be written as $X = X_1 + x$, $Y = Y_1 + y$, $Z = Z_1 + z$, $L = L_1 + l$, $M = M_1 + m_{pm}$, $N = N_1 + n$, $U = U_1 + u$, $V = V_1 + v$, $W = W_1 + w$, $P = P_1 + p$, $Q = Q_1 + q$, $R = R_1 + r$, $\Phi = \Phi_1 + \phi$, $\Theta = \Theta_1 + \theta$, $\Psi = \Psi_1 + \psi$, $\alpha_T = \alpha_1 + \alpha$, $\beta_T = \beta_1 + \beta$, where α_T and β_T denote total angle of attack and sideslip angle.

By considering that the perturbations of forces, moments and attitude angles vary with almost all state and control variables, a Taylor series is used about the trimmed flight condition. For instance; the force perturbation through X direction may be expressed as

$$\begin{aligned} x &= f(u, \beta, \alpha, p, q, r, \Phi, \Theta, \Psi, \delta_h, \delta_e, \delta_f, \delta_t, \delta_a, \delta_r, \dots) \\ &= \frac{\partial X}{\partial u} u + \frac{\partial X}{\partial \beta} \beta + \frac{\partial X}{\partial \alpha} \alpha + \frac{\partial X}{\partial p} p + \frac{\partial X}{\partial q} q + \frac{\partial X}{\partial r} r + \frac{\partial X}{\partial \Phi} \Phi + \frac{\partial X}{\partial \Theta} \Theta + \frac{\partial X}{\partial \Psi} \Psi + \frac{\partial X}{\partial \delta_h} \delta_h + \frac{\partial X}{\partial \delta_e} \delta_e + \frac{\partial X}{\partial \delta_f} \delta_f + \frac{\partial X}{\partial \delta_t} \delta_t + \frac{\partial X}{\partial \delta_a} \delta_a + \frac{\partial X}{\partial \delta_r} \delta_r + \dots \end{aligned} \quad (2.5)$$

Here, $\delta_h, \delta_e, \delta_f, \delta_t, \delta_a, \delta_r$ are control variables denoting the deflections of horizontal stabilizer, elevator, flap, thrust, aileron and rudder. These control surface deflections may vary according to type of aircraft. In trimmed conditions, all these variables basically are zero. However, they may take constant value for a certain time in terms of continuing external disturbances (wind, gust, ground effects, or other atmospheric variations), or internal model variations (decreasing fuel, fuel distribution, break or deformation of aircraft external components such as flap, slat, wing, panel, fairing, ice occurred on wing and control surfaces).

For the more convenient notation, let

$$\begin{aligned} X_u &= \frac{1}{m} \frac{\partial X}{\partial u} & Y_u &= \frac{1}{m} \frac{\partial Y}{\partial u} & Z_u &= \frac{1}{m} \frac{\partial Z}{\partial u} \\ L_u &= \frac{1}{I_{xx}} \frac{\partial L}{\partial u} & M_u &= \frac{1}{I_{yy}} \frac{\partial M}{\partial u} & N_u &= \frac{1}{I_{zz}} \frac{\partial N}{\partial u} \end{aligned} \quad (2.6)$$

Notations in (2.6) are valid for all other states and controls as well. In the literature, these expressions are called stability and control derivatives.

2.4 Trim Equations

The flight in trimmed conditions is defined as a flight condition for which all motion variables remain constant with time relative to a body fixed axes system. Trim flight, sometimes, may be called as steady state flight. In trim, there is no translational or rotational acceleration. Hence, by using (2.3), trim equations may be written as:

$$\begin{aligned} Q_1 W_1 - R_1 V_1 + g \sin \Theta_1 - (X_1 / m) &= 0 \\ R_1 U_1 - P_1 W_1 - g \sin \Phi_1 \cos \Theta_1 - (Y_1 / m) &= 0 \\ P_1 V_1 - Q_1 U_1 - g \cos \Phi_1 \cos \Theta_1 - (Z_1 / m) &= 0 \end{aligned} \quad (2.7a)$$

$$\begin{aligned} Q_1 R_1 I_5 - P_1 Q_1 I_1 - (L_1 / I_{xx}) &= 0 \\ P_1 R_1 I_3 + (P_1^2 - R_1^2) I_6 - (M_1 / I_{yy}) &= 0 \\ P_1 Q_1 I_4 + Q_1 R_1 I_2 - (N_1 / I_{zz}) &= 0 \\ P_1 + Q_1 \sin \Phi_1 \tan \Theta_1 + R_1 \cos \Phi_1 \tan \Theta_1 &= 0 \\ Q_1 \cos \Phi_1 - R_1 \sin \Phi_1 &= 0 \\ (Q_1 \sin \Phi_1 + R_1 \cos \Phi_1) \sec \Theta_1 &= 0 \end{aligned} \quad (2.7b)$$

In cruise conditions and shallow descents or dives, P_1, Q_1, R_1 are zero.

2.5 Nonlinear Perturbed State Equations

Considering the equation (2.3), a Taylor series may be obtained by ignoring all second or higher derivations with a certain approximation. Besides, some first derivations of states and controls almost do not change the forces, moments and attitude angles. They can usually be assumed insignificant.

Under these assumptions and notations, by using the equations (2.4), (2.5), (2.6), and (2.7) in (2.3), perturbed state equations may be expressed as:

$$\begin{aligned} \dot{v} = & R_1 v - Q_1 w - W_1 q + V_1 r - g \cos \Theta_1 \theta + v r - w q \\ & + X_u u + X_v \dot{v} + X_w w + X_{\dot{w}} \dot{w} + X_q q + X_{\dot{q}} \dot{q} \\ & + X_{\delta_e} \delta_e + X_{\delta_h} \delta_h + X_{\delta_f} \delta_f + X_{\delta_t} \delta_t \end{aligned} \quad (2.8a)$$

$$\begin{aligned} \dot{w} = & R_1 u + P_1 w + W_1 p - U_1 r - g \sin \Theta_1 \sin \Phi_1 \theta + g \cos \Theta_1 \cos \Phi_1 \phi \\ & - u r + w p - g \sin \Theta_1 \cos \Phi_1 \theta \phi + Y_v v + Y_{\dot{v}} \dot{v} + Y_p p + Y_{\dot{p}} \dot{p} + Y_r r \\ & + Y_{\dot{r}} \dot{r} + Y_{\delta_a} \delta_a + Y_{\delta_r} \delta_r + Y_{\delta_t} \delta_t \end{aligned} \quad (2.8b)$$

$$\begin{aligned} \dot{q} = & Q_1 u - P_1 v - V_1 p + U_1 q - g \cos \Phi_1 \sin \Theta_1 \theta - g \sin \Phi_1 \cos \Theta_1 \phi + u q \\ & - v p + g \sin \Phi_1 \sin \Theta_1 \theta \phi + Z_u u + Z_{\dot{u}} \dot{u} + Z_w w + Z_{\dot{w}} \dot{w} + Z_q q + Z_{\dot{q}} \dot{q} \\ & + Z_{\delta_e} \delta_e + Z_{\delta_h} \delta_h + Z_{\delta_f} \delta_f + Z_{\delta_t} \delta_t \end{aligned} \quad (2.8c)$$

$$\begin{aligned} \dot{p} - I_1 \dot{p} = & I_1 P_1 q + I_1 Q_1 p - I_5 R_1 q - I_5 Q_1 r + I_1 p q - I_5 r q + L_v v + L_{\dot{v}} \dot{v} + L_r r \\ & + L_{\dot{r}} \dot{r} + L_p p + L_{\dot{p}} \dot{p} + L_{\delta_a} \delta_a + L_{\delta_r} \delta_r \end{aligned} \quad (2.8d)$$

$$\begin{aligned} \dot{r} = & -I_3 P_1 r - I_3 R_1 p - 2I_6 P_1 p + 2I_6 R_1 r - I_3 p r - I_6 (p^2 - r^2) + M_u u + M_{\dot{u}} \dot{u} \\ & + M_w w + M_{\dot{w}} \dot{w} + M_q q + M_{\dot{q}} \dot{q} + M_{\delta_e} \delta_e + M_{\delta_h} \delta_h + M_{\delta_f} \delta_f + M_{\delta_t} \delta_t \end{aligned} \quad (2.8e)$$

$$\begin{aligned} \dot{p} - I_2 \dot{p} = & -I_4 P_1 q + I_4 Q_1 p - I_2 R_1 q - I_2 Q_1 r - I_4 p q - I_2 r q + N_v v + N_{\dot{v}} \dot{v} \\ & + N_r r + N_{\dot{r}} \dot{r} + N_p p + N_{\dot{p}} \dot{p} + N_{\delta_a} \delta_a + N_{\delta_r} \delta_r \end{aligned} \quad (2.8f)$$

$$\dot{\phi} - \dot{\phi} \sin \Theta_1 = p + \theta \dot{\phi}_1 \cos \Theta_1 + \dot{\phi} \cos \Theta_1 \quad (2.8g)$$

$$\begin{aligned} \dot{\theta} \cos \Phi_1 + \dot{\phi} \cos \Theta_1 \sin \Phi_1 = & q + \phi \dot{\theta}_1 \sin \Phi_1 - \phi \dot{\phi}_1 \cos \Theta_1 \cos \Phi_1 \\ & + \theta \dot{\phi}_1 \sin \Theta_1 \sin \Phi_1 + \dot{\theta} \phi \sin \Phi_1 + \theta \phi \dot{\phi}_1 \sin \Theta_1 \cos \Phi_1 \\ & - \dot{\phi} p \cos \Theta_1 \cos \Phi_1 + \dot{\phi} \phi \sin \Theta_1 \sin \Phi_1 + \dot{\phi} \theta \phi \sin \Theta_1 \cos \Phi_1 \end{aligned} \quad (2.8h)$$

$$\begin{aligned} \dot{\phi} \cos \Theta_1 \cos \Phi_1 - \dot{\theta} \sin \Phi_1 = & r + \phi \dot{\phi}_1 \cos \Theta_1 \sin \Phi_1 \\ & + \theta \dot{\phi}_1 \sin \Theta_1 \cos \Phi_1 + \phi \dot{\theta}_1 \cos \Phi_1 + \theta \phi \dot{\phi}_1 \sin \Theta_1 \sin \Phi_1 \\ & - \dot{\phi} p \cos \Theta_1 \sin \Phi_1 + \dot{\phi} \phi \sin \Theta_1 \cos \Phi_1 - \dot{\phi} \theta \phi \sin \Theta_1 \sin \Phi_1 \\ & + \dot{\theta} \phi \cos \Phi_1 \end{aligned} \quad (2.8i)$$

It is obvious that the set of equations (2.8) consists of linear and nonlinear terms. Using matrix notations these equations may be rewritten as

$$\mathbf{T}_1 \dot{\mathbf{x}} = \mathbf{A}_1 \mathbf{x} + \mathbf{B}_1 \mathbf{u} + \mathbf{G}_1(\mathbf{x}) \quad (2.9a)$$

where $\mathbf{x}$ and $\mathbf{u}$ are state and control vector, respectively. Note that these are bold letters, and should not be confused with perturbed state x and perturbed speed u . $\mathbf{T}_1$, $\mathbf{A}_1$, $\mathbf{B}_1$, and $\mathbf{G}_1$ are given in Table 2.1 and Table 2.2. The state and control vectors are represented as

$$\mathbf{x} = [u \ v \ w \ p \ q \ r \ \phi \ \theta \ \psi]^T$$

$$\mathbf{u} = [\delta_h \ \delta_e \ \delta_f \ \delta_t \ \delta_a \ \delta_r]^T$$

Note that these representations may be expressed in different configurations depending on the objectives. For instance, states of side speed (v) and downward speed (w) may be replaced with sideslip angle (β) and angle of attack (α). Control elements vary according to type of aircraft and flight.

Multiplying (2.9a) by the inverse of $\mathbf{T}_1$, the following equation is obtained:

$$\dot{\mathbf{x}} = (\mathbf{T}_1)^{-1} \mathbf{A}_1 \mathbf{x} + (\mathbf{T}_1)^{-1} \mathbf{B}_1 \mathbf{u} + (\mathbf{T}_1)^{-1} \mathbf{G}_1(\mathbf{x}) \quad (2.9b)$$

Using the representations

$$\bar{\mathbf{A}} = (\mathbf{T}_1)^{-1} \mathbf{A}_1 \quad (2.10a)$$

$$\bar{\mathbf{B}} = (\mathbf{T}_1)^{-1} \mathbf{B}_1 \quad (2.10b)$$

$$\bar{\mathbf{G}}(\mathbf{x}) = (\mathbf{T}_1)^{-1} \mathbf{G}_1(\mathbf{x}) \quad (2.10c)$$

(2.9b) can be written in most common form as follows:

$$\dot{\mathbf{x}} = \bar{\mathbf{A}} \mathbf{x} + \bar{\mathbf{B}} \mathbf{u} + \bar{\mathbf{G}}(\mathbf{x}) \quad (2.11)$$

The equations of motion may be separated consist of longitudinal (X-Z plane) and lateral (X-Z or Y-Z) (slip, roll and turn) equations.

2.6 Determination of Stability and Control Derivatives

As seen in Table 2.1 and Table 2.2 general aircraft flight dynamic equations consist of several parameters so called stability and control derivatives. These are usually found from wind-tunnel tests at first. Unfortunately, unavoidable differences between test environment and flight conditions, the wind-tunnel test data are considered only as initial estimates.

Table 2.1 Matrices A_1 and T_1 of general flight dynamic equations

$$A_1 = \begin{bmatrix} X_u & R_1 & X_w - Q_1 & 0 & X_q - W_1 & V_1 & 0 \\ -R_1 & Y_v & P_1 & Y_p + W_1 & 0 & Y_r - U_1 & 0 \\ Z_u + Q_1 & -P_1 & Z_w & -V_1 & Z_q + U_1 & 0 & 0 \\ 0 & L_v & 0 & L_p + I_1 Q_1 & I_1 P_1 - I_3 R_1 & L_r - I_3 Q_1 & 0 \\ M_u & 0 & M_w & -I_1 R_1 - 2I_5 P_1 & M_q & -I_1 P_1 + 2I_6 R_1 & 0 \\ 0 & N_v & 0 & N_p - I_4 Q_1 & -I_4 P_1 - I_2 R_1 & N_r - I_2 Q_1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$T_1 = \begin{bmatrix} 1 - X_c & 0 & -X_w & 0 & -X_q & 0 & 0 \\ 0 & 1 - Y_v & 0 & -Y_p & 0 & -Y_r & 0 \\ -Z_u & 0 & 1 - Z_w & 0 & -Z_q & 0 & 0 \\ 0 & -L_v & 0 & 1 - L_p & 0 & -I_1 - L_r & 0 \\ -M_u & 0 & -M_w & 0 & 1 - M_q & 0 & 0 \\ 0 & -N_v & 0 & -I_2 - N_p & 0 & 1 - N_r & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -\sin \Theta_1 \\ 0 & 0 & 0 & 0 & 0 & \cos \Theta_1 & \cos \Theta_1 \sin \Phi_1 \\ 0 & 0 & 0 & 0 & 0 & -\sin \Phi_1 & \cos \Theta_1 \cos \Phi_1 \end{bmatrix}$$

Table 2.2 Matrices B_1 and G_1 of general flight dynamic equations

$$B_1 = \begin{bmatrix} X_{\dot{x}_e} & X_{\dot{y}_e} & X_{\dot{z}_e} & X_{\dot{L}_e} & X_{\dot{M}_e} & X_{\dot{N}_e} & X_{\dot{\theta}} & X_{\dot{\psi}} & X_{\dot{\phi}} & X_{\dot{\theta}_1} & X_{\dot{\psi}_1} & X_{\dot{\phi}_1} \\ Y_{\dot{x}_e} & Y_{\dot{y}_e} & Y_{\dot{z}_e} & Y_{\dot{L}_e} & Y_{\dot{M}_e} & Y_{\dot{N}_e} & Y_{\dot{\theta}} & Y_{\dot{\psi}} & Y_{\dot{\phi}} & Y_{\dot{\theta}_1} & Y_{\dot{\psi}_1} & Y_{\dot{\phi}_1} \\ Z_{\dot{x}_e} & Z_{\dot{y}_e} & Z_{\dot{z}_e} & Z_{\dot{L}_e} & Z_{\dot{M}_e} & Z_{\dot{N}_e} & Z_{\dot{\theta}} & Z_{\dot{\psi}} & Z_{\dot{\phi}} & Z_{\dot{\theta}_1} & Z_{\dot{\psi}_1} & Z_{\dot{\phi}_1} \\ L_{\dot{x}_e} & L_{\dot{y}_e} & L_{\dot{z}_e} & L_{\dot{L}_e} & L_{\dot{M}_e} & L_{\dot{N}_e} & L_{\dot{\theta}} & L_{\dot{\psi}} & L_{\dot{\phi}} & L_{\dot{\theta}_1} & L_{\dot{\psi}_1} & L_{\dot{\phi}_1} \\ M_{\dot{x}_e} & M_{\dot{y}_e} & M_{\dot{z}_e} & M_{\dot{L}_e} & M_{\dot{M}_e} & M_{\dot{N}_e} & M_{\dot{\theta}} & M_{\dot{\psi}} & M_{\dot{\phi}} & M_{\dot{\theta}_1} & M_{\dot{\psi}_1} & M_{\dot{\phi}_1} \\ N_{\dot{x}_e} & N_{\dot{y}_e} & N_{\dot{z}_e} & N_{\dot{L}_e} & N_{\dot{M}_e} & N_{\dot{N}_e} & N_{\dot{\theta}} & N_{\dot{\psi}} & N_{\dot{\phi}} & N_{\dot{\theta}_1} & N_{\dot{\psi}_1} & N_{\dot{\phi}_1} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$G_1 = \begin{bmatrix} vr - wq & -ur + wp - g \sin \Theta_1 \cos \Phi_1 \theta \phi & uq - vp + g \sin \Phi_1 \sin \Theta_1 \theta \phi & l_1 p q - l_2 q r & -l_3 p r - l_4 (p^2 - r^2) & -l_4 p q - l_2 q r & \psi \theta \cos \Theta_1 & \dot{\theta} \phi \sin \Phi_1 + \theta \phi \dot{\psi}_1 \sin \Theta_1 \cos \Phi_1 - \dot{\psi} \phi \cos \Theta_1 \cos \Phi_1 + \dot{\psi} \theta \sin \Theta_1 \sin \Phi_1 + \dot{\psi} \theta \phi \sin \Theta_1 \cos \Phi_1 & \theta \phi \dot{\psi}_1 \sin \Theta_1 \sin \Phi_1 - \dot{\psi} \phi \cos \Theta_1 \sin \Phi_1 + \dot{\psi} \theta \sin \Theta_1 \cos \Phi_1 - \dot{\psi} \theta \phi \sin \Theta_1 \sin \Phi_1 + \dot{\theta} \phi \cos \Phi_1 \end{bmatrix}$$

Some derivatives can be calculated using Advanced Aircraft Analysis (AAA) software [32]. Such software programs use the interpolation procedures in calculation of the most derivatives or parameters. It means that the calculated derivatives are not certain for a chosen aircraft and flight. However, these may be initial values in the estimation procedure.

NASA performed early studies concerning the estimation of the stability and control derivatives from flight data in 1950s. It was tried to detect these derivatives more correctly by evaluating the actual flight test and wind-tunnel test results together, and issued several technical reports. A modified Newton Raphson Method [37] using least square means, which is also called Quasi-linearization Minimization Technique, or sometimes referred to as the Maximum Likelihood Estimation [38] method was proposed to estimate these coefficients by minimizing the error between simulated data and measured flight data, and a FORTRAN program [39] was developed. These studies required the very approximate initial values. The reference [33] describes the calculation method of stability and control derivatives. Airbus A340 model's derivatives have been calculated according to the procedures given in [31-33].

2.7 The Modeling of Flight Dynamics of the Investigated Aircraft

In this thesis two aircraft are investigated: As the applications to military and commercial aircraft, a modern fighter F16 and large body long range Airbus A340 are selected. Since we will use discrete equations in later chapters, the continuous form in (2.11) will be converted to discrete form. Additionally system disturbances, also called process noise, and measurement noise will be inserted the equations.

2.7.1 Discrete form of general flight dynamic equations

In order to convert to discrete form, using first order Taylor approximation around the point k , the derivative $\dot{\mathbf{x}}$ may be written as follows:

$$\dot{\mathbf{x}} \approx \frac{\mathbf{x}(k+1) - \mathbf{x}(k)}{\Delta t} \quad (2.12)$$

where Δt is called time step, or interval, or discretization step, k is the current point or iteration, $\mathbf{x}(k)$ is the state vector at k^{th} , and $\mathbf{x}(k+1)$ is the state vector at $(k+1)^{\text{th}}$ step.

Substituting (2.12) into (2.11), discrete aircraft equations may be written as

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{F}(\mathbf{x}(k)) \quad (2.13)$$

such that

$$\mathbf{A} = \mathbf{I} + \Delta t \bar{\mathbf{A}} \quad (2.14a)$$

$$\mathbf{B} = \Delta t \bar{\mathbf{B}} \quad (2.14b)$$

$$\mathbf{F}(\mathbf{x}(k)) = \Delta t \bar{\mathbf{G}}(\mathbf{x}(k)) \quad (2.14c)$$

On the other hand, in the linear systems or so considered, measurement equations may be expressed as

$$\mathbf{y}(k) = \mathbf{H}\mathbf{x}(k) \quad (2.15)$$

Furthermore, in the actual systems, system disturbances so called process noise, $\mathbf{w}(k)$, and measurement disturbance or sensor noise, $\mathbf{v}(k)$, exist. Hence, the general aircraft dynamic equations may be written as follows:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{F}(\mathbf{x}(k)) + \mathbf{G}\mathbf{w}(k) \quad (2.16a)$$

$$\mathbf{y}(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{v}(k) \quad (2.16b)$$

where $\mathbf{x}$ is the state vector, $\mathbf{A}$ is the system matrix, $\mathbf{B}$ is the control distribution matrix, $\mathbf{F}$ is a vector of nonlinear part of the system, and $\mathbf{G}$ is the process noise transition matrix, $\mathbf{u}$ is the control input vector, $\mathbf{y}$ is a vector of measurements, and $\mathbf{H}$ is the measurement distribution matrix.

2.7.2 Discrete model of the flight dynamics of Airbus A340-300

Airbus A340-300 is a modern, long range, large body passenger aircraft. Large aircraft means aircraft with a maximum takeoff weight exceeding 5,700 kg. The linear Airbus A340 flight dynamic model is specified according to data in A340 Airplane Characteristics [29], and its parameters are found at one special cruise condition by the methods in the literature. The flight of aircraft TC-JDM in Turkish Airlines, flying at 30,000 feet height over South Asia on 30 March 2003, is chosen for modeling. From take-off to landing all flight data of 2.5-hour flight are downloaded from Flight Data Recorder (FDR) or commonly known as Black Box. By using these flight data, stability and control derivatives are calculated with the

procedures, Advanced Aircraft Analysis (AAA), described in [31-33]. Linear model of the aircraft can be written from (2.16a) and (2.16b) as

$$\mathbf{x}(k+1) = \mathbf{A} \mathbf{x}(k) + \mathbf{B} \mathbf{u}(k) + \mathbf{G} \mathbf{w}(k) \quad (2.17a)$$

$$\mathbf{y}(k) = \mathbf{H} \mathbf{x}(k) + \mathbf{v}(k) \quad (2.17b)$$

The state vector is

$$\mathbf{x}(k) = [v(k) \quad \alpha(k) \quad q(k) \quad \theta(k) \quad \beta(k) \quad p(k) \quad r(k) \quad \phi(k) \quad \psi(k)]^T$$

where, v is the forward velocity, α is the angle of attack, q is the pitch rate, θ is the pitch angle, β is the side-slip angle, p is the roll rate, r is the yaw rate, ϕ is the roll angle, and ψ is the yaw angle.

$\mathbf{A}$ and $\mathbf{B}$ is given in Table 2.3. $\mathbf{G}$ and $\mathbf{H}$ are 9x9 unity matrices. $\mathbf{w}$ and $\mathbf{v}$ are 9x1 vectors with normally distributed random values. Airbus A340 has five control surfaces as given below.

$$\mathbf{u} = [\delta_H(k) \quad \delta_E(k) \quad \delta_F(k) \quad \delta_A(k) \quad \delta_R(k)]$$

where δ_H , δ_E , δ_F , δ_A and δ_R are the deflections of stabilizer, elevator, flap, aileron and rudder, respectively. We take the following hard bounds (mechanical limits) on the deflections of control surfaces of A340. Note that all units are in radian:

$$-0.26 \leq \delta_H \leq 0.04,$$

$$-0.54 \leq \delta_E \leq 0.26,$$

$$0.02 \leq \delta_F \leq 0.58,$$

$$0 \leq \delta_A \leq 0.44,$$

$$-0.54 \leq \delta_R \leq 0.54.$$

2.7.3 Discrete model of the flight dynamics of the F16 Fighter

The model of the aircraft is as follows

$$\mathbf{x}(k+1) = \mathbf{A} \mathbf{x}(k) + \mathbf{B} \mathbf{u}(k) + \mathbf{F}(\mathbf{x}(k)) + \mathbf{G} \mathbf{w}(k) \quad (2.18)$$

$$\mathbf{y}(k) = \mathbf{H} \mathbf{x}(k) + \mathbf{v}(k) \quad (2.19)$$

The aircraft state vector is the same as A340's. $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{F}(\mathbf{x})$ for the sampling period of 0.03 s. are taken from [34]. Matrices of $\mathbf{A}$ and $\mathbf{B}$ are given in Table 2.4.

Table 2.3 Matrices **A** and **B** of linear Airbus A340 flight dynamic model

$$\mathbf{A} = \begin{bmatrix} 1.0004 & -0.0013 & 0.0008 & 0.0001 & -0.4597 & -0.1378 & -0.0004 & -0.9558 & 0 \\ 0 & 0.8095 & 0 & 0.4380 & 0 & -19.5423 & 0.8940 & 0.0003 & 0 \\ -0.0035 & 0.0001 & 0.9800 & 0.1421 & 20.2723 & 0.0009 & 0.0184 & -0.0163 & 0 \\ 0 & 0.0008 & 0 & 0.9612 & 0 & 0.0086 & 0.0004 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.9723 & 0 & 0 & 0 \\ 0 & 0.0174 & 0 & 0.0012 & 0 & 0.8061 & 0.0086 & 0 & 0 \\ 0 & 0 & 0 & 0.0294 & 0 & 0.0007 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.0296 & 0.0005 & 0 & 1 & 0 \\ 0 & 0.0003 & 0 & 0 & 0.0005 & 0.0280 & 0.0001 & 0 & 1 \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} -0.0337 & -0.0144 & 0 & 0 & 0.0007 \\ 0 & 0 & 0.0201 & 0.4502 \\ -3.5858 & -0.9127 & 0 & 0.0051 & 0.0004 \\ 0 & 0 & 0.0701 & 0.0054 \\ -0.1335 & -0.0367 & 0 & 0 & 0 \\ 0 & 0 & -0.0004 & -0.0081 \\ 0 & 0 & 0.0011 & 0.0001 \\ -0.0020 & -0.0006 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.0001 \end{bmatrix}$$

Table 2.4 Matrices **A** and **B** of linear F16 flight dynamic model

$$\mathbf{A} = \begin{bmatrix} 0.9995 & 0.2457 & -0.0273 & -0.2885 & -0.0391 & -0.0075 & -0.0020 & 0 & 0 \\ -0.0001 & 0.9663 & 0.0291 & 0 & 0.0011 & 0.0017 & 0.0003 & 0 & 0 \\ 0 & 0.1135 & 0.9765 & 0 & 0.0007 & 0.0002 & 0.0012 & 0 & 0 \\ 0 & 0.0017 & 0.0296 & 1 & 0 & 0 & 0 & 0 & 0 \\ -0.0001 & 0.0049 & 0.0011 & 0.0288 & 0.9770 & 0.0037 & -0.0268 & 0 & 0 \\ 0.0001 & 0.0165 & 0.0005 & -0.0198 & -1.3515 & 0.8977 & 0.0250 & 0 & 0 \\ 0 & -0.0268 & 0.0015 & 0.0041 & 0.2716 & -0.0003 & 0.9811 & 0 & 0 \\ 0 & 0.0003 & 0 & -0.0002 & -0.0207 & 0.0285 & 0.0003 & 1 & 0 \\ 0 & -0.0004 & 0 & 0 & 0.0041 & 0 & 0.0297 & 0 & 1 \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} 0.0710 & 0.0067 & -0.0110 & -0.0117 & -0.0004 & -0.0001 \\ -0.0090 & -0.0088 & -0.0091 & -0.0090 & 0 & 0 \\ -0.2818 & -0.2819 & -0.0746 & -0.0746 & 0 & 0 \\ -0.0042 & -0.0042 & -0.0011 & -0.0011 & 0 & 0 \\ -0.0010 & 0.0007 & -0.0006 & 0.0005 & 0.0123 & 0.0018 \\ -0.0822 & 0.0819 & -0.0881 & 0.0879 & 0.0122 & 0.0250 \\ 0.0921 & -0.0924 & 0.0233 & -0.0232 & 0.0200 & -0.0132 \\ -0.0013 & 0.0130 & -0.0130 & 0.0130 & 0.0002 & 0.0004 \\ 0.0014 & -0.0014 & 0.0003 & -0.0003 & 0.0003 & -0.0002 \end{bmatrix}$$

Note that (2.18) is still nonlinear due to term $F(\mathbf{x})$, which is given as follows:

$$F(\mathbf{x}) = \begin{bmatrix} F_v \\ F_\alpha \\ F_q \\ F_\theta \\ F_\beta \\ F_p \\ F_r \\ F_\phi \\ F_\psi \end{bmatrix} = \begin{bmatrix} 0 \\ -0.03p \cos \alpha \tan \beta - 0.03r \sin \alpha \tan \beta \\ 0.028pr - 0.00018p^2 + 0.00018r^2 \\ 0.03q \cos \phi - 0.03r \sin \phi \\ 0.03p \sin \alpha - 0.03r \cos \alpha \\ 0.00026qp - 0.017qr \\ -0.025qp - 0.00026qr \\ 0.03q \tan \theta \sin \phi + 0.03r \tan \theta \cos \phi \\ 0.03q \cos^{-1} \theta \sin \phi + 0.03r \cos^{-1} \theta \cos \phi \end{bmatrix} \quad (2.20)$$

G and H are 9×9 unity matrices. w and v are 9×1 vectors with normally distributed random values. The F16 aircraft state vector is the same as in A340. The fighter has six control surfaces and hence six control inputs are:

$$\mathbf{u} = [\delta_{HR} \ \delta_{HL} \ \delta_{FR} \ \delta_{FL} \ \delta_C \ \delta_R]^T$$

where δ_{HR} and δ_{HL} are the deflections of the right and left horizontal stabilizers, δ_{FR} and δ_{FL} are the deflections of right and left flaps, δ_C and δ_R are the deflections of canard and rudder.

We assume the following mechanical limits on the deflections of control surfaces of F16: $|\delta_{HR}, \delta_{HL}| \leq 0.44$ rad, $|\delta_{FR}, \delta_{FL}| \leq 0.35$ rad, $|\delta_C| \leq 0.47$ rad and $|\delta_R| \leq 0.52$ rad.

2.8 Linear Quadratic Gaussian Regulator

In this study Linear Quadratic-Gaussian (LQG) state-feedback optimal dynamic regulator for the discrete-time plant in state space is used in the investigated aircraft for the following reasons:

- 1- The discrete F16 aircraft model is unstable. It is stabilized by the LQG for Kalman filter process.
- 2- During the simulations of the investigated aircraft for icing parameters with several magnitudes, some models of A340 are being unstable. It is stabilized by the LQG for Kalman filter process.

Therefore, we will briefly explain LQG in this section.

LQG regulator takes into account process disturbances and measurement noise. The LQG regulator consists of an optimal state-feedback gain and a Kalman state estimator. The quadratic performance index to be minimized is as follows:

$$J = \int_0^t [\mathbf{x}^T \mathbf{Q}_c \mathbf{x} + \mathbf{u}^T \mathbf{R}_c \mathbf{u}] dt \quad (2.21)$$

where $\mathbf{Q}_c$ is a semi-positive definite symmetric matrix and $\mathbf{R}_c$ is a positive definite symmetric matrix. $\mathbf{Q}_c$ and $\mathbf{R}_c$ is specified by user according to regulation performance and control objectives. For example, they are related with how fast $\mathbf{x}$ goes to zero. The goal of LQG is to regulate the plant output, $\mathbf{y}$, around zero. The control input is computed as:

$$\mathbf{u} = -\mathbf{K} \mathbf{x} \quad (2.22)$$

where $\mathbf{K}$ is called LQ-optimal gain and computed from the following discrete-time Riccati equation:

$$\mathbf{A}^T \mathbf{S} \mathbf{A} - \mathbf{S} - \mathbf{A}^T \mathbf{S} \mathbf{B} (\mathbf{B}^T \mathbf{S} \mathbf{B} + \mathbf{R}_c)^{-1} \mathbf{B}^T \mathbf{S} \mathbf{A} + \mathbf{Q}_c = 0 \quad (2.23)$$

$$\mathbf{K} = (\mathbf{B}^T \mathbf{S} \mathbf{B} + \mathbf{R}_c)^{-1} \mathbf{B}^T \mathbf{S} \mathbf{A} \quad (2.23)$$

where $\mathbf{S}$ is solution of (2.23). The above problem must satisfy the following requirements:

- 1- $(\mathbf{A}, \mathbf{B})$ stabilizable
- 2- $\mathbf{R}_c > 0$
- 3- $\mathbf{Q}_c \geq 0$
- 4- $(\mathbf{Q}_c, \mathbf{A})$ has no observable mode on the unit circle

LQ-optimal state feedback is not applicable without full state measurement. Therefore, state estimates will be derived by KF as explained in Chapter 4.

3. AIRCRAFT ICING

In-flight icing decreases the aerodynamic quality of aircraft such that aircraft weight increases, drag increases, lift decreases, and hence the effectiveness of angle of attack and pitch angle change. Accordingly, the effectiveness of control surfaces may decrease. All these directly affect aircraft safe flight. As well as this subject is clearly important in the respect of aviation safety, by taking into account extra fuel consumption due to icing, it is important for economical reasons.

By including icing effects, the control and stability of more correct aircraft model improve flight performance, passenger comfort and tight flight plans. It is clearly obvious that military aircraft have to fly at all places on air and weather conditions as possible. On the other hand, intensive air traffic has forced aircraft should fly at all weather conditions as much as possible.

Civil aviation authorities and other organizations such as Federal Aviation Authority, FAA, and Joint Aviation Authority, JAA, which provide aircraft certificates and quality assurances, have restricted the flight of the aircraft which do not have installed anti-icing system and icing detection system. In order to make sure that whether the aircraft is safe in icing weather conditions or not, the flight tests are mandated by these organizations prior to first aircraft approvals. These flight tests are very much time-consuming and expensive. Instead of these tests, flight simulations of exactly modeled iced aircraft by using modern technology products would be better for aircraft manufacturers. At least, these simulations could support to flight tests data.

Some icing sensors in nose sections are used on some modern aircraft to detect in-flight icing. However, these sensors only show an indication or a possibility for icing when it comes to some levels. They do not measure the icing effects such as its shape, thickness and location. It is impossible to evaluate the degradation of aircraft performance due to in-flight wing and tail icing. Hence, the existing sensors do not provide enough information to pilot or autopilot.

By an improved icing detection, monitoring and control system, pilot/aircraft system can safely continue its route regardless of weather icing conditions within acceptable safety margins.

On the subject of aircraft in-flight icing detection and identification, there has not been enough academic research for the time being. Especially, some icing related accidents in Turkey and worldwide during last 20-25 years, and additional requirements of civil aviation authorities have forced researchers to work on this subject in deeper. The several works related aircraft is continuing with the support of NATO, NASA and some universities. The special working groups have been assigned by these research centers for icing

3.1 Icing Characteristics

Icing occurs from the particles so called super-cooled water droplets hitting the airframe in certain air and airframe temperatures. Ice accumulation is more likely at locations when the air velocity is very low, called as stagnation locations. Icing at an airfoil may grow in several configurations at different locations of aircraft depending on air temperature, surface temperature, and type of clouds that aircraft is flying through, etc. In general, the results of ice on an aircraft may be grouped as follows:

- Poor aerodynamic quality,
- More aircraft weight,
- Engine problems,
- Blocked air data probes,
- Reduced visibility

These effects mainly depend on the location of ice. Figure 3.1 shows the most critical locations for icing [40].

Airframe icing results in decreasing aircraft aerodynamic performance, which are affected by changes in lift, drag, weight and pitching moment, and their effectiveness with regard to aircraft position angles and velocities. The effects of icing change by depending on its shape as well. In general, icing shape in a wing or tail surface is like in Figure 3.2 in cruise conditions [40]. The figure also reflects the changes in lift, drag and wing by arrows. In some cases, protuberances in leading edge like in the figure occur only. This type of icing is called “rime ice”. If there is no

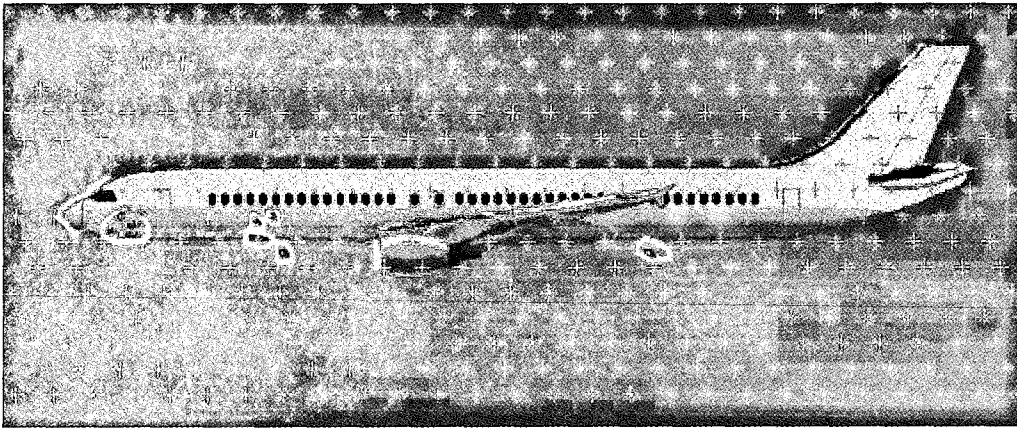


Figure 3.1 Icing locations

any protuberance in ice shape, it is called “clear ice”. Rime ice occurs at leading edges in the high speed flight due to hitting frozen droplets below -10°C . It has commonly double horn shape. Droplets freeze immediately after hitting. Clear ice slowly occurs at the temperatures between 0°C and -10°C . If rime ice and clear ice are present together, it is called mixed ice which is illustrated in Figure 3.2

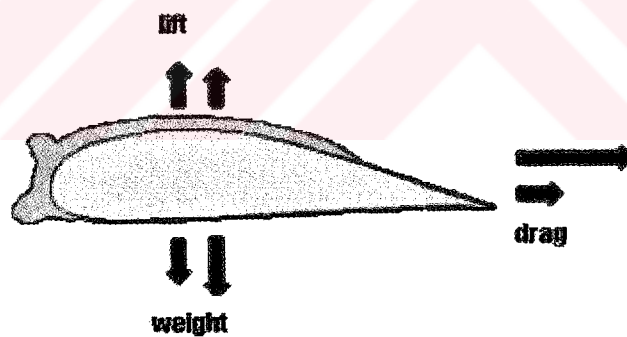


Figure 3.2 Icing shape at wing in cruise conditions

Experts from BAE Systems investigated new type of icing so called “runback ice”. It particularly occurs at aircraft with leading edge heating device against icing. Even anti-icing / de-icing devices are installed in modern aircraft such as Airbus A340, it may not prevent icing. The results obtained from flight tests of BAE Systems are

illustrated in Figure 3.3. Video cameras were used in the flight tests at different temperatures and water flow rates [41].



Figure 3.3 Runback icing in aircraft with leading edge heating device

The experimental studies have showed that, in the result of wing icing, drag may increase to values of 500%, and lift may decrease to values of 40% [42-44].

3.2 Iced Aircraft Model Parameters

Icing has been studied experimentally and analytically by a few scientists. Tailplane icing was considered by Schuchard at al., and only an icing severity factor (η_{ice}) was classified as several levels between 0.0 (no icing) and 1.0 (severe icing). A linear variation of the parameters with respect to η_{ice} was assumed as follows:

$$C_{*}^{iced} = C_{*}^{clean} (1 + k'_{C_{*}} \eta_{ice}) \tag{3.1}$$

where the slope, $k'_{C_{*}}$, was assumed constant and determined from the ice affected parameter, C_{*}^{iced} . After extensive simulations they found that only the pitching moment derivatives M_{α} and M_{δ_e} provided useful estimates for tail icing. Therefore they produced icing detection and classification by evaluating these two parameters [13].

In the work of Bragg at al. [6] similar model was used in [13] for ice effects, and slope for specific aircraft was given as

$$k'_{C_A} = \frac{\eta}{\eta_{ice}} k_{C_A} \tag{3.2}$$

where η_{ice} indicates an icing severity parameter representing the amount and severity of the icing, based on NACA 0012 airfoil drag rise ratio under icing conditions. η is an aircraft specific icing severity parameter, k_{CA} is the relative icing effect on a particular stability and control parameter.

In the study of Merret et al. [3] stability and control derivatives based upon the flight dynamics model were calculated for the NASA DH-6 Twin Otter based on flight data. These calculations have indicated that ice accretion causes certain variations only in the $M_\alpha, M_q, Z_\alpha, Z_q, X_\alpha$ and X_u stability derivatives and the M_{δ_E} and Z_{δ_E} control derivatives in tailplane icing. Extensive simulations on [11] have shown that the Z-parameters generally converge too slowly, and the X-parameters are too sensitive to noise. This research used only the M_{δ_E} and M_α parameter estimates for icing detection and classification.

In order to determine the limits for safe flight in icing conditions, minimum speed, maximum AOA, maximum bank angle, maximum control deflections and their change rates must be considered. Certain critical parameters must be chosen in order to formulate the proposed envelope protection scheme. Aerodynamically, the aircraft should be protected from wing stall, horizontal tail stall, roll upset and loss of longitudinal and lateral control. The critical parameters are the angle of attack of wing and tail, and roll angle; α_w, α_t and ϕ , respectively. Boundaries need to be defined for these parameters as functions of ice accretion, aerodynamic parameters, and stability and control derivatives.

In common representatives of aircraft linearized dynamic equations; this effect may be reflected by stability and control derivatives. Especially, the researches in NASA Icing Research Group and Icing Institute of Illinois University have showed that the most affected parameters from in-flight wing icing are the following [3-18]:

$$C_{D_\alpha} = \frac{\partial C_D}{\partial \alpha}, C_{L_\alpha} = \frac{\partial C_L}{\partial \alpha}, C_{L_q} = \frac{\partial C_L}{\partial q}, C_{M_\alpha} = \frac{\partial C_M}{\partial \alpha}, C_{M_q} = \frac{\partial C_M}{\partial q}$$

where $C_{D_\alpha}, C_{L_\alpha}, C_{L_q}, C_{M_\alpha}$, and C_{M_q} are stability derivatives; C_D, C_L, C_M are drag, lift and pitch moment coefficients, respectively [23]. The change in lift coefficient with a change in angle of attack, C_{L_α} , often called the lift curve slope. The lift curve

slope for the total airframe includes the components due to the wing, the fuselage, and the tail. For most conventional aircraft, it is generally true that the wing contribution 85-90 percent to the value of C_{L_α} [36]. As well as ice accumulation increases C_{D_α} , it decreases C_{L_α} , C_{L_q} , C_{M_α} , and C_{M_q} [10].

Stability and control derivatives are usually found from wind-tunnel tests at first. Unfortunately, unavoidable differences between test environment and flight conditions, the wind-tunnel test data are considered only as initial estimates.

In this study, as being in the previous research on icing, the changes of other derivatives are assumed to be small and negligible. In the aircraft equations, sometimes these derivatives can be written in dimensional form as,

$$X_w(C_{D_\alpha}) = \frac{-\bar{q}S(C_{D_\alpha} - C_L)}{mU_1} \quad (3.3)$$

$$Z_w(C_{L_\alpha}) = \frac{\bar{q}S(C_{L_\alpha} + C_D)}{mU_1} \quad (3.4)$$

$$Z_q(C_{L_q}) = \frac{\bar{q}SC_{L_q}\bar{c}}{2mU_1} \quad (3.5)$$

$$M_w(C_{M_\alpha}) = \frac{\bar{q}SC_{M_\alpha}\bar{c}}{I_{yy}U_1} \quad (3.6)$$

$$M_q(C_{M_q}) = \frac{\bar{q}S(C_{M_q})(\bar{c})^2}{2I_{yy}U_1} \quad (3.7)$$

where $\bar{q}$ is dynamic pressure, S is the reference area, U_1 is total aircraft speed, $\bar{c}$ is wing chord, and I_{yy} is aircraft inertial moment per aircraft pitch axis [31]. U_1 may be approximately equivalent to V_T . Like many studies, this study uses the terms with angle of attack, α , instead of downward speed, w , in the aircraft state space equations in accordance with

$$\alpha = \frac{w}{U_1} \quad (3.8)$$

When aircraft linearized equations are examined, it is easily found that all these derivatives are in the matrix A shown in the chapter 2. Icing affected parameters of

aircraft dynamics models are $A(1,2)$, $A(2,2)$, $A(2,3)$, $A(3,2)$ and $A(3,3)$, which are written from former equations (3.3) thru (3.7) as

$$A(1,2) = k_1(C_{D_\alpha} - C_L) \quad (3.9)$$

$$A(2,2) = k_2(C_{L_\alpha} + C_D) \quad (3.10)$$

$$A(2,3) = k_3 C_{L_q} \quad (3.11)$$

$$A(3,2) = k_4 C_{M_\alpha} \quad (3.12)$$

$$A(3,3) = k_5 C_{M_q} \quad (3.13)$$

where k_i , $i = 1,2,3,4,5$, consist of all other flight parameters which are considered constant for a certain time. These constants may be calculated from certain flight conditions such as take off, climb, cruise, and landing.

Aircraft parameters mentioned above can be also affected by other factors such as aircraft configuration (shape, weight, etc), environmental conditions, turbulence, trim point creep, unmodeled dynamics, and nonlinear terms. All of these effects are not covered in this icing identification technique.

In the simulations in Chapter 7, $A(1,2)$, $A(2,2)$, $A(2,3)$, $A(3,2)$, and $A(3,3)$ are expressed as a_{12} , a_{22} , a_{23} , a_{32} , and a_{33} , respectively. In this study, duration of two minutes, four ice-affected parameters are assumed to decrease their halves, and one parameter to increase fifty percent more in parallel to studies in the literature.

3.3 In-flight Icing Detection Techniques

The methods of icing detection which are used currently or are considered to be used in future can be categorized in two groups: Model-free methods, model based methods [45]. This classification may be considered not only for icing but also faults in any dynamic system. Among the model-free methods, physical redundancy with multiple sensors, special sensors, limit checking according to preset limits in a memory, spectrum analysis of the plant measurements, logic reasoning techniques including IF-THEN rules and expert systems may be given as examples.

The aircraft Airbus A340-300, which is one of the investigated aircraft in the thesis, have two special icing sensors under fuselage nose and two different types of visual

sensors in cockpit window called as windshield. The operational principle of the sensors on fuselage is shown in Figure 3.4. There is a counter to track the oscillations, a circuit and an oscillating needle outside fuselage. While ice accumulates at the end of this needle, its vibration frequency decreases. The limit checking is performed according to the vibration frequency of the sensors [30].

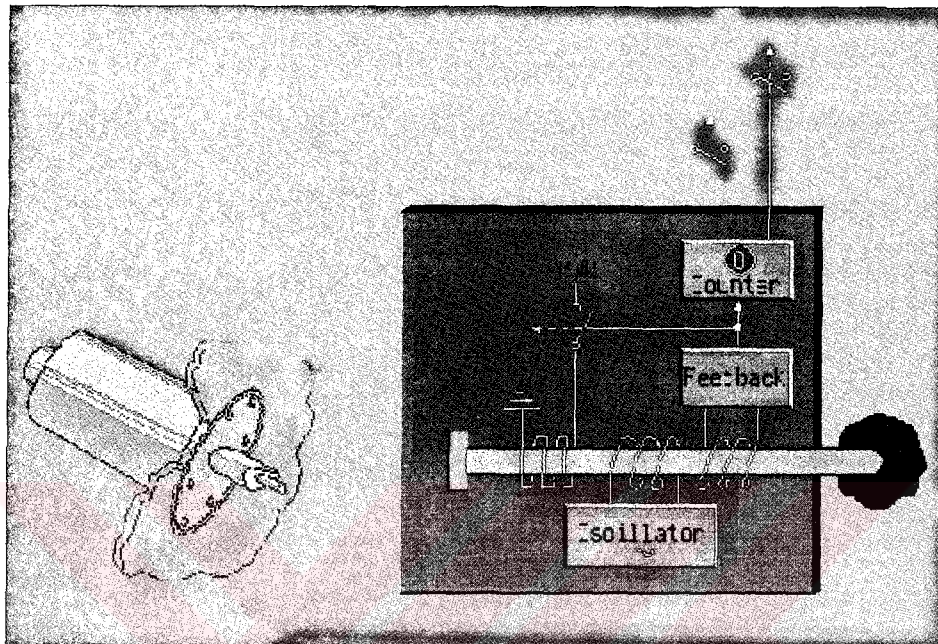


Figure 3.4 Icing detector on Airbus A340-300 and the scheme of its detection process

The traditional approaches to icing diagnosis are based on physical redundancy. This means extra equipment. In aviation, it is impractical to install extensive equipment.

Model-based icing diagnosis can be defined as the determination of airframe icing from the comparison of available system measurements with a priori information represented by the system's mathematical model, through generation of residual quantities and their analysis. Model-based methods use analytical redundancy, and do not need additional hardware. Furthermore, analytical redundancy is potentially more reliable than hardware redundancy [46-47]. The difference generated from the consistency checking of different variables is called as residual signal. The residual should be zero-valued when the icing is not present, and should diverge from zero when icing starts. Consistency checking in analytical redundancy is normally achieved through a comparison between a measured signal and its estimation. This

property will be used to detect ice occurrence, and will be explained in more detailed in Chapter 4. The developments in computer technology have made model-based methods very feasible and practical [48].

3.4 Inflight Icing Identification Techniques

Recursive H-infinity algorithm applied to the icing problem in earlier work at [11] was shown to be superior to that of more traditional identification methods of batch least squares and EKF.

In Ref [3] steady and unsteady airfoil hinge moment measurements were used as ice indication. It was assumed that during dynamic trim the following equations would hold

$$\dot{\alpha} = \dot{\beta} = \dot{p} = \dot{q} = \dot{r} = \dot{\eta}_{ice} = 0 \quad (3.14)$$

At the onset of a maneuver, the equations of motion were solved for a future dynamic trim state. The estimated state was then used to calculate the value of the critical parameters at dynamic trim. The limits of the critical parameters were found as functions of control inputs, state parameters and icing severity parameter by using simulations. The envelope protection vector was given as

$$y_p = [\alpha \ \varphi] \quad (3.15)$$

$$y_{p\text{limit}} = [\alpha_{\max} \ \varphi_{\max}]^T \quad (3.16)$$

where α and φ represent angle of attack and bank angle, respectively. This vector introduced stall warning during severe icing.

In Ref [13] neural network icing detection and classification was applied to an experimental aircraft. It was assumed that no information regarding icing is available prior to the maneuver. This absence of prior information is consistent with the lack of parameter estimate convergence under no excitation, and is conservative in that the information gained from other available sensors was ignored. After the commencement of the maneuver, parameter identification takes place, and the parameter estimates are being available for icing characterization. The scenario maneuver was modeled by an elevator doublet (i.e., one period of a sinusoid whose

frequency and amplitude are specified). The baseline maneuver was a 5 degrees doublet with period of 10s. The disturbance was not used to capture unmodeled dynamics such as those due to nonlinear terms since the nonlinear effects were not well understood for iced aircraft. The disturbance was assumed as entirely turbulence. The goal was to be no false alarms in icing conditions. In order to capture the richness of this class of scenarios, they run 3300 simulations for various icing severity levels, doublet amplitudes and periods, and noise time histories. Initial parameter estimate error was used in order to capture trim point creep. A simple threshold to separate all clean cases from iced cases was not enough.

In Ref [14], a method of using NN and Kohonen Self-Organizing Maps (SOMs) to detect airframe ice was proposed and investigated. It was hypothesized that NN systems trained on the aircraft dynamics in real time would converge to different connection weights for iced and clean aircraft [14].

In Ref [18], a NN system was developed to estimate stability and control derivatives by an H-infinity parameter identification algorithm during a longitudinal maneuver in the absence of pilot input when poor excitation of the flight dynamics limits the accuracy of parameter estimates.

In this study, a NN approach based on Kalman filter (KF) estimates is used to identify aircraft ice accretion. Growing ice effects in an Airbus A340 and F16 fighter models at cruise conditions are considered. The estimates of flight dynamics are used as inputs to a neural network model to identify icing parameters. The proposed technique and simulation results are given in Chapter 5, 6 and 7.

3.5 Flight Control System Reconfiguration Techniques for Icing

The existing methods in modern aircraft for flight control in icing conditions are very primitive. There is no automatic control system which particularly is modified for icing. In case of icing presence or possibility, the flight envelope is modified in predetermined amounts by restricting control surface deflections to avoid possible stall.

The approach in this thesis is to design a new automatic flight control system modified for icing conditions in particular. It is called Icing Tolerant Flight Control System (ITFCS), which is detailed in Chapter 6.

4. ICING DETECTION VIA KALMAN FILTERING

Airframe icing may be considered as a fault since it causes an unexpected and unacceptable deterioration of the aerodynamic performance of aircraft or even perhaps leads to hazardous flights. Icing must be diagnosed as early as possible. It may be tolerable at its early stages. An icing diagnosis system must consist of the stages of detection, isolation and identification. Icing detection system produces the information of ice occurrence on airframe. We will present one special model-based approach in this chapter. Icing isolation determines the location of ice occurrences, which is assumed that icing occurs at the wing leading edges in right and left. Identification problem of icing is to estimate the size or nature of the icing, which will be explained in Chapter 5. First two steps are called fault detection and isolation (FDI) in the literature.

Faults in dynamical systems can be detected with the aid of innovation sequence of the KF. If the system operates normally, the normalized innovation sequence in a correlated KF is a Gaussian white noise with a zero mean and with a unit covariance matrix. Faults changing the system dynamics affect the characteristics of the normalized innovation sequence by changing its white noise nature, displacing its zero mean, and varying unit covariance matrix. KF presents the practical advantage of requiring the memorization of the last estimation only, contrary to other recursive filter structures.

In this thesis, KF innovation sequence is considered as an icing detection method. We will also use KF for state estimation which is required for icing identification and reconfigurable control.

In this chapter, the linear KF equations in discrete and continuous forms are explained in terms of Airbus A340 linear model. Extended Kalman Filter (EKF) is described for the nonlinear F16 aircraft model. The innovation sequence approach for icing detection in both aircraft is given.

4.1 Kalman Filter (KF)

Kalman Filter (KF) is the method that is often used in signal processing in discrete systems for the estimation of the solution of a first order differential equation with quadratic nonlinearities. This estimation algorithm was originally developed by Kalman [49] and latter by Bucy in 1960s as an extension of Wiener's classical work in 1949. Therefore, KF is also known as "Wiener-Kalman filter" or "Kalman-Bucy filter" in the literature. KF algorithm has been successfully applied to the areas of navigation [50], space guidance and orbit determination. It finds more accurate measurement estimates by minimizing the measurement errors, integrates more than one sources of information, calculates unknown parameters or states of the aircraft dynamic motion, and diagnosis of the faults that may occur in aircraft flight system [51].

The validity of an assumed mathematical model and detection of any misspecification in the model could be verified by the performance analysis of Kalman filter. The difference between the actual system output and the predicted output based on the predicted state by KF is defined as the innovation sequence, which may be considered an error signal. It represents the new information taken from the latest observation vector. Under normal conditions, the error signal is relatively small and corresponds to random fluctuations in the output during all the systematic trends are eliminated by the model. However, under icing conditions, the error signal is relatively large and contains systematic trends because the model no longer represents the physical system adequately [51].

4.1.1 Representations of discrete KF

KF may be represented in several ways depending on the objectives of the work. Therefore, it will be convenient for better understanding to briefly give the complete process of KF here. Let us consider a linear dynamic system in discrete form

$$\mathbf{x}(k+1) = \Phi(k+1, k) \mathbf{x}(k) + \mathbf{B}(k) \mathbf{u}(k) + \mathbf{G}(k+1, k) \mathbf{w}(k) \quad (4.1)$$

$$\mathbf{y}(k) = \mathbf{H}(k) \mathbf{x}(k) + \mathbf{v}(k) \quad (4.2)$$

where $\mathbf{x}(k)$ is the n -dimensional state vector of the system, $\Phi(k+1, k)$ is the $n \times n$ -transfer matrix of the system, $\mathbf{B}(k)$ is the $n \times m$ -dimensional control distribution matrix, $\mathbf{u}(k)$ is the m -dimensional control vector, $\mathbf{G}(k+1, k)$ is the $n \times r$ -dimensional transfer

matrix of the system noise, $\mathbf{w}(k)$ is the r -dimensional random Gaussian noise (white noise) of the system, which is also called system disturbance, $\mathbf{H}(k)$ is the $s \times n$ -dimensional measurement matrix of the system, and $\mathbf{v}(k)$ is the s -dimensional measurement white noise vector. Since the system disturbance and measurement noise are assumed as white noise, it can be written the following.

$$\bar{\mathbf{w}} = E[\mathbf{w}(k)] = 0 \quad (4.3)$$

$$\bar{\mathbf{v}} = E[\mathbf{v}(k)] = 0 \quad (4.4)$$

where $E[\dots]$ is the statistics average or expected value operator. It means that process noise and measurement noise have zero mean. Additionally, their covariance is also assumed as follows:

$$E[\mathbf{w}(k) \mathbf{w}^T(j)] = \mathbf{Q}(k)\delta(kj) \quad (4.5)$$

$$E[\mathbf{v}(k) \mathbf{v}^T(j)] = \mathbf{R}(k)\delta(kj) \quad (4.6)$$

$$E[\mathbf{w}(k) \mathbf{v}^T(j)] = \mathbf{0}, \forall k, j \quad (4.7)$$

where $\delta(kj)$ is the Kronecker symbol as follows

$$\delta(kj) = \begin{cases} 1, & \text{if } k = j, \\ 0, & \text{if } k \neq j \end{cases} \quad (4.8)$$

Note that process noise and measurement noise are uncorrelated.

KF requires that the measurements, $\mathbf{y}(k)$ must be linearly related to the states $\mathbf{x}(k)$ as in (4.2). The KF uses the information contained in the new measurement $\mathbf{y}(k)$ and a **a priori** estimate, $\hat{\mathbf{x}}^-(k)$, to update a **a posteriori** estimate, $\hat{\mathbf{x}}(k)$, of the unknown state $\mathbf{x}(k)$. A priori state estimate and a posteriori state estimate are also called a **state prediction** and a **current state estimate**, respectively. The error vectors of state estimation and state prediction are, respectively

$$\tilde{\mathbf{x}}(k) = \mathbf{x}(k) - \hat{\mathbf{x}}(k) \quad (4.9)$$

$$\tilde{\mathbf{x}}^-(k) = \mathbf{x}(k) - \hat{\mathbf{x}}^-(k) \quad (4.10)$$

Let $\hat{\mathbf{y}}(k)$ denotes the measurement estimate, which is the estimate of $\mathbf{y}(k)$ given the previous measurements $\mathbf{y}(1), \mathbf{y}(2), \dots, \mathbf{y}(k-1)$. The measurement estimate and measurement estimation error are written as, respectively

$$\hat{\mathbf{y}}(k) = \mathbf{H}(k) \hat{\mathbf{x}}^-(k) \quad (4.11)$$

$$\tilde{\mathbf{y}}(k) = \mathbf{y}(k) - \hat{\mathbf{y}}(k) \quad (4.12)$$

As stated before, note that $\tilde{\mathbf{y}}(k)$ is also called innovation. Let us define a priori covariance matrix and a posteriori covariance matrix as, respectively

$$\mathbf{P}^-(k) = E[(\tilde{\mathbf{x}}^-(k)) (\tilde{\mathbf{x}}^-(k))^T] \quad (4.13)$$

$$\mathbf{P}(k) = E[(\tilde{\mathbf{x}}(k)) (\tilde{\mathbf{x}}(k))^T] \quad (4.14)$$

The derivation of KF equations may be found in [52-53] in more details. For non-zero-mean process and measurement noises ($\bar{\mathbf{w}} = E[\mathbf{w}(k)] \neq 0$ and $\bar{\mathbf{v}} = E[\mathbf{v}(k)] \neq 0$), KF equations may be derived as given in [51].

4.1.2 Steps of discrete KF

In Figure 4.1, discrete KF flow chart is illustrated. Let us summarize the steps of the algorithm as follows:

1. Initialization: For $k = 0$, given initial state, $\mathbf{x}(0)$, we may choose

initial posteriori state estimate:

$$\hat{\mathbf{x}}(0) = E[\mathbf{x}(0)] \quad (4.15)$$

initial posteriori covariance matrix

$$\mathbf{P}(0) = E[(\mathbf{x}(0) - \hat{\mathbf{x}}(0))(\mathbf{x}(0) - \hat{\mathbf{x}}(0))^T] \quad (4.16)$$

2. State estimate propagation (prediction): For $k = 1, 2, \dots$ This is time update which predicts the state value at the next sample (one-step-ahead predictor).

$$\hat{\mathbf{x}}^-(k) = \Phi(k, k-1) \hat{\mathbf{x}}(k-1) + \mathbf{B}(k-1) \mathbf{u}(k-1)$$

3. Error covariance propagation: For $k = 1, 2, \dots$ a priori covariance matrix at time k is updated.

$$\mathbf{P}^-(k) = \Phi(k, k-1) \mathbf{P}(k-1) \Phi^T(k, k-1) + \mathbf{G}(k, k-1) \mathbf{Q}(k-1) \mathbf{G}^T(k, k-1) \quad (4.17)$$

4. Kalman gain matrix: For $k = 1, 2, \dots$ Kalman gain at time k is updated such that the steady state covariance of the estimation error is minimized. Noise covariance vectors are given. This is also called innovation gain

$$\mathbf{K}(k) = \mathbf{P}^-(k) \mathbf{H}^T(k) (\mathbf{R}(k) + \mathbf{H}(k) \mathbf{P}^-(k) \mathbf{H}^T(k))^{-1} \quad (4.18)$$

5. State estimate update (correction term): For $k = 1, 2, \dots$ This includes measurement update and output estimate. The correction term is a function of the innovation, that is, the discrepancy between the measured and predicted values of $\mathbf{y}(k)$. The measurement update adjusts the prediction in step 2 based on the new measurement. A posteriori state estimate and measurement estimate are updated in terms of the last measurement $\mathbf{y}(k)$. Note that estimated output, $\hat{\mathbf{y}}(k)$, is optimal.

measurement update:

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}^-(k) + \mathbf{K}(k) (\mathbf{y}(k) - \mathbf{H}(k) \hat{\mathbf{x}}^-(k)) \quad (4.19)$$

output estimate

$$\hat{\mathbf{y}}(k) = \mathbf{H}(k) \hat{\mathbf{x}}^-(k) \quad (4.20)$$

innovation sequence

$$\tilde{\mathbf{y}}(k) = \mathbf{y}(k) - \hat{\mathbf{y}}(k) \quad (4.21)$$

6. Error covariance update (LSM error matrix correction): For $k = 1, 2, \dots$ A posteriori covariance matrix at time k is updated as given in (4.21). This is also called Least Squares Matrix (LSM) error matrix.

error covariance update

$$\mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k) \mathbf{H}(k)) \mathbf{P}^-(k) \quad (4.22)$$

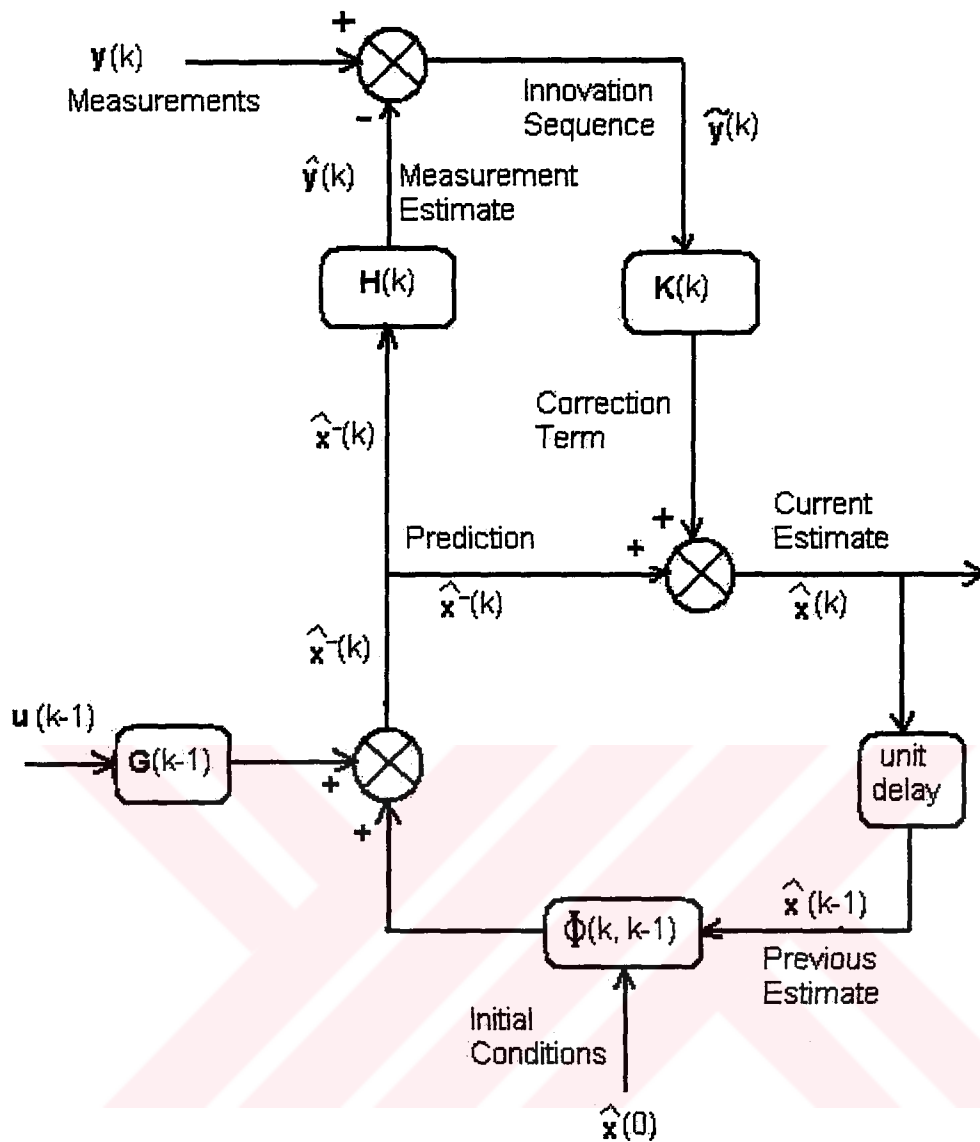


Figure 4.1: Discrete KF Flow Chart

4.1.3 Extended Kalman filter (EKF)

KF problem considered up to this point in the discussion has been about a linear model of a dynamical system. Most systems comprise nonlinear terms which are ignored in initial modeling. In most realistic problems the most real problems are described by nonlinear differential equations. KF can be applied to nonlinear dynamical systems after the linearization around the suitable operating point is

performed. This type of KF is called Extended Kalman Filter (EKF). The main idea is the linearization of the nonlinear systems around a reference point.

Let a general nonlinear discrete system be

$$\mathbf{x}(k+1) = \mathbf{f}(k, \mathbf{x}(k)) + \mathbf{B}(k) \mathbf{u}(k) + \mathbf{G}(k) \mathbf{w}(k) \quad (4.23)$$

$$\mathbf{y}(k) = \mathbf{h}(k, \mathbf{x}(k)) + \mathbf{v}(k) \quad (4.24)$$

where $\mathbf{f}(\mathbf{x}(k))$ and $\mathbf{h}(\mathbf{x}(k))$ represent nonlinear functions of states. The remaining notations are as before. Note that the dynamical system is also considered time-variant. The model may be linearized at each time instant around the most recent state estimate as follow.

$$\mathbf{F}(k+1, k) = \left. \frac{\partial \mathbf{f}(k, \mathbf{x}(k))}{\partial \mathbf{x}(k)} \right|_{\mathbf{x}(k) = \hat{\mathbf{x}}(k)} \quad (4.25)$$

$$\mathbf{H}(k+1, k) = \left. \frac{\partial \mathbf{h}(k, \mathbf{x}(k))}{\partial \mathbf{x}(k)} \right|_{\mathbf{x}(k) = \hat{\mathbf{x}}^-(k)} \quad (4.26)$$

The elements of the matrix $\mathbf{F}$, which is denoted as $(\mathbf{F}_{k+1, k})_{ij}$, are obtained by taking the partial derivative of the i -th component of $\mathbf{f}(k, \mathbf{x}(k))$ with respect to the j -th component of $\mathbf{x}(k)$ at the estimated state $\hat{\mathbf{x}}(k)$ and the iteration k . Similarly, $(\mathbf{H}_{k+1, k})_{ij}$ are obtained by taking the partial derivative of the i -th component of $\mathbf{h}(k, \mathbf{x}(k))$ with respect to the j -th component of $\mathbf{x}(k)$ at the predicted state $\hat{\mathbf{x}}^-(k)$ and the iteration k . Using (4.25) - (4.26) and first order Taylor approximations of $\mathbf{f}$ and $\mathbf{h}$ around $\hat{\mathbf{x}}(k)$ and $\hat{\mathbf{x}}^-(k)$, respectively, EKF equations are reached as follows:

$$\hat{\mathbf{x}}^-(k) = \mathbf{f}(k, \hat{\mathbf{x}}(k-1)) + \mathbf{B}(k-1) \mathbf{u}(k-1) \quad (4.27)$$

$$\mathbf{P}^-(k) = \mathbf{F}(k, k-1) \mathbf{P}(k-1) \mathbf{F}^T(k, k-1) + \mathbf{G}(k, k-1) \mathbf{Q}(k-1) \mathbf{G}^T(k, k-1) \quad (4.28)$$

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}^-(k) + \mathbf{K}(k) (\mathbf{y}(k) - \mathbf{h}(k, \hat{\mathbf{x}}^-(k))) \quad (4.29)$$

and other equations of the basic KF remain the same.

4.2 Icing Detection via Innovation Approach

KF or EKF may be used as an icing detection sensor by so called innovation sequence. Here, the properties of innovation sequence and some criterions for checking innovation sequence statistical characteristics will be discussed. Then new approach for icing detection will be defined.

4.2.1 Properties of innovation sequence of optimal Kalman filtering

As explained in section 4.2 in linear systems, the output is Gaussian if the input is Gaussian. Thus, the innovation sequence is considered to be Gaussian. Hence only the mean and covariance of the innovation sequence have to be specified to describe the statistical properties of the innovation sequence completely. Kailath [55] has shown that if the filter is optimal, the error signal or the innovation sequence is a white Gaussian noise with zero mean and known covariance.

The innovation sequence of Kalman Filter can be used to detect faults such as airframe icing in the aircraft which have white Gaussian process and measurement noise. This sequence in normal operating conditions is calculated with

$$\Delta(k) = \tilde{y}(k) = y(k) - H(k) \hat{x}^-(k) \quad (4.30)$$

In Kalman filtering process this is adjusted according to the actual system measurements. If the system operates normally, then the innovation sequence will be white Gaussian noise with zero mean and the following covariance matrix [56].

$$P_{\Delta}(k) = H(k) P^-(k) H^T(k) + R(k) \quad (4.31)$$

where $P^-(k)$ is known as the covariance matrix of extrapolation errors. This can be calculated with (4.17). $P(k-1)$ is the covariance matrix of estimation errors in the previous step, which can be obtained from (4.22). The estimated value of state vector $\hat{x}(k)$ can be found from (4.29) as well.

It is more appropriate to use normalized innovation sequence to detect the faults as given below [57]

$$\tilde{\Delta}(k) = [H(k) P^-(k) H^T(k) + R(k)]^{-1/2} \Delta(k) \quad (4.32)$$

such that the covariance of normalized innovation sequence is

$$E[\tilde{\Delta}(k) \tilde{\Delta}^T(k)] = P_{\Delta} = I \delta(kj) \quad (4.33)$$

The icing or similar faults changing the system dynamic also change the characteristic of $\tilde{\Delta}(k)$ sequence and make it different from white noise. This faults shift the average of $\tilde{\Delta}(k)$ sequence, which is also zero and changes its unit covariance matrix. Therefore the supervision brings up the problem to a stage, which will detect the deviations at the nominal values of regarding characteristics instantly.

Methods for the detection of departures from optimality are all based on the innovation sequence. Performance analysis of Kalman filter based on the innovation sequence was introduced by Mehra and Peschon [56]. The innovation sequence of an optimal filter has precisely defined characteristics, which can be compared with the output of an actually implemented Kalman filter. The innovation process contains all information to assess the optimality of filter operations. Furthermore the innovation process is the primary source for the detection of misspecifications of the model and adaptive filtering.

Now the statistical properties of the innovation sequence have been described. Since the properties of the innovation sequence are strictly defined if the filter is optimal, the innovation sequence resulting from an actually implemented filter can be monitored and compared to faultless model description. Deviations from the theoretical characteristics may be caused by mismodelling of the dynamic and/or measurement model, failure of sensors, and outliers in data. Mismodelling of any kind will make the innovation sequence to depart from its theoretically defined nominal values.

The general performance of the filter can be monitored by analyzing the zero mean, Gaussianness, covariance, and whiteness of the innovation sequence. Furthermore the innovation sequence is the sole source of outlier detection. Outlier detection is also related to the wider field of fault detection in dynamic systems. Finally the innovation sequence offers a possible approach to adaptive filtering.

4.2.2 Checking the statistical characteristics of innovation sequence

The analysis of the innovation sequence in Kalman filtering was applied to fault diagnosis in [56-63]. These approaches did not require a priori statistical characteristics of the faults, and the computational burden was not very heavy. Generally, fault detection algorithms developed to check the statistical characteristics of the innovation sequence in real-time are based on the following fact. If an estimation process operates normally, the normalized innovation sequence in the KF coordinated with a dynamics model represents the white Gauss noise with zero average value and unit covariance matrix. The changes in the statistical characteristics of the normalized innovation sequence are caused by a variety of problems: faults of measuring sensors, abnormal measurements, sudden shifts arising in the measurement channel, changing the statistical characteristics of the object or measurements noises, computer malfunctions, reduction in actuator effectiveness, troubles with the deterioration precision of instruments, increasing noise background of instruments, as well as divergence of real process trajectories and divergence of estimations generated by the KF. The task of efficiently detecting such changes has to be undertaken in real operating conditions in order to correct the estimations. It is also essential to take decisions in a timely manner to change test and operating conditions. Thus, the problem is how to detect as quickly as possible any change of these parameters from their nominal value.

4.2.3 The appropriateness criterions of innovation sequence to the white noise

Whiteness is the most important property of the innovation sequence. If the whiteness of the innovation sequence is not established, data analysis cannot be performed properly. To test if the sequence of innovations is independent, Ref [60] introduce two non-parametric tests, namely, "the run test" and "the reverse arrangements test". Non-parametric means that; no assumptions concerning the probability distribution of the data being evaluated are made.

Although it has to be stated that the innovation sequence is Gaussian if the observations are distributed normally, normality has to be verified. The equivalent of the probability density function of the innovations to normal density function is tested by means of the (Chi-square) goodness-of-fit test, once more a parametric test [60].

The appropriateness of innovation sequence to the white noise can be tested by using the help of classical mathematical statistics methods.

Mostly the value of autocorrelation function is being calculated according to the N experiment results to test the appropriateness of every random sequence to the white noise as

$$R_{\tilde{\Delta}(k)\tilde{\Delta}(k-j)} = \frac{1}{N} \sum_{k=j}^N \left[\tilde{\Delta}(k) - \bar{\tilde{\Delta}} \right] \left[\tilde{\Delta}(k-j) - \bar{\tilde{\Delta}} \right]^T \quad (4.34)$$

Here, the mean value $\bar{\tilde{\Delta}}$ is equal to the below expression;

$$\bar{\tilde{\Delta}} = \frac{1}{N} \sum_{k=1}^N \tilde{\Delta}(k) \quad (4.35)$$

In monitoring the innovation sequence the assumption is that the filter operates at optimum, i.e., the innovation sequence is zero mean, Gaussian, white, and of known covariance. This constitutes the so-called null hypothesis. Although it has to be mentioned that the innovation sequence is Gaussian if the observations are distributed normally, normality has to be verified.

4.2.4 The criterions, checking the mean of the innovation sequence

Under the null hypothesis the innovation sequence is zero mean and the mean (4.35) is normally distributed and has a covariance of $1/N$. At the α -level of significance the null hypothesis concerning the zero mean is rejected whenever

$$|\tilde{\Delta}(k)| > N_{1/2\alpha} \quad (4.36)$$

It is proper to arrange the below statistics to test that the mean value of innovation sequence is equal to zero [61].

$$B(k) = \sum_{j=k-N+1}^k \tilde{\Delta}^T(j) P_{\tilde{\Delta}}^{-1} \tilde{\Delta}(j) \quad (4.37)$$

Above (4.37) statistics is subject to the χ^2 distribution with “Ns” degree of freedom. Here “N” is the amount of used realizations and “s” is dimension of $\tilde{\Delta}(k)$ vector.

In this case, $P_{\tilde{\Delta}}$ is unit matrix so then the below is,

$$B(k) = \sum_{j=k-N+1}^k \tilde{\Delta}^T(j) \tilde{\Delta}(j) \quad (4.38)$$

By selecting α -level of significance as,

$$P\{\chi^2 > \chi_{\alpha, Ns}^2\} = \alpha, \quad 0 < \alpha < 1$$

So from the equation above, the threshold value $\chi_{\alpha, Ns}^2$ will be determined.

Because of the condition $\beta(k) > \chi_{\alpha, Ns}^2$, a signal is indicated consisting that a fault has been occurred in the system. So by giving the threshold value $\chi_{\alpha, Ns}^2$, a threshold ellipse of innovation sequence will be formed near the zero value in the parameter space. If the instant value of $\tilde{\Delta}(k)$ vector is located inside of the ellipse then it is assumed that the system is normally operating. In case of fault condition, χ will try to exceed the selected table value for the given level of significance. It is possible to calculate the probability of false alarm as a function of valid N measurement values and α level of significance. This calculation can be done by using the table values of χ^2 distribution. The quantity of used realizations N is attractive. The probability of finding correct solutions as a supervision result will be decreased when N is increased. Because the great values of N is being smooth (decreasing) the effect of fault. On the other hand, very low values of N cause frequently false alarms [51].

4.2.5 The criterions, checking the covariance matrices of the innovation sequence

The estimate of the autocorrelation function (4.34) for a zero lag is nothing but the estimate of the covariance matrix of the innovation sequence:

$$\hat{R}_0 = \frac{1}{N} \sum_{k=1}^N (\tilde{\Delta}(k) - \bar{\tilde{\Delta}})(\tilde{\Delta}(k) - \bar{\tilde{\Delta}})^T \quad (4.39)$$

Under the null hypothesis the separate elements of the s -dimensional innovation sequence are uncorrelated. Each correlation coefficient (of a total of $1/2s(s-1)$) can be tested for significance separately. It is prudent, however, to begin each study with a test of the hypothesis.

$$H_0 : \hat{R}_0 = I$$

against the alternative hypothesis.

$$H_a : \hat{R}_0 \neq I$$

An approximation of a test statistic for this test is given by [63]:

$$X^2 = (N - 1 - (2s + 5)/6) \sum_{i < j} \hat{r}_{ij}^2 \quad (4.40)$$

where $\hat{r}_{ij}$ are the elements of matrix $\hat{R}_0$. The statistic X^2 has a Chi-squared distribution with $1/2s(s-1)$ degrees of freedom. The null hypothesis is rejected at the α -level of significance whenever

$$X^2 > \chi_{\alpha, 1/2s(s-1)}^2$$

where $\chi_{\alpha, 1/2s(s-1)}^2$ is the upper α probability point of the Chi-squared distribution $\chi_{\alpha, 1/2s(s-1)}^2$ with $1/2s(s-1)$ degrees of freedom.

The real time test of the covariance matrix of random sequence is a very difficult problem because of the difficulty at determining the confidence domains for random matrices. At the situation of which normalized innovation sequence $\tilde{\Delta}(k)$ depends on normal distribution; random matrix depends on Wishart distribution.

By using Wishart distribution, it is required to determine a confidence domain for the random matrix. Determining confidence domain for random matrix will be a so difficult problem because of the difficulty at calculation and practical application of Wishart distribution.

Therefore, one of the scalar measures of Wishart matrix is mostly used. Thus, matrix trace (sum of diagonal components), matrix general variance (determinant of

matrix), maximum eigenvalue of matrix, the sum of all matrix components, etc. can be taken up as scalar measures. Every interested measurement will characterize a geometrical parameter of correlation ellipse.

The classical methods of mathematical statistics allow examining the scalar measures of random Wishart matrix just according to the general measurement's sets.

Some new methods for checking the covariance matrices of innovation sequence in real time are presented in [58-59].

The check of the covariance matrix of the innovation sequence is always a problem because of the difficulties involved in determining the confidence domain of a random matrix. In practice, therefore, one makes use of a scalar measure of this matrix such as the trace (the sum of diagonal elements), the generalized variance (determinant), the maximal eigenvalue of a matrix, the sum of the matrix elements, etc., each characterizing one or another geometrical parameter of the correlation ellipsoid. The choice of the scalar measure of the covariance matrix of the innovation sequence is based on human expertise and intuition, with mathematical simplicity and convenience in obtaining the analytical results regarded as significant considerations.

Although the trace of the sample covariance matrix is the easiest to check, it might lead to incorrect decisions at detection of failures because it disregards the off-diagonal matrix elements.

In Ref [58] a method was described for checking the sum of all elements of the inverted covariance matrix of the innovation sequence. An approach based on the ratio of two quadratic forms of which matrices are theoretic and sample covariance matrices of KF innovation sequence was presented. The optimal arguments of the quadratic forms were found to quickly detect the faults in the KF.

In Ref [59] for multidimensional dynamic systems a fault detection algorithm based on the confidence interval of the generalized variance of the Kalman filter innovation sequence, is presented. The algorithm allows one to make a substantiated decision about the state of the system in the real operational environment.

4.2.6 Application of KF innovation approach to icing detection

In this thesis, to detect iced flight dynamics changing the mean of the innovation sequence the following statistical function is used:

$$B(k) = \sum_{j=k-N+1}^k \tilde{\Delta}(j)^T \tilde{\Delta}(j) \quad (4.41)$$

where $\tilde{\Delta}(j)$ is the s -dimensional normalized innovation sequence of Kalman filter, N is the number of implementations (window length). Normalized innovation sequence means $\sigma_1^2 = 1$. This statistical function has the property of the chi-square (χ^2) distribution with Ns degree of freedom since $\tilde{\Delta}(j)$ is the result of Kalman filtering process having a normal distribution or Gaussian distribution. From this respect, the chi-square test can be used to troubleshoot the icing existence.

For our application, past values of innovation sequence in 20 time instants are collected ($N = 20$), all nine states are measurable ($s = 9$), and the reliability of data is selected 80% according to evaluation between detection accuracy and detection time ($\alpha = 0.80$), the corresponding chi-square distribution function is found from the tables as

$$\chi_{\alpha, Ns}^2 = 196$$

Now consider the following two hypotheses.

$$H_0 : B(k) \leq 196, \forall k, \text{ No icing is present in the airframe.}$$

$$H_1 : B(k) > 196, \exists k, \text{ Icing is present in the airframe}$$

Perhaps, it is better to combine the information from the existing icing or environmental sensors in future studies, which was explained in Chapter 3.

4.3 Design of KF for A340 Aircraft Flight Dynamics

Linear equations of the A340 aircraft flight dynamics were given in (2.17a) and (2.17b) as

$$\mathbf{x}(k+1) = \mathbf{A} \mathbf{x}(k) + \mathbf{B} \mathbf{u}(k) + \mathbf{G} \mathbf{w}(k) \quad (4.42)$$

$$\mathbf{y}(k) = \mathbf{H} \mathbf{x}(k) + \mathbf{v}(k) \quad (4.43)$$

Now, let's form KF equations for the estimation of A340 flight dynamics according to steps given in 4.2.2.

$$\text{initial states: } \mathbf{x}(0) = [1 \ 0.1 \ 0.01 \ 0.1 \ 0.01 \ 0.01 \ 0.01 \ 0.1 \ 0.1]^T$$

$$\text{initial posteriori state estimate: } \hat{\mathbf{x}}(0) = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]^T$$

$$\text{process error covariance matrix: } \mathbf{Q}(k) = (0.0004) \mathbf{I}_{9 \times 9}$$

measurement error covariance matrix:

$$\mathbf{R}(k) = \text{diag}[D_v \ D_\alpha \ D_q \ D_\theta \ D_\beta \ D_p \ D_r \ D_\phi \ D_\psi]$$

$$\text{initial posteriori covariance matrix: } \mathbf{P}(0) = \mathbf{I}_{9 \times 9}$$

KF equations:

$$\hat{\mathbf{x}}^-(k) = \mathbf{A}(k, k-1) \hat{\mathbf{x}}(k-1) + \mathbf{B}(k-1) \mathbf{u}(k-1) \quad (4.44)$$

$$\mathbf{P}^-(k) = \mathbf{A}(k, k-1) \mathbf{P}(k-1) \mathbf{A}^T(k, k-1) + \mathbf{B} \mathbf{D}_u \mathbf{B}^T + \mathbf{G} \mathbf{Q}(k-1) \mathbf{G}^T \quad (4.45)$$

$$\mathbf{K}(k) = \mathbf{P}^-(k) (\mathbf{R}(k) + \mathbf{P}^-(k))^{-1} \quad (4.46)$$

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}^-(k) + \mathbf{K}(k) (\mathbf{y}(k) - \hat{\mathbf{x}}^-(k)) \quad (4.47)$$

$$\hat{\mathbf{y}}(k) = \hat{\mathbf{x}}^-(k) \quad (4.48)$$

$$\mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k) \mathbf{H}(k)) \mathbf{P}^-(k) \quad (4.49)$$

Detection equations:

$$\Delta(k) = \mathbf{y}(k) - \hat{\mathbf{y}}(k) \quad (4.50)$$

$$\tilde{\Delta}(k) = [\mathbf{H}(k) \mathbf{P}^-(k) \mathbf{H}^T(k) + \mathbf{R}(k)]^{-1/2} \Delta(k) \quad (4.51)$$

$$B(k) = \sum_{j=k-N+1}^k \tilde{\Delta}^T(j) \tilde{\Delta}(j) \quad (4.52)$$

The components of measurement noise matrix [65] are $D_v = 0.8464$, $D_\alpha = 0.0056$, $D_q = 0.0069$, $D_\theta = 0.0289$, $D_\beta = 0.0025$, $D_p = 0.0025$, $D_r = 0.0069$, $D_\phi = 0.0289$, and $D_\psi = 0.0289$.

The control signal covariance matrix is selected as $\mathbf{D}_u = 0.001 \times \mathbf{I}_{5 \times 5}$

The system noise weight matrix and measurement noise matrix are selected as 9x9 unit matrices.

4.4 Design of EKF for F16 Aircraft Flight Dynamics

Nonlinear equations of the F16 aircraft flight dynamics are as follows

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{F}(\mathbf{x}(k)) + \mathbf{G}\mathbf{w}(k) \quad (4.53)$$

$$\mathbf{y}(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{v}(k) \quad (4.54)$$

Now, let's form EKF equations for the estimation of F16 flight dynamics according to steps given in 4.2.2 and 4.2.4. Since $\mathbf{H}$ is taken as a 9x9 unit matrix, there is no need to linearize the measurement equation.

$$\mathbf{F}_u(k+1, k) = \left. \frac{\partial \mathbf{F}(k, \mathbf{x}(k))}{\partial \mathbf{x}(k)} \right|_{\mathbf{x}(k) = \hat{\mathbf{x}}(k)} \quad (4.55)$$

$$\mathbf{x}(k+1) \approx \mathbf{A}(k+1, k) \mathbf{x}(k) + \mathbf{F}_u(k+1, k) \mathbf{x}(k) + \mathbf{B}(k) \mathbf{u}(k) + \mathbf{G}(k) \mathbf{w}(k) + \bar{\mathbf{x}}(k) \quad (4.56)$$

$$\hat{\mathbf{x}}^-(k+1) = \mathbf{A}(k) \mathbf{x}(k) + \mathbf{B}(k) \mathbf{u}(k) + \mathbf{F}_u(k) \mathbf{x}(k) \quad (4.57)$$

$$\begin{aligned} \mathbf{P}^-(k+1) = & \mathbf{A}(k+1, k) \mathbf{P}(k) \mathbf{A}^T(k+1, k) + \mathbf{B}(k+1, k) \mathbf{D}_u(k) \mathbf{B}^T(k+1, k) \\ & + \mathbf{F}_u(k+1, k) \mathbf{P}(k) \mathbf{F}_u^T(k+1, k) + \mathbf{G}(k+1, k) \mathbf{Q}(k) \mathbf{G}^T(k+1, k) \end{aligned} \quad (4.58)$$

Other equations remain the same as that of A340. $\mathbf{F}_u$ has been calculated from (2.20) and given in Appendix A. Initial actual states and estimates, initial covariance matrix, $\mathbf{Q}$, $\mathbf{G}$, $\mathbf{R}$, $\mathbf{H}$ and $\mathbf{D}_u$ are selected as those of A340.

Kalman filter requires a stable system. Aircraft may fly in the unstable flight conditions. In order to identify model parameters of an unstable system, first of all system must be made stable by using suitable control algorithm such as linear quadratic control.

In the early stages of this study, identification of icing parameters by EKF was performed. However, no good solution was obtained. Even if the system matrix is stable, when the number of unknown parameters increases, Kalman filter fails. Therefore EKF itself is not a good method for icing identification.

4.5 LQG Regulator with KF

KF and/or EKF may be applied to several control problems. Linear Quadratic-Gaussian (LQG) state-feedback regulator is one of them. We will use this regulator in Chapter 6. However, the LQ-optimal state feedback is not applicable without full state measurements by the following control.

$$\mathbf{u} = -\mathbf{K} \mathbf{x} \quad (4.59)$$

Therefore, instead of actual states shown as $\mathbf{x}$, state estimates shown as $\hat{\mathbf{x}}$, generated by KF is used in this study.

The inputs of KF optimal state estimator are $\mathbf{u}$ and $\mathbf{y}$, which are control and noisy measurements vectors, respectively. Thus, the optimal control according to the separation principle can be found as follows

$$\mathbf{u} = -\mathbf{K} \hat{\mathbf{x}} \quad (4.60)$$

4.6 Neural Networks with KF

In section 4.1 and 4.2 the advantages of KF have been explained. KF may be used in neural network for several purposes. For example, training in NN can be performed by connection weight update of KF. In this thesis KF is used for producing input data for NN.

It is obvious that the training data of a NN should be accurate as much as possible. In our application the inputs of NN algorithm are the states of aircraft flight dynamics. These dynamics are measured with noises in certain level. In order to minimize these measurement errors, estimates of KF will be used as inputs of NN algorithm. This process will be explained in the next chapter.

5. ICING IDENTIFICATION BASED ON NEURAL NETWORK

Neural networks (NN) have increasingly been shown as effective tools for mapping nonlinear systems and for the purpose of parameter identification. It is very efficient method in the analysis of nonlinear and complex models if enough data are available for its training phase. Unfortunately, icing in flight occurs in many different ways, and there is no enough experimental training data available regarding stability and control derivatives affected by in-flight icing. There are little data only for a few research aircraft obtained from tunnel or flight tests. After enough data are collected from real flights or other methods, neural networks may be used effectively for control, even for icing detection.

Neural network has many interesting, complex, and attractive features such as, parallel processing, learning, self-organizing, nonlinear capabilities. Neural networks 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. Rapid computation can be achieved because the majority of mathematical operations involve addition, subtraction, or multiplication. A quick response is especially critical for icing determination applications because ice accretion during flight requires immediate action. NN also have the capability to be trained on-line using real data or off-line with recorded or simulated data.

The objectives of a NN may be classified into two groups: pattern recognition also known discriminant analysis, and function approximation so called regression. The application in this thesis may be considered a function approximation of the relationship between flight data and icing effects.

The structure of NN may be classified as dynamic and static. If it has feedback or delays, it is called as dynamic network; otherwise, it is called as static network. A static network is here used for icing identification because of the nature of the problem. In the simulations, it has been found that feedback and delays have not improved the performance. The application of NN to adaptive filters may be given as an example for a dynamic network.

Icing identification may be accomplished through a variety of other methods, but 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. This study aims to find the stability and control derivatives of an iced configuration. By monitoring the flight data, after the statistical function (Beta Function) of EKF innovation sequence together with the existing icing sensors produces icing detection signal, as explained in Chapter 4, and a new model are obtained by Neural Network Icing Identification (NNII) method explained in this chapter, and then new control system is designed.

Figure 5.1 illustrates the NN identification process used in this thesis. First, the selected NN is trained until desired performance is reached, and then the trained NN is used as a real application for icing identification and control. The inputs are nine state variables, which are aircraft speed, angle of attack, pitch rate, pitch angle, sideslip angle, roll rate, yaw rate, roll angle, and yaw angle. Outputs are five icing parameters assumed most affected based on previous experimental results as explained in Chapter 3.

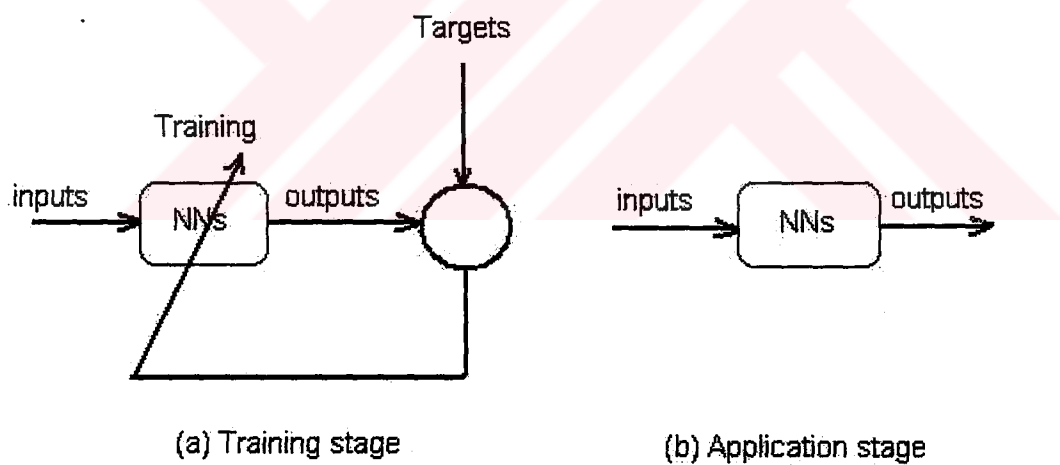


Figure 5.1 Training and application of NN

In the following sections, the agents of NN and our selections are described. Several training algorithms are explained and the advantages of Levenberg-Marquardt algorithm are explained, which are used in our application. System identification steps are explained, and then our NNII structure is given.

5.1 The Agents of NNs

The central idea of NNs is that weights and biases of connections between processing elements so called neurons can be adjusted according to inputs and/or outputs so that the network exhibits some desired or interesting behavior. Thus, the network can be trained to do a particular job by adjusting the weight or bias parameters, or perhaps the network itself will adjust these parameters to achieve some desired end.

5.1.1 Neurons

A neuron, which is also called as node or unit, is a processing element that takes a number of inputs, weights them, sums them up, and uses the result as the argument for a singular valued function, the activation function. In Figure 5.2, p , w , b , f , and n represent input, weight, bias, activation function, and input to f .

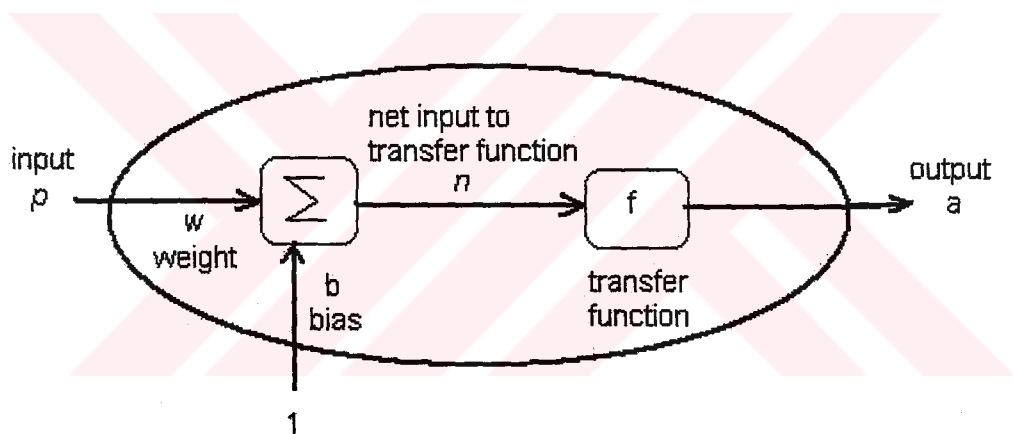


Figure 5.2 Basic elements of a neuron and data flow scheme

The basic relationship between input and output of a neuron can be written as

$$a = f(wp + b) \tag{5.1}$$

These parameters and variables may be vectors or matrices. More than one input to a neuron can be entered. Note that w and b are both adjustable scalar parameters of neuron. The adjustment of these parameters gains network learning capability.

Each connection between neurons is assigned a "weight". These weights are adjusted during training until the ANN learns to make a decision depending on the inputs and/or outputs. In this thesis, the number of neurons totally used is ten, which is in two layers.

5.1.2 Activation Functions

The activation function can take any form in terms of the objectives of the neural network. It must be singular valued function. It is also called transfer function. The following activation functions are commonly used: hard-limit, linear, logarithmic-sigmoid, and tangent-sigmoid. They are shown in Figure 5.3.

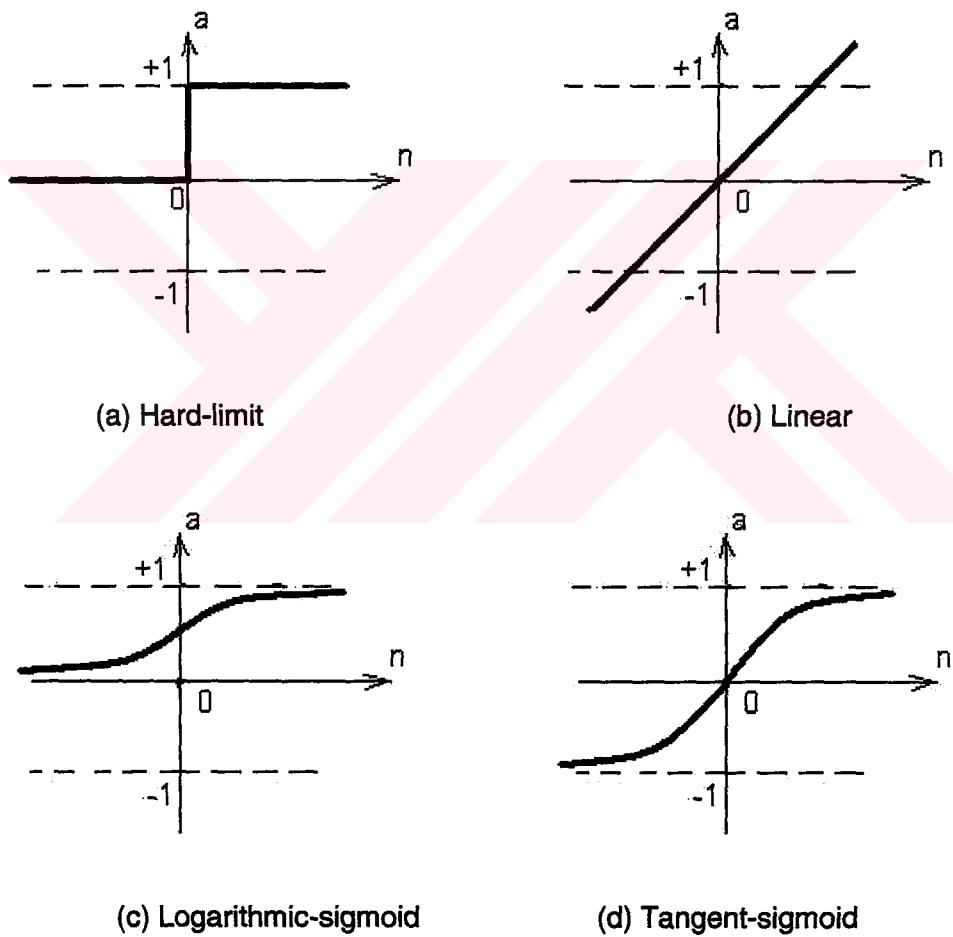


Figure 5.3 Common activation functions.

5.1.3 Layers

The combination of two or more neurons forms a layer. NN could contain one or more such layers. A single layer of neurons can represent a very simple problem. However, single-layer networks cannot solve certain problems.

In conventional multilayer feed-forward networks, each network contains an input layer, several hidden layers, and an output layer. The input layer receives sampled data. The hidden layers then perform decision-making computations, and the output layer presents the characterization.

The input and output layers have one neuron for each input or output. The layers between these are called hidden layers. They have as many neurons as the complexity of the data requires, in as many layers as required, but generally fewer than three layers. In a fully connected NN, there are also direct weighted connections between the input and output neurons.

1 hidden layer with 10 sigmoidal neurons and 1 output layer with 5 linear neurons are used in this study.

5.1.4 Inputs and Outputs

Inputs and outputs may be vectors or matrices. In fact, two basic types of inputs and outputs:

- 1- Concurrent inputs and outputs that occur at the same time. There is no particular time sequence, and the order is not important.
- 2- Sequential inputs and outputs. The order is important.

In this thesis, concurrent inputs and outputs are used in the training stage. In the application stage, the states sequentially are added to a concurrent input vector. For each concurrent input vector, one output sequential vector exists. Inputs are 9 states, and outputs are 5 ice parameters.

5.2 The Architectures of NNs

In terms of the model complexity and purposes, several types of NN architectures exist. They may be listed as follows:

- 1- Perceptrons,
- 2- Linear networks,
- 3- Fully or partially connected multilayer networks,
- 4- Feed forward networks,
- 5- Recurrent networks

The list may be extended by adding types of networks combining above networks.

Perceptrons are the networks which use target vectors corresponding input vectors. They use hard-limit transfer functions in neurons and a special training algorithm, which is called the perceptron learning rule. Perceptrons are not used in this thesis for icing detection or identification. However, it can be used in decision making for suitable controller selection, and providing icing signal by categorizing the icing parameters. Perceptrons may be used effectively on icing detection rather than identification providing enough training data is collected from real flights. These subjects are out of this work for now.

The linear networks are similar to the perceptron, but their transfer function is linear rather than hard limiting. This allows their outputs to take on any value. Linear networks, like the perceptrons, can only solve linearly separable problems. They may learn only linear relationships between input and output vectors. Thus, they cannot find solutions to some problems.

If the relationship between inputs and targets is not linear or a linear approximation, backpropagation may be a good alternative. Pure linear networks are not used in this thesis. Neurons in the output layer are selected linear only because of the nature of the problem. It means that true values of parameters are desired at the end of final solution. This type of networks may have been useful if the relationship between icing variables and aircraft states is linear or so assumed.

5.3 Learning and Training

A neural network is trained to perform a particular function by adjusting the values of the connection weights between neurons. Adjustment is performed by applying inputs, and by making corrections in terms of the corresponding targets.

Each pass through the input vectors is called an epoch. After each epoch is completed, errors between outputs and targets are compared. If desired error is maintained, then training stops. Otherwise, another epoch is performed. This correction is done on the weights and biases as follows

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \Delta\mathbf{W}(k+1, k) \quad (5.2)$$

$$\mathbf{b}(k+1) = \mathbf{b}(k) + \Delta\mathbf{b}(k+1, k) \quad (5.3)$$

where $\mathbf{W}(k)$ and $\mathbf{b}(k)$ are the weight and bias matrices at the epoch k . The increments $\Delta\mathbf{W}(k+1, k)$ and $\Delta\mathbf{b}(k+1, k)$ are calculated according to several learning rules. In the representations from this point, it is assumed that $\Delta\mathbf{b}(k+1, k)$ is expressed in $\Delta\mathbf{W}(k+1, k)$ by small modification. Therefore, we will not state biases separately. This increment is also called weight update. This may be written in a more compact form as

$$\Delta\mathbf{W}(k+1, k) = \alpha_1(k) \mathbf{x}(k) \mathbf{p}^T(k) \quad (5.4)$$

where $\alpha_1(k)$, $\mathbf{x}(k)$ and $\mathbf{p}(k)$ are the learning rate, the search direction and the vector of the inputs. In some algorithms, $\mathbf{p}(k)$ may not be used. There are two different styles of training: incremental, also called as on-line or adaptive training, and batch training. In incremental training the weights and biases of the network are updated each time an input is presented to the network. In batch training the weights and biases are only updated after all of the inputs are presented. Batching of concurrent inputs is computationally more efficient and may be what is desired in any case.

The meanings of “training” and “learning” are not the same. Training is the procedure of the network learning, but learning is the end result of that procedure. Training seems to be an external procedure, but learning an internal activity [20]. Learning may be also classified in two different groups: supervised and unsupervised. In supervised learning, there are input/target pairs to train a network. Unsupervised learning is commonly used to identify groups of data. Hebb Learning Rule is one of the unsupervised learning rules. The supervised learning rule has a teacher. The perceptron learning rule, the LMS algorithm, and backpropagation algorithm are examples of supervised training, in which the learning rule is provided with a set of examples of desired network behavior.

Perceptron learning rule is only used on perceptrons, and the update increment for each epoch may be expressed as

$$\Delta \mathbf{W} = \mathbf{e} \mathbf{p}^T \quad (5.5)$$

$$\mathbf{e} = \mathbf{t} - \mathbf{a} \quad (5.6)$$

where $\mathbf{e}$ is the network error, $\mathbf{t}$ is the target vector of outputs, $\mathbf{a}$ is the vector of network outputs, and $\mathbf{p}$ is the vector or matrix of inputs. Other modified learning algorithms are also available in the literature [54].

The LMS algorithm is based on an approximate steepest descent procedure. It is also called Widrow-Hoff Learning Rule, or Delta Rule. It adjusts the weights and biases of the network so as to minimize the mean square error (MSE), E , given as

$$E(k) = \frac{1}{2} \sum_{i=1}^{N_o} (\mathbf{t}_i(k) - \mathbf{a}_i(k))^2 \quad (5.7)$$

where N_o is the number of network outputs or targets. E is also called performance index. Since $E(k)$ is a quadratic function, it either has one global minimum, a weak minimum or no minimum, depending on the characteristics of the input vectors. Specifically, the characteristics of the input vectors determine whether or not a unique solution exists. The LMS algorithm is commonly used in a single layer feed forward neural networks. Weight update is performed as follow

$$\Delta w_{ij}(k+1, k) = -\alpha_i \frac{\partial E(k)}{\partial w_{ij}(k)} \quad (5.8)$$

where w_{ij} is the element of matrix $\mathbf{W}$. Many training algorithms requires the use of above steepest descent gradient. We can represent it as

$$\mathbf{g}_{ij}(k) = -\frac{\partial E(k)}{\partial w_{ij}(k)} \quad (5.9)$$

The matrix having the elements $\mathbf{g}_{ij}$ is denoted as $\mathbf{g}$.

The backpropagation algorithm is a first order optimization algorithm for the supervised learning in the multi layered feed forward neural networks, which has been successfully used in the system identification in spite of its slow convergence

rate. Backpropagation consists of a gradient-based approach that runs training sets through the neural network and adjusts various weights and biases until the correct output is given for all training sets. Using back propagation algorithms for some problems may lead to slow rates of convergence and many local minima. The presence of local minima may cause the algorithm to stop weight adjustment before the desired performance is reached. The Levenberg-Marquardt optimization method is of the second order and faster than standard backpropagation. In our work, we used this type of training algorithm. Therefore, more details are given in Section 5.5.

There are generally four steps in the training process:

- 1- Collecting the training data,
- 2- Creating the network architecture,
- 3- Training the network,
- 4- Simulating the network response to new inputs

It is very difficult to know which training algorithm will be the fastest for a given problem. It will depend on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression). In this section we perform a number of benchmark comparisons of the various training algorithms.

5.4 Backpropagation

Backpropagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Backpropagation can train the networks with differentiable transfer functions to perform function approximation, pattern association, and pattern classification. This is commonly used in the multilayer networks. The term backpropagation refers to the process by which derivatives of network error, with respect to network weights and biases, can be computed. This process can be used with a number of different optimization strategies.

Many training algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance. The gradient is determined by the technique of backpropagation, which involves performing computations

backwards through the network. The backpropagation computation is derived using the chain rule of calculus. In the basic backpropagation training algorithm, weights are moved in the direction of the negative gradient. However, there are many variations of the backpropagation algorithm. The simplest implementation of backpropagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly - the negative of the gradient. As seen in (5.8), it is important for backpropagation to be able to calculate the derivatives of any transfer functions used.

Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods.

Properly trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

Standard backpropagation technique is based on batch gradient descent method. In this method, a learning rate is chosen, and remains constant throughout training. The performance of the algorithm is very sensitive to the proper setting of the learning rate. The larger the learning rate, the bigger the step. If the learning rate is made too large, the algorithm becomes unstable. If the learning rate is set too small, the algorithm takes a long time to converge. This type of backpropagation algorithms is often too slow for practical problems. Therefore, faster backpropagation algorithms are offered, which can be categorized in two main groups. The first category uses heuristic techniques, which were developed from an analysis of the performance of the standard steepest descent algorithm. The second category of fast algorithms uses standard numerical optimization techniques.

As a numerical optimization technique, Newton's method is basically expressed as

$$\mathbf{W}(k+1) = \mathbf{W}(k) - \mathbf{H}^{-1}(k)\mathbf{g}(k) \quad (5.9)$$

where $H(k)$ is the Hessian matrix as follow

$$H(k) = \frac{\partial^2 E(k)}{\partial W^2(k-1)} \quad (5.10)$$

Newton's method often converges faster than many other methods. Unfortunately, it is complex and expensive to compute the Hessian matrix for most neural networks.

5.5 Levenberg-Marquardt Algorithm

Like the quasi-Newton methods, the Levenberg-Marquardt (LM) algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. Jacobian matrix at each of iterations may be expressed as

$$J(k) = \begin{bmatrix} \frac{\partial E(k)}{\partial w_{11}(k-1)} & \frac{\partial E(k)}{\partial w_{12}(k-1)} & \Lambda & \frac{\partial E(k)}{\partial w_{1r}(k-1)} \\ \frac{\partial E(k)}{\partial w_{21}(k-1)} & \frac{\partial E(k)}{\partial w_{22}(k-1)} & \Lambda & \frac{\partial E(k)}{\partial w_{2r}(k-1)} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial E(k)}{\partial w_{p1}(k-1)} & \frac{\partial E(k)}{\partial w_{p2}(k-1)} & \Lambda & \frac{\partial E(k)}{\partial w_{pr}(k-1)} \end{bmatrix} \quad (5.11)$$

where w_{ij} is the elements of the weight matrix, p is the number of arriving points to the connections, and r is the number of departing points from the connections. In our application, as shown in Figure 5.5, $p = 5+5 = 10$ and $r = 9+5 = 14$. (5.16) may be written in a compact form as

$$J(k) = \frac{\partial E(k)}{\partial W(k-1)} \quad (5.12)$$

The Gauss-Newton (GN) method approximates the Hessian matrix as [54]

$$H(k) = J^T(k) J(k) \quad (5.13)$$

However, this method may have problems if $H(k)$ is close to or is singular. LM method overcomes this difficulty by including an additional term μ to the above GN approximation of H as given

$$\mathbf{H}(k) = \mathbf{J}^T(k) \mathbf{J}(k) + \mu \mathbf{I} \quad (5.14)$$

where μ is a small positive value and $\mathbf{I}$ is the identity matrix. Using (5.19), the LM weight update equation becomes

$$\mathbf{W}(k+1) = \mathbf{W}(k) - [\mathbf{J}^T(k) \mathbf{J}(k) + \mu \mathbf{I}]^{-1} \mathbf{J}^T(k) \mathbf{e}(k) \quad (5.15)$$

When the scalar μ is zero, it is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm. This algorithm appears to be the fastest method for training moderate-sized feedforward neural networks (up to several hundred weights). The main drawback of the Levenberg-Marquardt algorithm is that it requires the storage of some matrices that can be quite large for certain problems.

5.6 Comparison of BP Algorithms:

The selection of a suitable training method for a certain NN problem mainly depends on the objectives (function approximation, pattern recognition, etc), architecture of NN (complex, basic, feedforward, etc), and desired training performance (error goal, learning rate, training time, etc). The powerful and weak features of the various BP algorithms are given in Table 5.1. These features are obtained from the simulations and the literature [66-72]. The underlying icing identification problem is classified as a function approximation for the relationship between flight data and certain icing parameters. Since the variations of icing parameters during flight are small NN process should produce accurate results as much as possible. In addition a quick response is needed against severe icing. Therefore, LM algorithm is considered as the most suitable training method for this study.

Table 5.1 Comparison of BP Algorithms

Algorithm	Good	Weak
LM	-fastest on function approximation problems, -small and medium size networks, a few hundred weights, -meet very accurate training requirement,	-too much weights decrease the advantages, -much storage requirements, -poor on pattern recognition, -increasing execution time in reduced memory method
RBP	-fastest on pattern recognition problems, -better memory requirement	-poor on function approximation problems -decreasing performance in case decreasing error goal selected
SCG	-as fast as LM on function approximation, and as fast as RBP on pattern recognition, -a wide variety of applications, -modest memory requirement	-decreasing performance in case decreasing error goal selected, but not so much as in the others
BFGS	-performance similar to LM, -better memory requirement, -better in small size networks	-computation increasing geometrically with the size of network
VLR	-better memory requirement	-slower than the others
GD	-easy to perform	-constant learning rate -very slow -stability in large learning rates
GDM	-higher learning rate, -better in incremental training, -faster than GD	-slow

5.7 Overcoming Difficulties on NN Training

In multilayer networks, a learning rate that is too large leads to unstable learning. Conversely, a learning rate that is too small results in long training times. Unlike linear networks, there is no easy way of picking a good learning rate for nonlinear multilayer networks.

One of the problems associated with NN is the fact that two networks starting with two different sets of weights may arrive at two different sets of final weights after training. This is a natural consequence of a nonlinear mapping in which there may be more than one relationship between the input and the output. The error surface of a nonlinear network is more complex than the error surface of a linear network. The problem is that nonlinear transfer functions in multilayer networks introduce many local minima in the error surface. As gradient descent is performed on the error surface it is possible for the network solution to become trapped in one of these local minima. This may happen depending on the initial starting conditions. Settling in a local minimum may be good or bad depending on how close the local minimum is to the global minimum and how low an error is required. In any case, be cautioned that although a multilayer backpropagation network with enough neurons can implement just about any function, backpropagation will not always find the correct weights for the optimum solution. You may want to reinitialize the network and retrain several times to guarantee that you have the best solution.

Networks are also sensitive to the number of neurons in their hidden layers. Too few neurons can lead to **underfitting**. Too many neurons can contribute to **overfitting**, in which all training points are well fit, but the fitting curve takes wild oscillations between these points. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations.

One method for improving network generalization is to use a network that is just large enough to provide an adequate fit. The larger a network you use, the more complex the functions the network can create. If we use a small enough network, it will not have enough power to overfit the data. Unfortunately, it is difficult to know beforehand how large a network should be for a specific application.

There are two other methods for improving generalization: **regularization** and **early stopping**. If the number of parameters in the network is much smaller than the total number of points in the training set, then there is little or no chance of overfitting. **Regularization** involves modifying the performance function, which is normally chosen to be the sum of squares of the network errors on the training set. The typical performance function (5.7) is used for training feedforward neural networks. It is possible to improve generalization by modifying performance function. Using this modification will cause the network to have smaller weights and biases, and this will force the network response to be smoother and less likely to overfit.

Another method for improving generalization is called **early stopping**. In this technique the available data are divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on the validation set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The test set error is not used during the training, but it is used to compare different models. It is also useful to plot the test set error during the training process. If the error in the test set reaches a minimum at a significantly different iteration number than the validation set error, this may indicate a poor division of the data set. With early stopping, the choice of the validation set is also important. The validation set should be representative of all points in the training set.

With both regularization and early stopping, it is a good idea to train the network starting from several different initial conditions. It is possible for either method to fail in certain circumstances. By testing several different initial conditions, you can verify robust network performance. Based on the literature, Bayesian regularization generally provides better generalization performance than early stopping, when training function approximation networks. This is because Bayesian regularization does not require that a validation data set be separated out of the training data set. It uses all of the data. This advantage is especially noticeable when the size of the data set is small.

5.8 Preprocessing and Postprocessing of NN Data

Neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets. Before training, it is often useful to scale the inputs and targets so that they always fall within a specified range.

Another approach for scaling network inputs and targets is to normalize the mean and standard deviation of the training set. For instance, they may have zero mean and unity standard deviation. After the network has been trained, these vectors should be used to transform any future inputs that are applied to the network. They effectively become a part of the network, just like the network weights and biases.

In some situations, the dimension of the input vector is large, but the components of the vectors are highly correlated (redundant). It is useful in this situation to reduce the dimension of the input vectors. An effective procedure for performing this operation is principal component analysis. This technique has three effects: it orthogonalizes the components of the input vectors (so that they are uncorrelated with each other); it orders the resulting orthogonal components (principal components) so that those with the largest variation come first; and it eliminates those components that contribute the least to the variation in the data set.

5.9 System Identification

System identification seeks to derive the mathematical representation of the system behavior based on observed input/output data. It provides a relation between some sets of the observed input and output data of the process. Although, system identification not always results in exactly accurate models, a satisfactory model can be obtained. For system identification, certain knowledge about the system and a practical experiment with the system's entire range of operation will be required. Identification may become off-line with finite input-output data sets or on-line with a continuous monitoring of input-output data. In the system identification, firstly input/output data examples are collected. Model structure is chosen, then model parameters are estimated, finally the validation of the identified model is examined.

Parametric Identification Methods are techniques to estimate parameters in given model structures. Basically it is a matter of finding (by numerical search) those numerical values of the parameters that give the best agreement between the

model's (simulated or predicted) output and the measured one. **Nonparametric Identification Methods** are techniques to estimate model behavior without necessarily using a given parameterized model set. Typical nonparametric methods include Correlation analysis, which estimates a system's impulse response, and Spectral analysis, which estimates a system's frequency response.

The identification process amounts to repeatedly selecting a model structure, computing the best model in the structure, and evaluating this model's properties to see if they are satisfactory. The flow chart of the steps is shown in Figure 5.4.

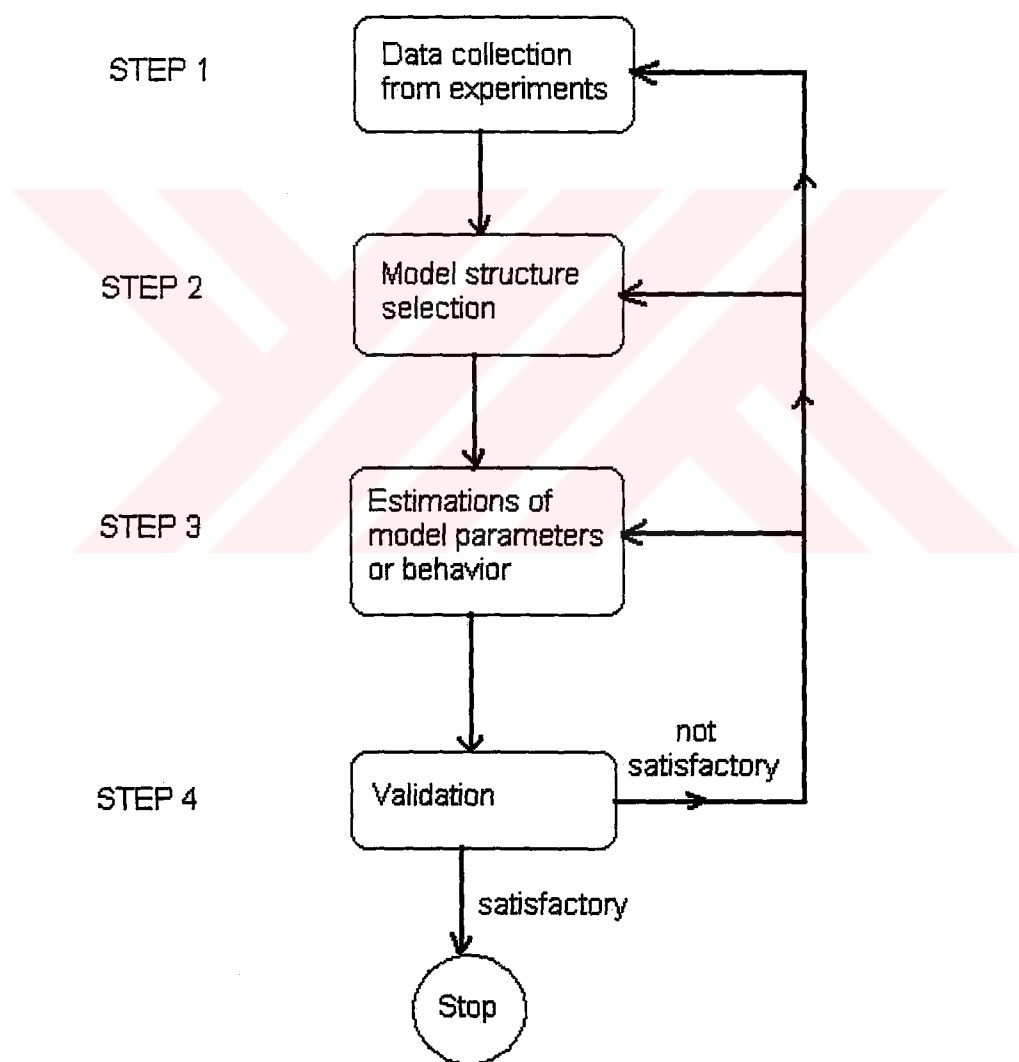


Figure 5.4 Flow chart of system identification process

In the first step, an experiment is designed, and input-output data sets are collected from the process to be identified. The obtained data are examined, and useful portions of the original data are selected. If necessary filtering may be applied to add various important frequencies ranges. Some of data are selected for validation purposes. In the second step a model structure is selected and constructed. It may be nonparametric, or parametric such as in a state-space model, in terms of the identification purposes. In general, correlation analysis, ARX model with a delay, and state space model are considered together for comparison by looking at the agreements between them. Linear or nonlinear model and its order are selected. Some nonlinearities may be entered in terms of the observed data estimation results, and physical insights. In step 3, the best model in the model structure is computed according to the input-output data and a given criterion of fit by the several methods such as least squared error analysis, correlation analysis, and spectral analysis. If there is a feedback from the output to the input, due to some regulators, then spectral and correlation analyses estimates are not reliable, and measured and estimated outputs are compared.

Finally, in step 4, the obtained model's properties are examined. If the model is good enough, then stop; otherwise go back to step 1 to work on the further input-output data, or step 2 to try another model set, or possibly step 3 to try other estimation methods. If none of validation tests is reasonable well, there may be many reasons. The system may have some quite complicated nonlinearities, which cannot be realized on physical grounds. In such cases, nonlinear black box models could be a solution. As the subject of this thesis, aircraft icing is similar to this type of problems.

In this thesis, data have been collected by simulating two aircraft with artificial ice represented by five parameters. Parametric nonlinear model of aircraft flight dynamics are considered in this stage. In step 2, black box NN model of iced aircraft is selected. Several architectures are simulated. The inputs in the training set are applied to the trained network to estimate parameters. The estimations of NN are compared to measurements, which have been already estimated by EKF.

5.10 Neural Network Icing Identification Based on KF

System identification by NNs is basically efficient for the black-box models, which have several unknown dynamic parameters. As stated in Chapter 3, the

experimental results show that icing may affect certain aircraft dynamics. Therefore, NN approach to icing identification is considered as an efficient method.

Neural network icing detection and classification was applied to an experimental aircraft. Separate neural networks assigned to each parameter were used for detection and classification in order to make the implementation more efficient [13]. A method of using NN and Kohonen Self-Organizing Maps (SOMs) to detect airframe ice was proposed and investigated. It was hypothesized that NN systems trained on the aircraft dynamics in real time would converge to different connection weights for iced and clean aircraft. Kohonen SOMs were proposed for detecting these differences automatically and therefore recognizing airframe ice accretion. This approach is shown to be capable of acting in an advisory role for the flight crew. NN models of the system state variables were developed using a back propagation algorithm and were shown to be in good agreement with the flight test data. Therefore, it was concluded that the NN effectively learned the aircraft dynamics for the purpose of this research. These NN models were compared to each other to determine if models representing an iced aircraft could be differentiated from those representing a clean aircraft [14].

A neural network system was developed to estimate stability and control derivatives by an H -infinity parameter identification algorithm during a longitudinal maneuver in the *absence of pilot input* when poor excitation of the flight dynamics limits the accuracy of parameter estimates. In order to improve this accuracy, the neural network integrated steady-state characterization and hinge moment sensing with parameter estimates. The neural network provided icing characterization in terms of an estimate of an icing severity factor [18].

As illustrated in Figure 5.5, in this study, since there are nine states measured and five parameters to be estimated, a neural network structure has nine inputs and five outputs. The selection of five neurons in one hidden layer is found suitable for this application in result of several simulations. For this selection, training or identification time and performance goal, the magnitude of control surface deflections, aircraft flight envelope are taken into considerations. There are these activation functions, respectively: logarithmic-sigmoidal and linear. This neural network is trained with the estimates of EKF as shown in Figure 5.6. For training method the Levenberg-Marquardt Backpropagation algorithm is used to maintain second-order training speed without having to compute the Hessian matrix.

The trained NN model will be used for icing parameters' estimation as shown in Figure 5.7. The new controller gain will be adjusted according to these estimated parameters.

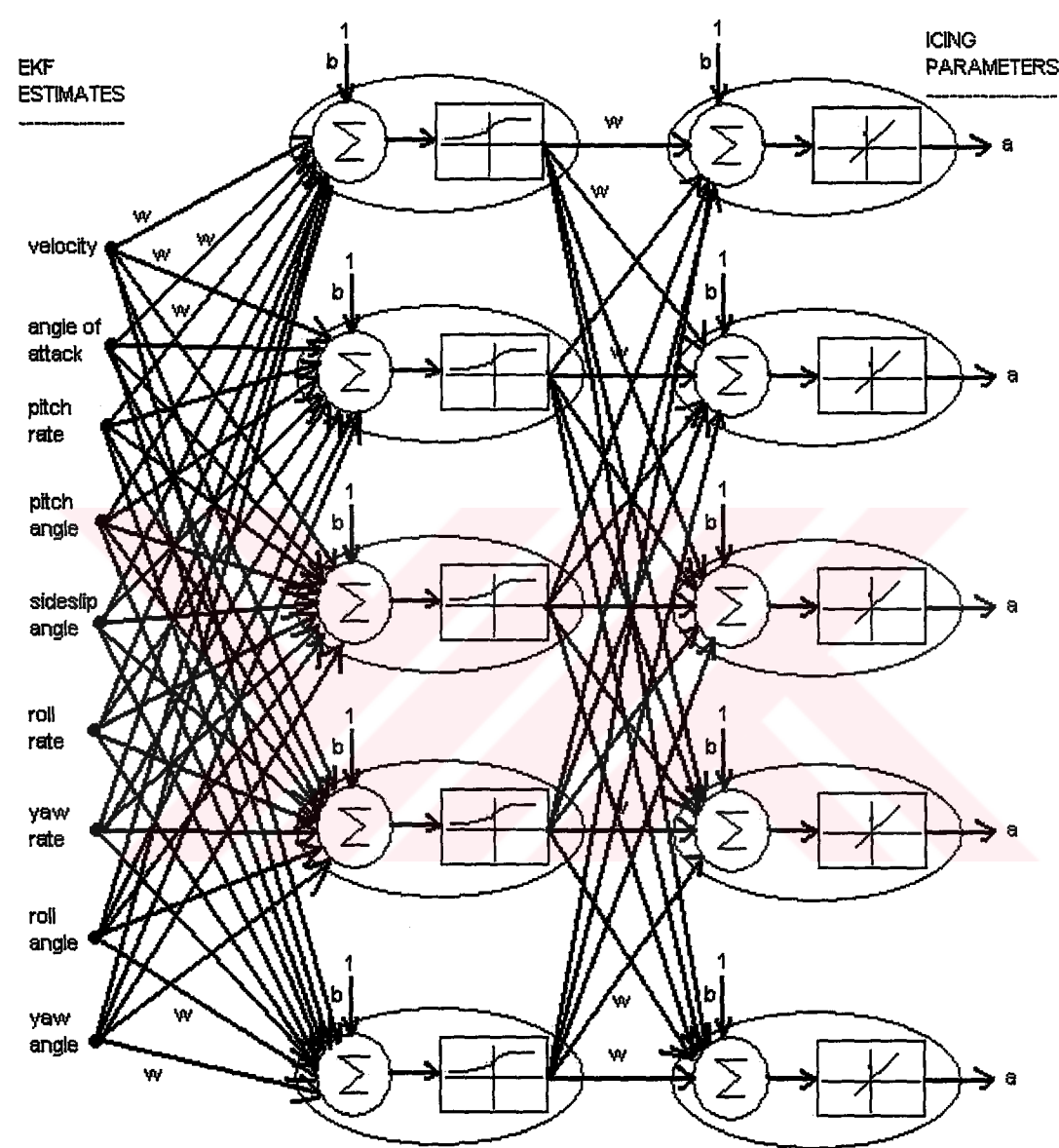


Figure 5.5 Structure of neural network for icing identification

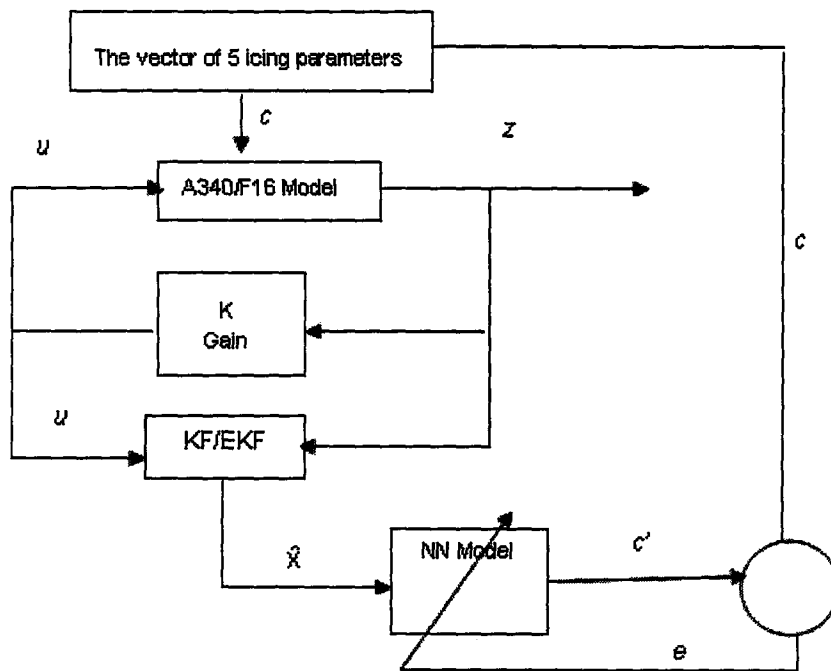


Figure 5.6 The scheme of training process of NN icing model

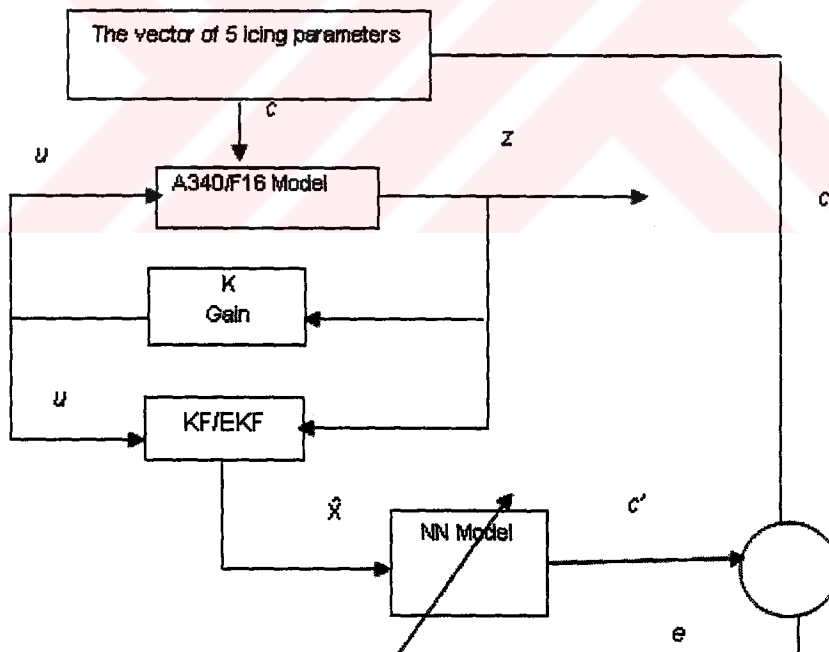


Figure 5.7 The process of icing parameter estimation of the training NN model for control reconfiguration purposes

6. ICING TOLERANT FLIGHT CONTROL SYSTEM DESIGN

Reliability of flight control systems must be maintained in all flight conditions. The objective of this work is to improve the reliability of the existing flight control systems in severe icing conditions. In fact, there are two main approaches to provide the reliability in a system [73]: Designing very reliable systems for many failures in production, and/or tolerating aircraft in case of failures' presence. Reliability in a system requires redundancy to bypass a failure so that the system mission would be continued despite of the error. Our objective is to design a flight control system against icing by using redundancy when it occurs. Fault diagnosis and reconfigurable control has recently become the useful tool on the aircraft control applications due to the necessity of more reliable and safe flight.

As two new approaches, inflight icing detection based on EKF and inflight icing identification based on NN have been explained in Chapter 4 and Chapter 5, respectively. These two techniques together with existing sensors will provide a new icing monitoring and automatic protection system. We will call it as "Icing Tolerant Flight Control System" or shortly ITFCS. Figure 6.1 shows the block diagram of ITFCS.

In Chapter 7, the results of the applications to F16 and A340 aircraft are illustrated with several figures, and discussed the advantages in Chapter 8.

6.1. Automatic Flight Control System (AFCS)

For ensuring a successful flight within the throughout flight regimes including take off, climb, cruise, maneuvering, descending, landing, all modern commercial and military aircraft are controlled by Automatic Flight Control System (AFCS). AFCS employ multi-loop feedback to achieve several benefits such as better response speed, compensating some unwanted disturbances and accuracy of commands. Adaptive control concept was considered for adapting AFCS to various flight conditions during entire flight regime. After some fatal accidents occurred due to the failed control elements in later 1970s, the concept of Self Repairing Flight Control System (SRFCS) was proposed in early 1980s. This type of systems was employed in some modern aircraft. It is also called Fault Tolerant Flight Control system (FTFCS).

6.2. Fault Tolerant Flight Control System (FTFCS)

A SRFCS or FTFCS mainly detect and isolates failed or damaged elements in the flight control system, and then recovers the system to continue flight [74]. These systems can be divided into two main steps:

- 1- Fault Detection and Isolation (FDI) scheme, composing of monitoring, detecting and diagnosing,
- 2- Restructurable or Reconfigurable control scheme, altering the control law to the plant

A FTFCS use redundancy techniques. They are basically classified in two groups: Hardware redundancy (extra components, sensors, etc.), and analytical redundancy (logical approach), which is also called software redundancy or coding redundancy. Redundant hardware structures also fall into two basic categories, i.e. static and dynamic redundancy. Static redundancy is also known as fault masking, which involves masking and hiding the fault by reconfiguring the system around the fault with the additional components or circuits. Dynamic redundancy requires additional parts to serve as spares within the system [75].

A FTFCS can be used for the failures in all aircraft systems, which may be mainly classified as actuators, airframe, and instrumentation. If icing is considered as a failure, it may be in the second category. Infact, aircraft icing can affect all of these subsystems in terms of the icing location. Icing can obstruct actuators to move, cause mismeasuring of instrumentational probes such as pitot/static tubes, and degrade aerodynamical smoothness of airframe. In this thesis, we have taken airframe icing only. We have showed the effect of airframe icing in flight control, and proposed a method for icing detection given in Chapter 4, a method for icing identification given in Chapter 5, and a method for control reconfiguration which will be explained in this chapter.

Proposed solutions to fault tolerant control systems can be considered in two categories:

- 1- Passive: The impaired aircraft continues to operate with the same controller. The effectiveness of the scheme depends upon the original control law's possessing a considerable degree of robustness. Adaptive control and robust control may be classified in this group.
- 2- Active: This involves either a on-line re-design of the control law after failure has occurred and has been detected, or the selection of a new pre-computed control law. This consists of two basic sub-systems: 1- FDI or system identification, 2- Control reconfiguration or restructurable control

From this perspective, ITFCS is classified as active method. We will briefly explain basic issues of FTFCS in the following.

6.2.1 Fault detection and isolation (FDI)

FDI methods may be categorized as model-free and model-based as explained in Chapter 3. We will apply a model-based approach to icing detection and isolation problem by combining model-free methods, since the existing model-free methods are not so reliable. However, the existing model free icing detection methods using multiple sensors can improve the detection performance. Model-based methods are implemented in two stages: residual generation and decision-making. Research on FDI has started in the early 1970s [76-77]. Several modern techniques were applied to FDI [46-47,75]. The analytical redundancy in FDI was employed with state estimation using filter/observer techniques [48], parameter estimation using recursive least squares estimators [74], adaptive filtering [75], probabilistic decision theory [62], possibilistic decision theory [76], etc. In fact, state estimation is mainly obtained by observers. Common observers are the Luenberger observer for determining process and the Kalman filter for stochastic process, which is considered in this work.

FDI consists of monitors, detectors and diagnosticians. Monitors continuously evaluate the system status, detectors differentiate the normal and abnormal operation of the system, and then diagnosticians isolate the failed element of the system. In the literature, the following approaches in monitoring have been reported:

- 1- The parity space approach,
- 2- Parameter identification approach,
- 3- The fault detection filter,
- 4- Dedicated observer approach,
- 5- KF Innovation-based approach

We will use KF innovation-based approach in this thesis. However, parameter identification approach based on neural networks may be combined in future studies if the relationship between icing and system model parameters is well known.

In the literature, the known model based detectors can be given as: Hypothesis testing, Neymann-Pearson detector, tests for difference in residual mean, chi-square test for significance, variance ratio test, trend analysis, Page-Hinkley stopping rule, the Maximum Likelihood (ML) detector, the Sequential Probability Ratio test (SPRT), and the

Generalized Likelihood Ratio (GLR) test [47-48]. We will use the combination of hypothesis testing, tests for difference in residual mean and chi-square test in this thesis. The hypotheses are statements of the possible decisions. Two probabilistic hypotheses are defined based on chi-square distribution confidence reliability, which are the presence of icing and no icing.

Diagnosticians determine the location, size and cause of the fault by using damage assessment methods. In general hypotheses are generated according to possible failure modes, and then fault tree analysis is performed. In this thesis, we assume the icing location is known, it is at the leading edges of wings. However, we will improve the study by assuming that icing may occur at tail, fuselage or only one wing, etc.

6.2.2 Reconfigurable Control

Existing AFCS uses the several controllers in terms of the flight stages during entire flight envelope. Such controllers are robust to external disturbances and failures up to certain amounts. The investigations on many accidents have showed that the reconfiguration of the control law would have survived the aircraft. The simulations in Chapter 7 also show the reconfigurable control in case of severe icing can protect the aircraft from the instability, perhaps any accident.

In an AFCS, control reconfiguration can be made by gain scheduling, control structure modification, real-time redesign, and real-time search techniques. Gain scheduling requires that the various gains in the control law must be varied according to the variation in the flight conditions such as aircraft velocity and altitude [36]. In control structure modification, all of the coefficients or time constants of the control filters are continuously scheduled and not merely some of the gains. Control filters are designed a priori corresponding to each failure mode. The coefficients of these control filters are all stored in the flight control computer's memory. Real-time search techniques use real-time search and optimization for redesign of the control system. The real-time redesign is based on the complete online redesign of the control law and control filters depending on the identified models. Adaptive control may be classified in this group as example of stochastic process. Our reconfiguration of control seems to be an adaptive control [78]. In deterministic approach, the system parameters are available in the form of mean values and covariances.

In this study, LQG control algorithm is applied both to F16 and A340 aircraft. In case of icing, the reconfigurable control is used such that the gain of LQG is recalculated from NN identification method as explained in Chapter 5.

6.3. Icing Tolerant Flight Control System (ITFCS)

Aircraft accident investigations showed that in many cases aircraft could have been survived in non-standard set of flight conditions if proper control procedure was traced. This has led to the use of modern fault tolerant control systems. Icing formation on airframe may be considered as a variety of fault disrupting the original aerodynamic shape of wing and hence air flow around. From this point of view, airframe icing can be regarded as a structural fault detection and identification problem. KF, NN, fuzzy logic and hybrid systems have been known useful means for the solution of this kind of problems in aerospace applications.

The performance of the proposed ITFCS may be measured by the promptness, sensitivity, false decisions rate, missed icing detections, incorrect icing detections, computational burden, robustness and reliable algorithms. Robustness in ITFCS means invariance of the system property defined on a set or region under a class of finite icing parameter changes. It can be also defined as insensitivity to small parametric changes, unmodeled nonlinearities or uncertain dynamics, disturbances or faults other than icing.

The proposed ITFCS have the following objectives:

- 1- Detection of airframe inflight icing without additional physical sensors,
- 2- Monitoring icing severity,
- 3- Advisory role for pilot,
- 4- Providing automatic flight control system reconfiguration

The components and flow chart of the new ITFCS are illustrated in Figure 6.1. Nominal AFCS of the application aircraft is represented with solid lines in the figure. The components of the ITFCS are explained below.

6.3.1 KF of ITFCS

The KF of ITFCS takes inputs and outputs of the existing AFCS of aircraft as its own inputs. Inputs of the AFCS are control surfaces deflections, and its outputs are the measurable variables such as angle of attack, speed, acceleration. These variables may not consist of entire states of the aircraft dynamic motion. There are process disturbances, w , and measurement noises, v . They are modeled as Gaussian white noises. The KF produces estimates of the states including measurable and immeasurable ones.

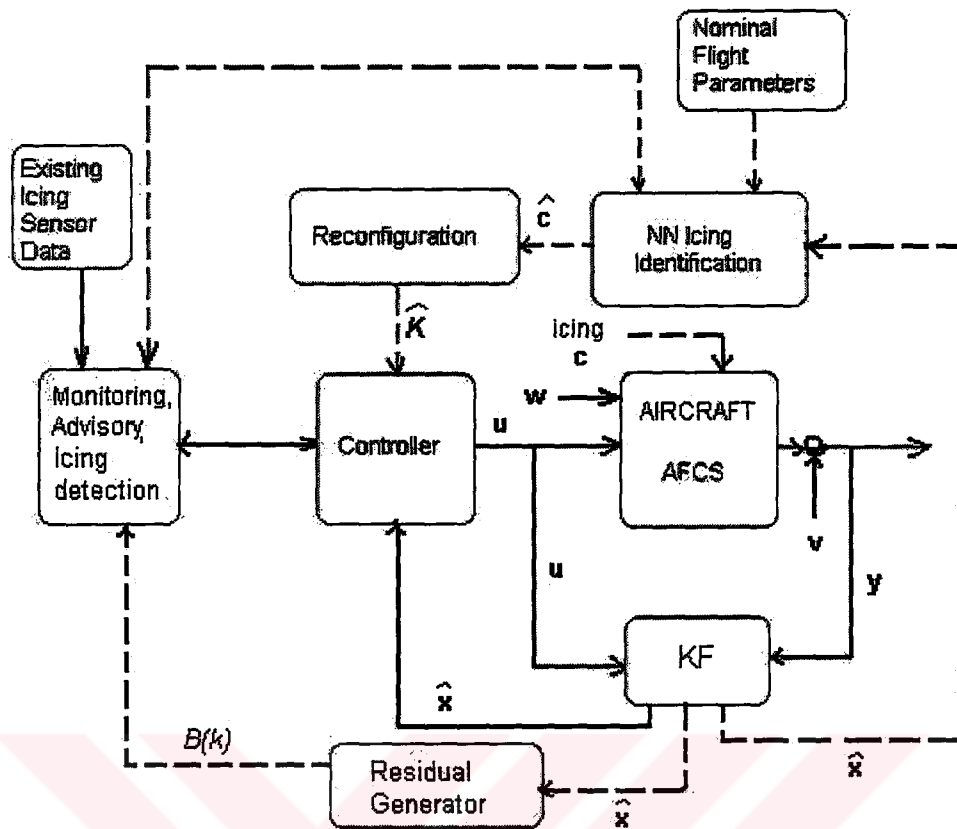


Figure 6.1: The components and flow chart of the Icing Tolerant Flight Control System (ITFCS)

6.3.2 Residual generator

Residual generator block in Figure 6.1 consists of collecting innovation sequence of EKF. This information is sent to the block of monitoring, advisory, and icing detection.

6.3.3 Icing detection, monitoring, and advisory

A threshold is selected in terms of confidence reliability of chi-square distribution of the normalized innovation sequence. This block compares residuals according to the selected threshold value. If residuals go beyond the threshold, and if icing sensors inform any icing occurrence, the decision is made on icing presence, and then NN icing identification block is informed for reconfiguration. This block can be also defined as a decision making.

6.3.4 Nominal flight parameters

Trim values of states, control surface deflections, atmospheric conditions such as air density, altitude and pressure, trim values of stability and control derivatives included in system matrix, **A** and control input matrix, **B**. The nominal values of icing parameters are specified.

6.3.5 NN icing identification

Before NN is used online, off-line training is performed according to existing flight conditions. From look-up tables, suitable parameters of the flight equations of the aircraft are taken, and artificial icing is entered as modified parameters to NN for training. After the required performance goal is met, the trained NN takes on-line inputs of EKF state estimates in order to find the icing parameters. These parameters can be also used monitoring the system.

6.3.6 Reconfiguration

The icing parameters found in NN icing identification stage are used for reconfiguration. Control gain parameters are recalculated. The block of reconfiguration shown in Figure 6.1 consists of the calculation of the new system matrix, **A'**.

6.3.7 Controller

Nominal or new control deflections are applied to aircraft depending on the information received from the decision making block. As explained in Chapter 2, the LQG regulator was used in the existing AFCS. The advantages of the use of the KF estimates were explained in Chapter 4. Therefore, the nominal controller is written as

$$\mathbf{u}(k) = -\mathbf{K} \hat{\mathbf{x}}(k) \quad (6.1)$$

where **u** is nominal control vector, and **K** is constant gain matrix and not modified by icing effects. On the other hand, the reconfigurable control gain is adjusted at certain steps during control activity from the Riccati equation as follows:

$$\mathbf{u}_r(k) = -\hat{\mathbf{K}} \hat{\mathbf{x}}(k) \quad (6.2)$$

where **u_r** is the new control vector, and **K̂** is calculated from (2.15) at certain steps during control activity from Riccati equation as:

$$\hat{\mathbf{K}} = (\mathbf{B}^T \mathbf{S} \mathbf{B} + \mathbf{R})^{-1} \mathbf{B}^T \mathbf{S} \hat{\mathbf{A}} \quad (6.3)$$

where $\hat{\mathbf{A}}$ is the new system matrix calculated in terms of the identified icing parameters. $\mathbf{B}$, $\mathbf{S}$ and $\mathbf{R}$ are considered as constant at certain flight conditions, and not affected by icing effects. The controller block in ITFCS also includes the new LQG regulator, which calculates the new gain, $\hat{\mathbf{K}}$.



7. SIMULATIONS

The proposed method is applied to iced configurations of F16 and A340 models such that ice is growing during the simulated time frame. EKF is used for Ice detection via innovation sequence approach. Threshold is determined from chi-square distribution. To compensate measurement noise levels during the system identification stage and provide estimations of immeasurable states, all states are also filtered through EKF. In this study, it is assumed that all of nine states (velocity, angle of attack, pitch rate, pitch angle, sideslip angle, roll rate, yaw rate, roll angle, yaw angle) are measurable. Six control surfaces of F16 and five control surfaces of A340 are used in this simulated flight. Model and sensor noises are considered at acceptable levels as in the other works in this area. It is assumed that five parameters affected by icing are linearly changing due to wing leading edge icing. Whilst one of them, related to drag and angle of attack, is increasing, the other four are increasing at the same gradient as an assumption.

48,000 data set including the column vectors of 9 states and 5 ice parameters is produced by simulation of F16 or A340 aircraft model in 0.03 sec time interval. Every one third of the data (16,000 data sets) is taken for training, validation and testing. 16,000 data span 8 minutes. No icing condition is represented in the time between minute 0-1, and increasing ice conditions are represented in the time between minute 1 and 8. Not every case these time frames were used because of computational burden. Batch size for training is chosen such that icing can be severe within that time frame.

As an application in this study, training, validation and test batch is taken between For the batch size of 30 sec, 1000 data sets are obtained by simulating F16 aircraft model. 2000 different data sets are used for validation, and again third group of 2000 data sets are used for testing.

In all of the graphics, subscripts “e”, “12”, “22”, “23”, “32”, and “33” are not written in their exact place for convenience. For instance, “ve” is used instead of “ v_e ”, “a12” is used instead of “ a_{12} ”, and so on.

In the following simulations icing detection and reconfiguration of F16 and A340 aircraft is shown in several figures. Section 7.1 illustrates the change of the icing parameters in clear and iced conditions for both aircraft. Actual states and their estimations by EKF are presented in section 7.2. The figures comparing measured noisy outputs and EKF estimates are also given in this part. The simulation results for icing detection via EKF innovation sequence are given in 7.3. If the structure of control is renewed according to exactly identified icing parameters, new controls and states would be as shown in 7.4 and 7.5, respectively. Training and validation simulations for 30 seconds around threshold of icing detection specified in 7.3 are shown in 7.6 and 7.7, respectively. In section 7.8, an application of reconfiguration via neural network outputs for 10 seconds is given. In this reconfiguration, new controls and states are shown in 7.9 and 7.10, respectively.

7.1 The Simulated Icing Parameters

In Chapter 2, how much icing parameters change in flight was explained, and experimental results have provided us some approximations about these parameters. In the simulations of this study, it is assumed that the icing parameters are changing within 2 minutes as following:

$$(C_{D_{\alpha}})_{iced} = 5 \times (C_{D_{\alpha}})_{nominal} \quad (7.1)$$

$$(C_{L_{\alpha}})_{iced} = 0.5 \times (C_{L_{\alpha}})_{nominal} \quad (7.2)$$

$$(C_{M_{\alpha}})_{iced} = 0.5 \times (C_{M_{\alpha}})_{nominal} \quad (7.3)$$

$$(C_{L_q})_{iced} = 0.7 \times (C_{L_q})_{nominal} \quad (7.4)$$

$$(C_{M_q})_{iced} = 0.5 \times (C_{M_q})_{nominal} \quad (7.5)$$

Figure 7.1 for F16 and Figure 7.2 for A340 shows the history of icing parameters in the simulated time frame, 8 minutes. Icing is assumed to start one minute later than the simulation start. In the figures solid line and dashed lines represent no-icing condition and icing condition, respectively. Dimensions of the parameters are also shown in the figures. Note that parameter “a23” does not have any dimension. Additionally, all parameters during icing are not linearly changing. There are some random white noises around 0.5-1% of the original values.

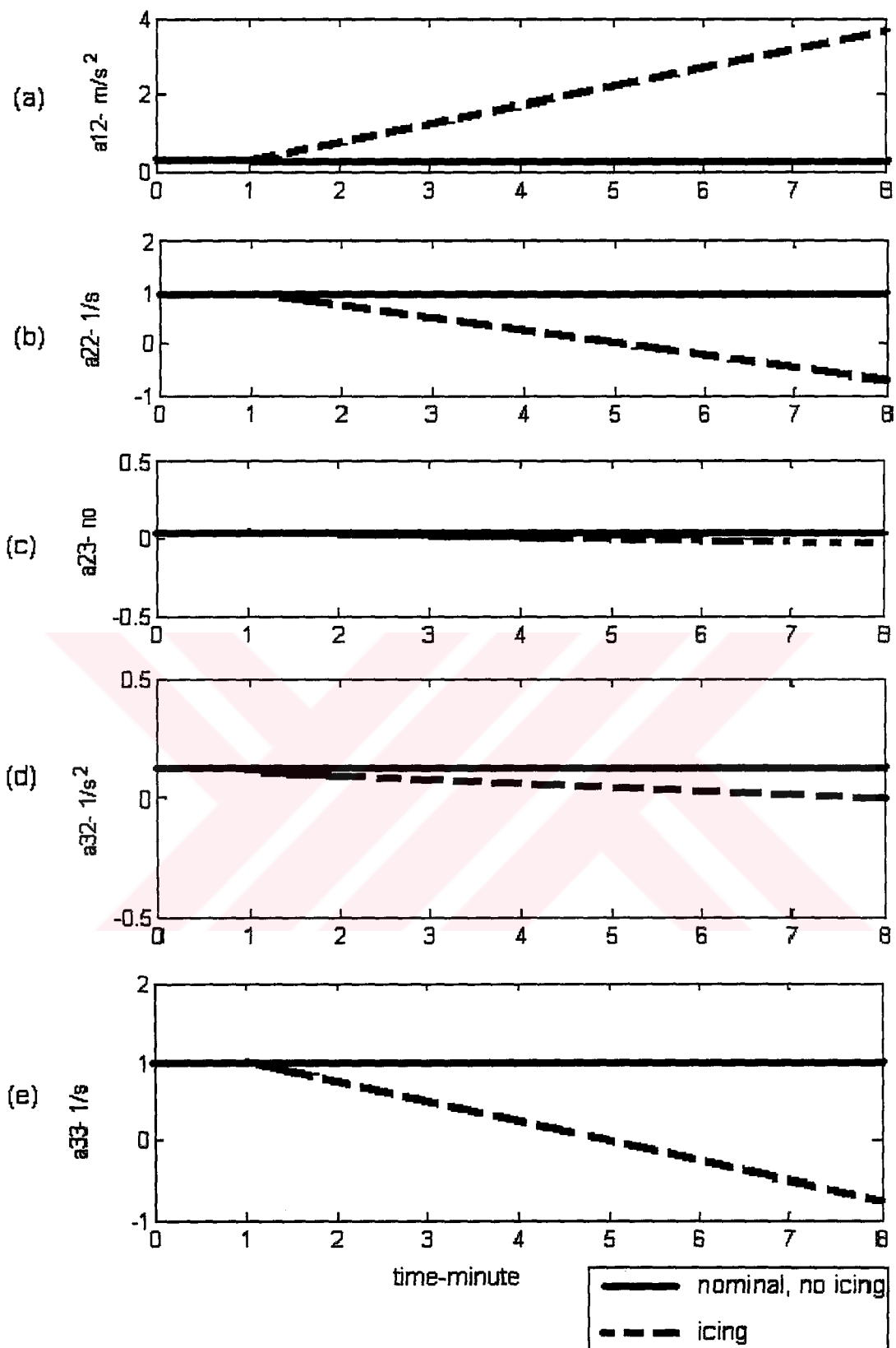


Figure 7.1 Parameters of F16 in nominal and simulated ice conditions.

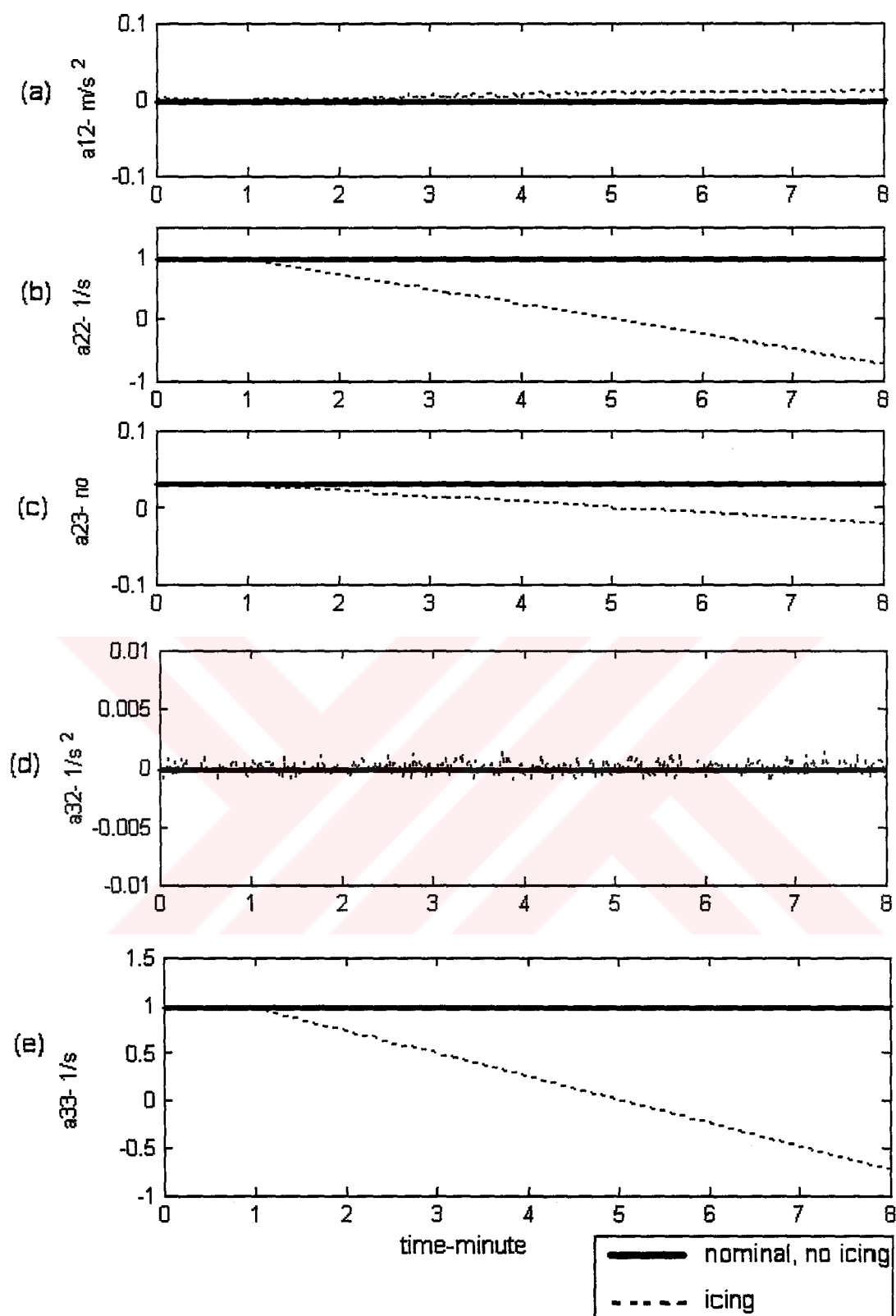


Figure 7.2 Parameters of A340 in nominal and simulated ice conditions.

7.2 Kalman Filtering Results without Control Reconfiguration for Icing

Actual aircraft dynamic states and Kalman filtering estimations under the icing conditions specified in section 7.1 are given here in this section. In the icing conditions the aircraft is continuing to use the same controller as before. No configuration is applied to controller. In all of the figures in this chapter directional velocity (v) is meter/second, angular velocity (p , q , and r) is 1/second or radian/second and angle (α , β , θ , Φ , and Ψ) is in radian. The results of pitch angle and pitch rate are only given here. See Appendix B for additional figures for other states. Estimates will be used later for neural network training, validation and test. Solid lines and dashed lines represent actual states and estimates, respectively.

As seen in Figure 7.3, EKF estimates are getting more and more different from actual states. Figure 7.4 focuses the variations at the instable time frame between minute 7 and 8 because of icing. Figure 7.5 is related to pitch rate variations on A340 aircraft simulations. Note that the estimations are not so good in A340.

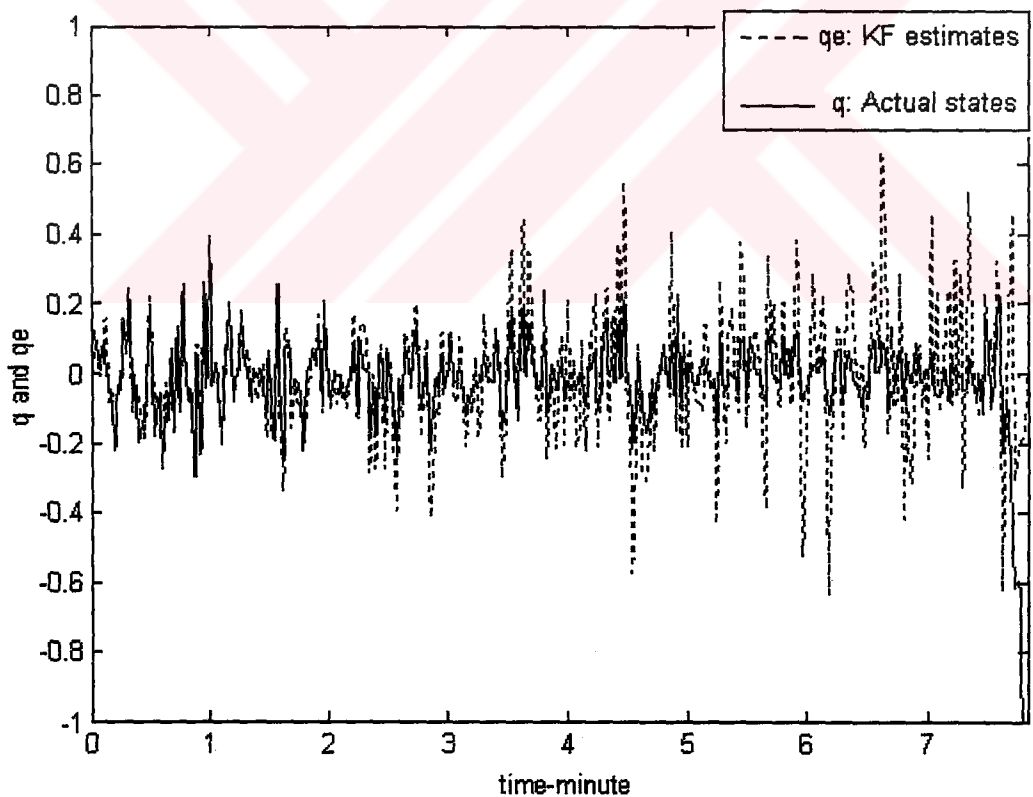


Figure 7.3 Actual pitch rate (q) and EKF results (q_e) in F16 Aircraft

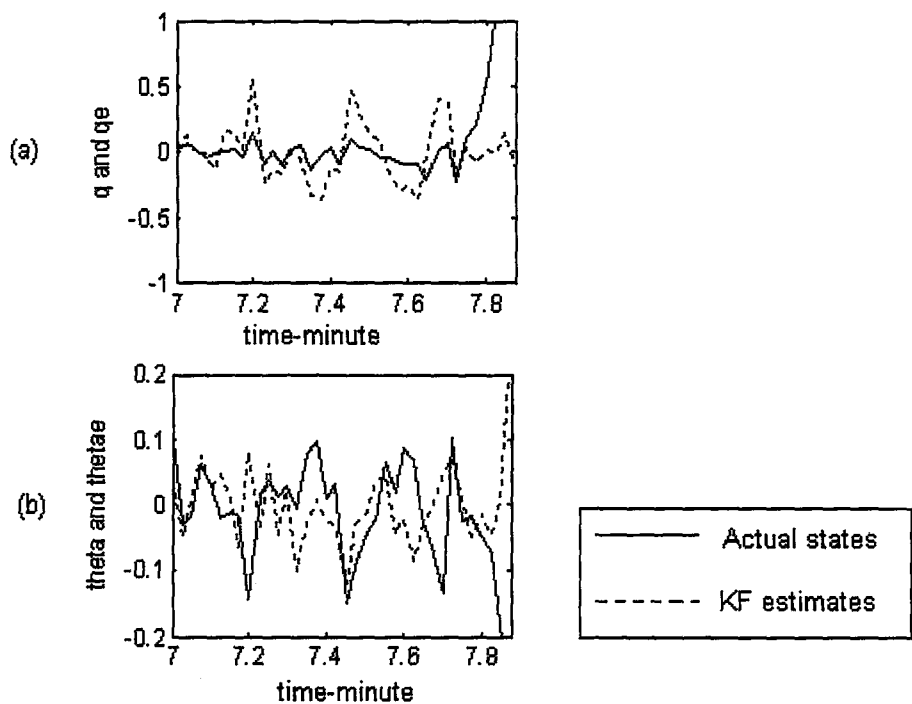


Figure 7.4 Pitch rate (q and q_e), pitch angle (θ and θ_e), and errors of estimates, focused on the time around unstable flight of F16.

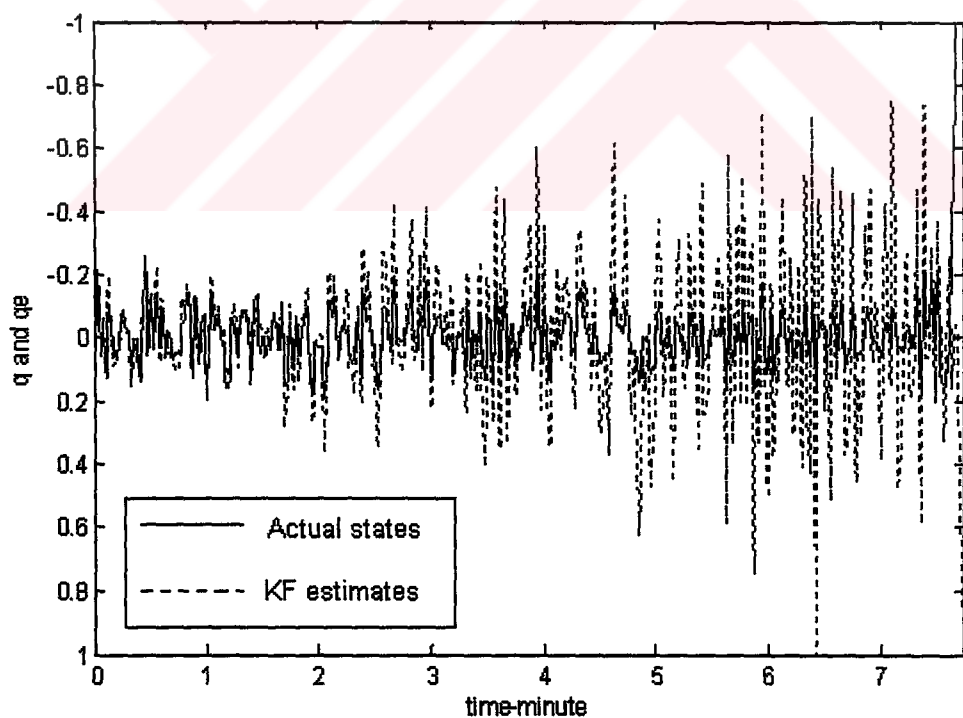


Figure 7.5 Actual pitch rate (q) and KF results (q_e) in A340 Aircraft

7.3 Checking of Means of Innovation Sequence

In the simulations, threshold is found 196 per Chi-Square Distribution, having 80% reliability (alpha), window length of $M = 20$, and measurements of $s = 9$. As shown in Figure 7.6, $\beta(k)$ passes the threshold at 4th minute on F16 simulation, and 2nd minute on A340 simulation, respectively. After icing is detected at 4th minute, reconfigurable control is applied. In order to make the best reconfiguration, the icing model should be exactly identified and true control deflections should be applied to aircraft. These control deflections are called “desired controls”. It means that the parameters should be identified. Since this study uses simulations, and parameters are entered by the user, advantages of reconfiguration by these known parameters could be shown by the use of these simulated icing parameters.

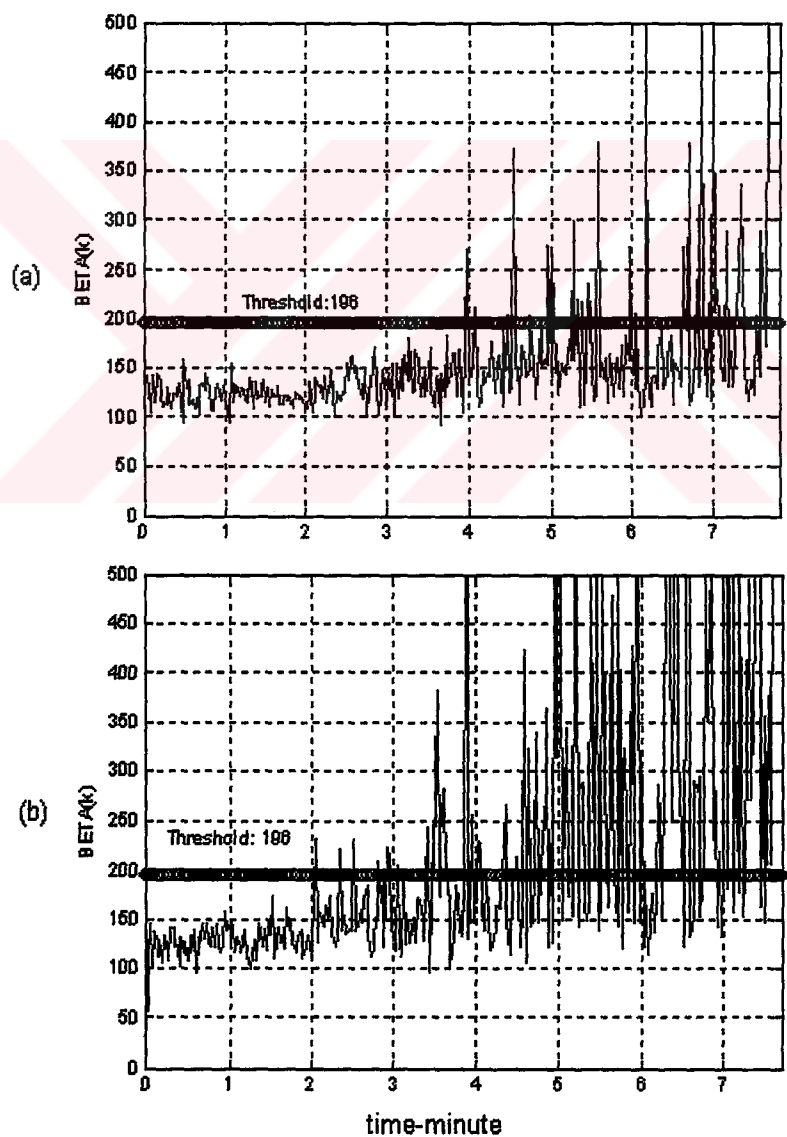


Figure 7.6 Beta (β) function history: (a) F16, (b) A340.

7.4 Nominal and Desired Controls under Simulated Icing Conditions

Nominal control deflections are found in terms of nominal system matrix, A , and nominal control matrix, B . It was explained that matrix B is not primarily affected by icing. Desired control deflections could be found in terms of the changed matrix A by recalculating control gain, K , from the Riccati equation. In nominal control, the constant gain K is used, and the control deflections at each discrete time only depend on the states at that time. In new control system, the variable gain K is used, and the controls depend on both states and variable gain. K varies with the matrix A . Figure 7.7 and 7.8 show the nominal controls represented by solid lines and modified or reconfigured controls represented by dashed lines. Note that the reconfigured control deflections are within the reasonable margins, which means that the aircraft can safely fly in severe icing conditions around minute 8.

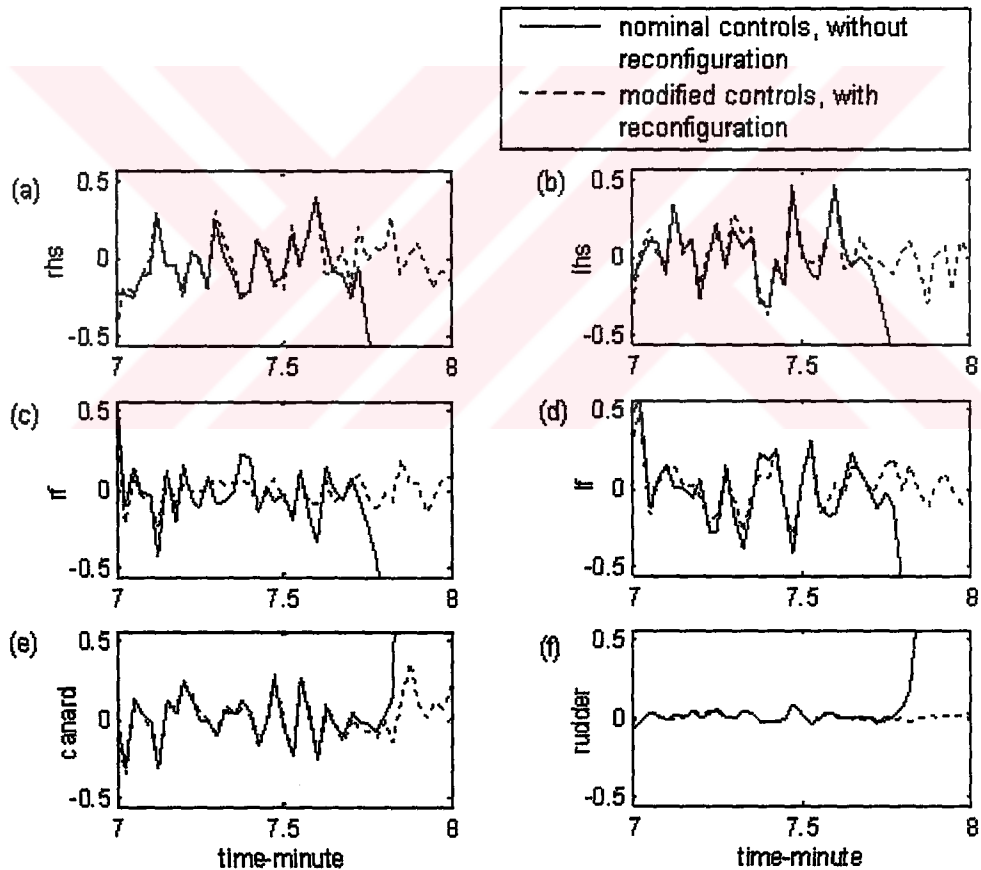


Figure 7.7 Control surface deflections of F16 Aircraft in severe icing conditions in radian.
(a) right horizontal stabilizer, (b) left horizontal stabilizer, (c) right flap,
(d) left flap, (e) canard, (f) rudder

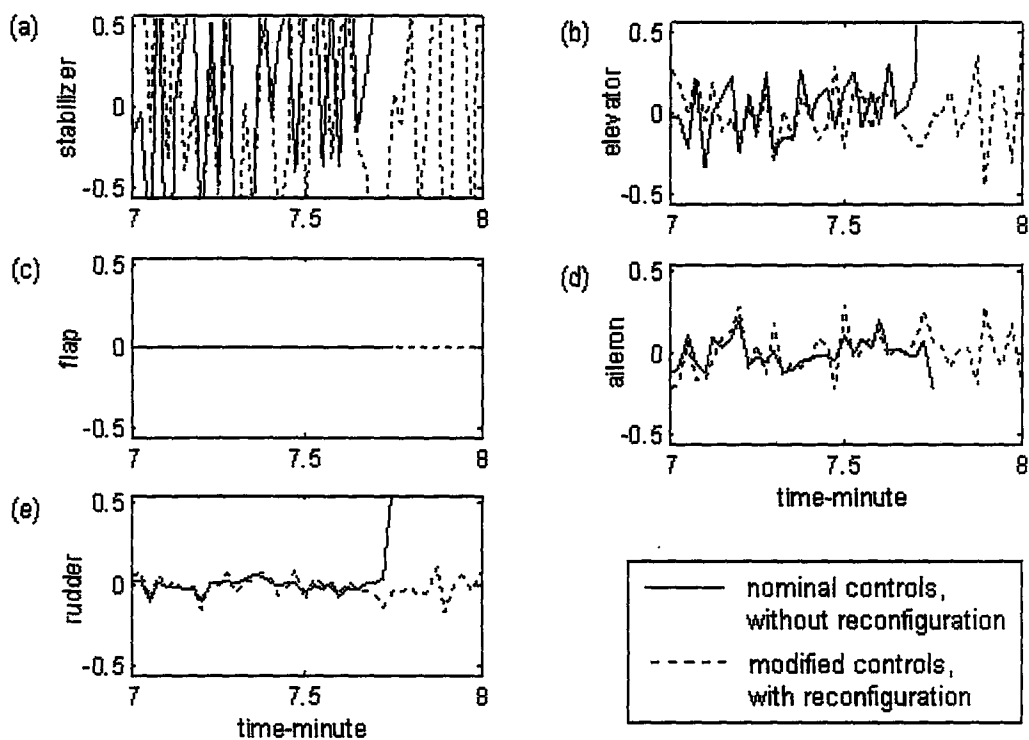


Figure 7.8 Control surface deflections of A340 Aircraft in severe icing conditions in radian.
(a) stabilizer, (b) elevator, (c) flap, (d) aileron, (e) rudder

7.5 States with Desired Controls under Simulated Icing Conditions

Figure 7.9 and 7.10 show the comparison between the states in normal control represented by solid lines and the states in reconfiguration represented by dashed lines. Note that the aircraft are stable with reconfigured controls.

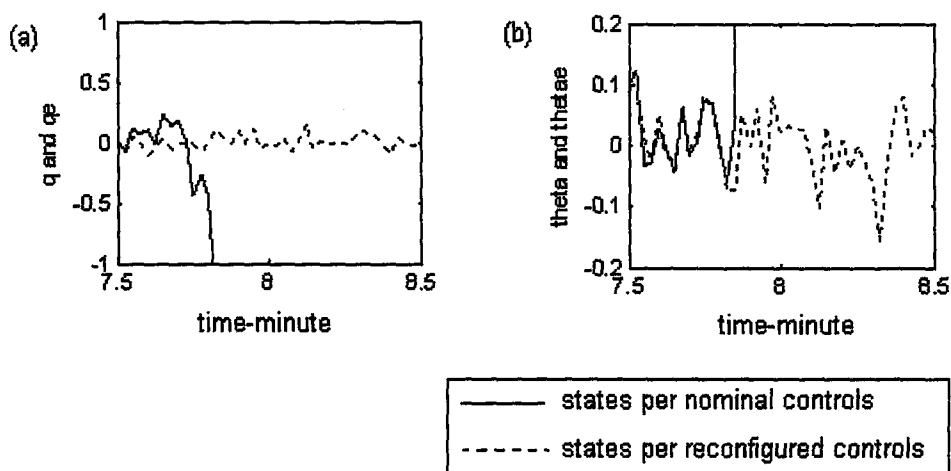


Figure 7.9 States per nominal and reconfigured controls in F16 aircraft
(a) pitch rate, (b) pitch angle

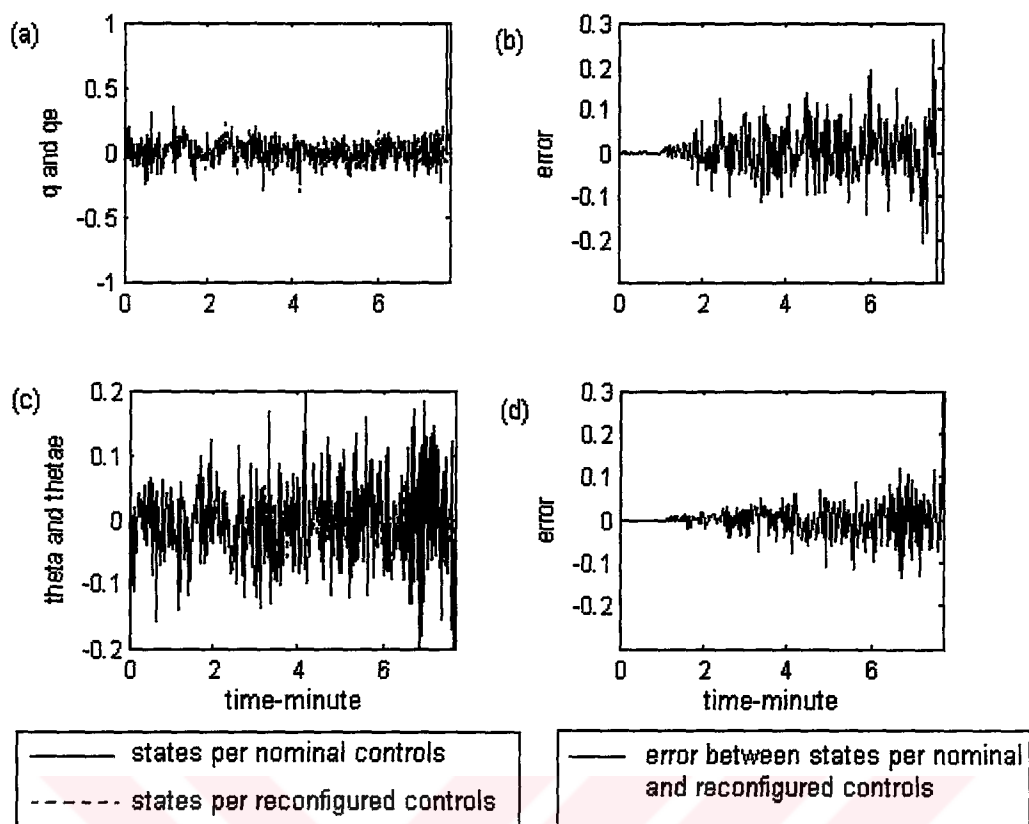


Figure 7.10 States per nominal and reconfigured control in A340 aircraft during whole simulation time. (a) pitch rate, (b) pitch rate error, (c) pitch angle, (d) pitch angle error

7.6 NN Training and Validation of the Iced Aircraft Models

Figure 7.11 shows the history of parameter a_{23} as output of neural network in case that training data set of F16 aircraft is applied to the network. Figure 7.12 shows the results in case that validation data set of F16 aircraft is applied to the network. Figure 7.13 shows the results in case that training data set of A340 aircraft is applied to the network. Target values are represented by solid lines, and neural network outputs are represented by dashed lines. The results of the other parameters are not shown intentionally because they produce similar results.

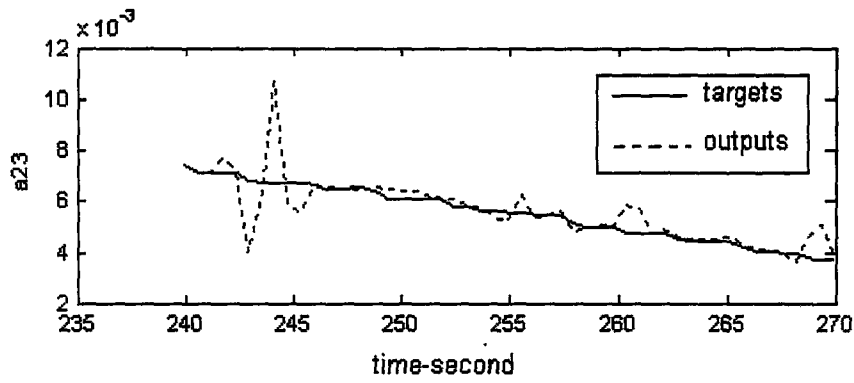


Figure 7.11 Parameter a23 of F16 per training data set

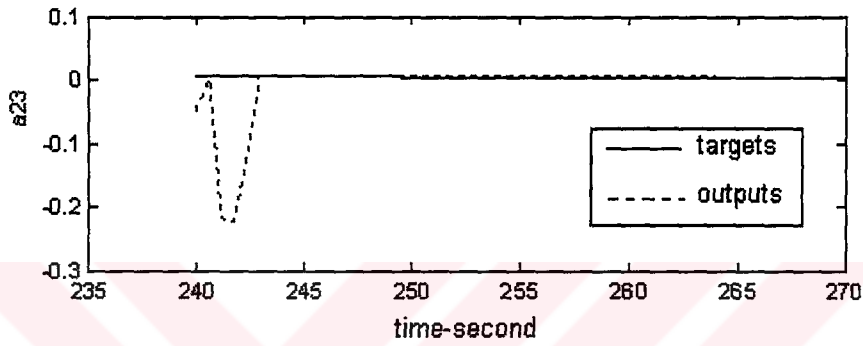


Figure 7.12 Parameter a23 of F16 per validation data set

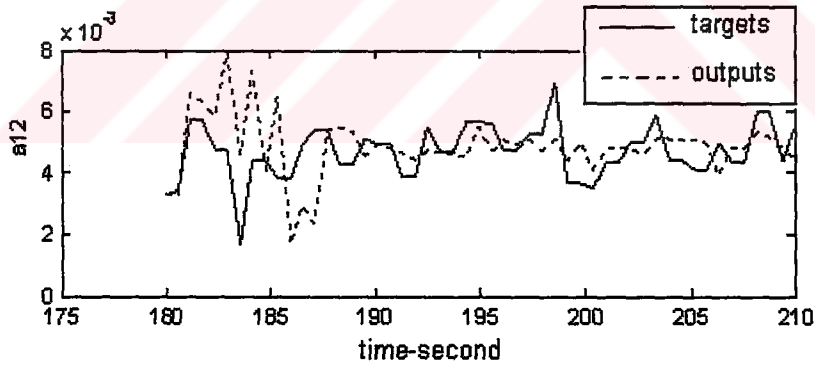


Figure 7.13 Parameter a12 of A340 per training data set

7.7 NN Application for Icing Parameters Identification

Figure 7.14 thru 7.15 show the outputs of the trained neural network for online inputs other than those used in training and validation stages. In the figures, outputs, targets and nominal values of parameters are represented by dashed lines, dotted-solid lines and solid lines, respectively. Errors in the figures are the difference

between outputs and targets. Some parameters are not shown intentionally because they produce similar results as shown in the figures here.

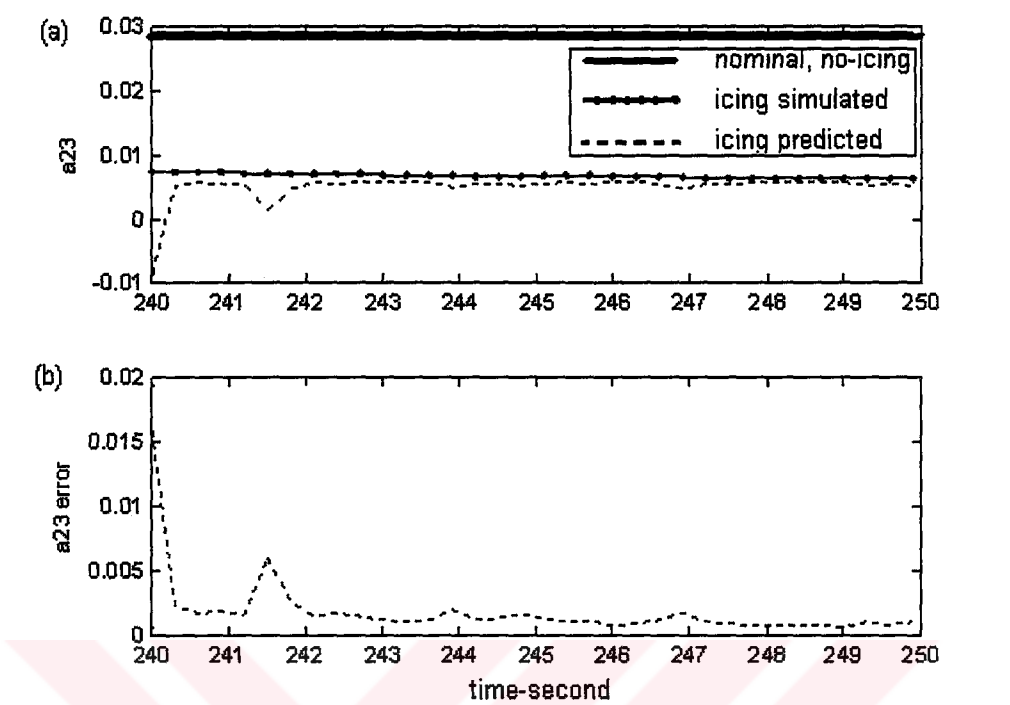


Figure 7.14 Parameter a_{23} of F16.
 (a) NN output of a_{23} with comparison per nominal and simulated icing history,
 (b) The error history of predicted output of a_{23} per simulated icing

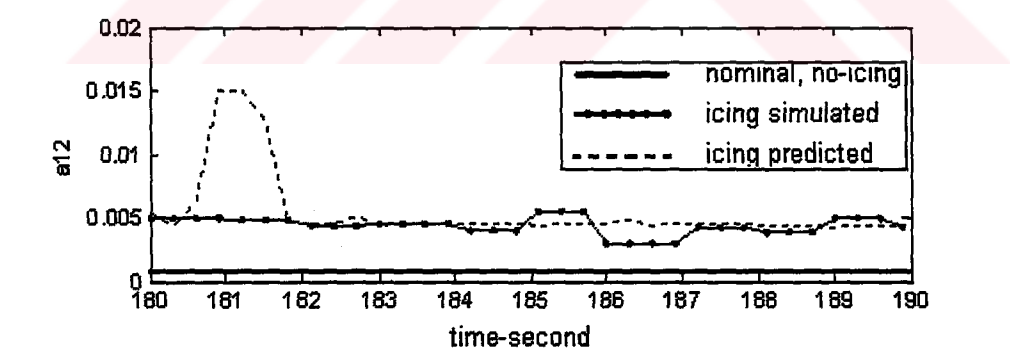


Figure 7.15 Parameter a_{12} of A340. NN output of a_{23} with comparison per nominal and simulated icing history

7.8 Neural Network Reconfiguration for Icing Control

Figure 7.16 thru 7.17 show the new controls and states of F16 aircraft with reconfigured controls obtained by NN parameter identification. Note that icing starts

at 60th second, and detection is at 240th second. Around icing detection time aircraft states and control surface deflections with reconfigured control system are not so different from those without reconfiguration. However, as shown in the earlier figures, states and controls with simulated ice conditions around 420th-430th second abruptly change with nominal control system.

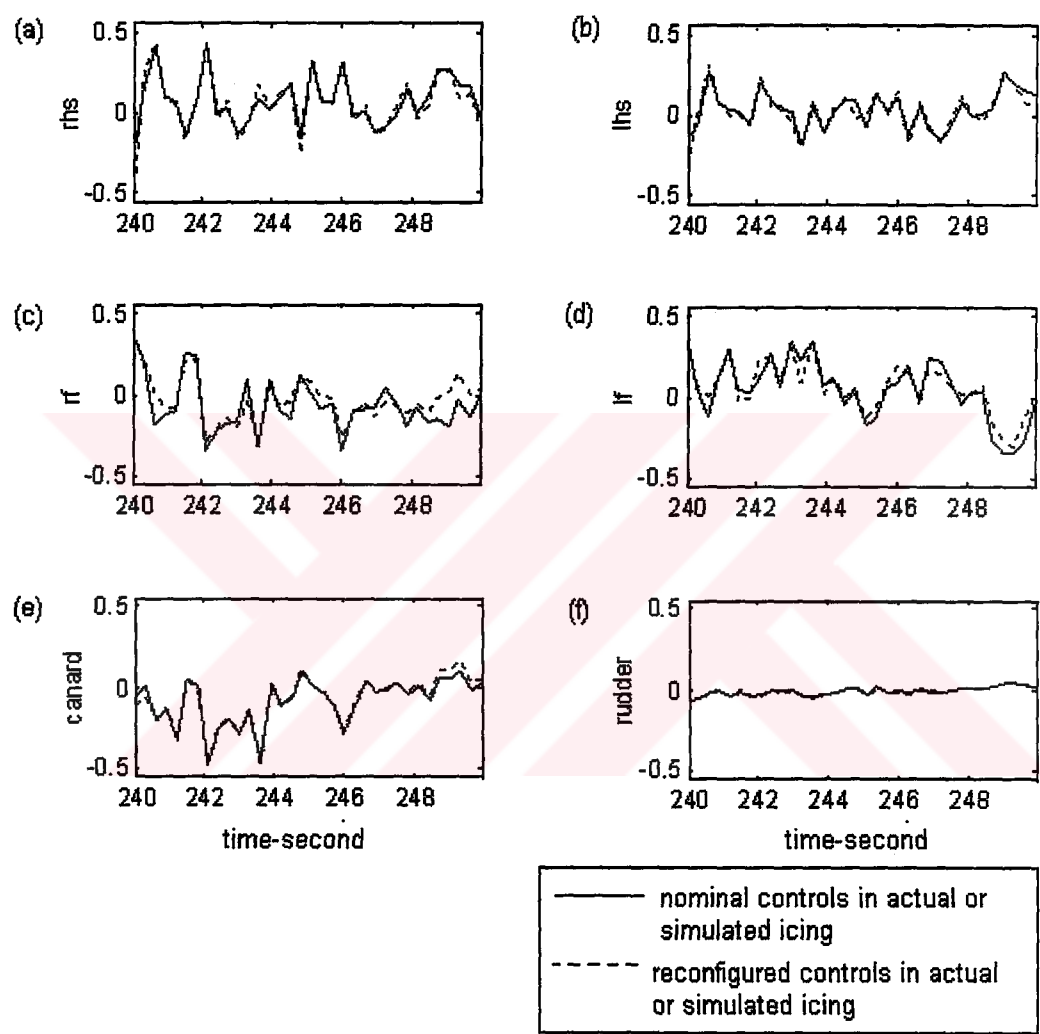


Figure 7.16 Controls of F16 Aircraft by NN Identification
 (a) right horizontal stabilizer, (b) left horizontal stabilizer,
 (c) right flap, (d) left flap, (e) canard, (f) rudder

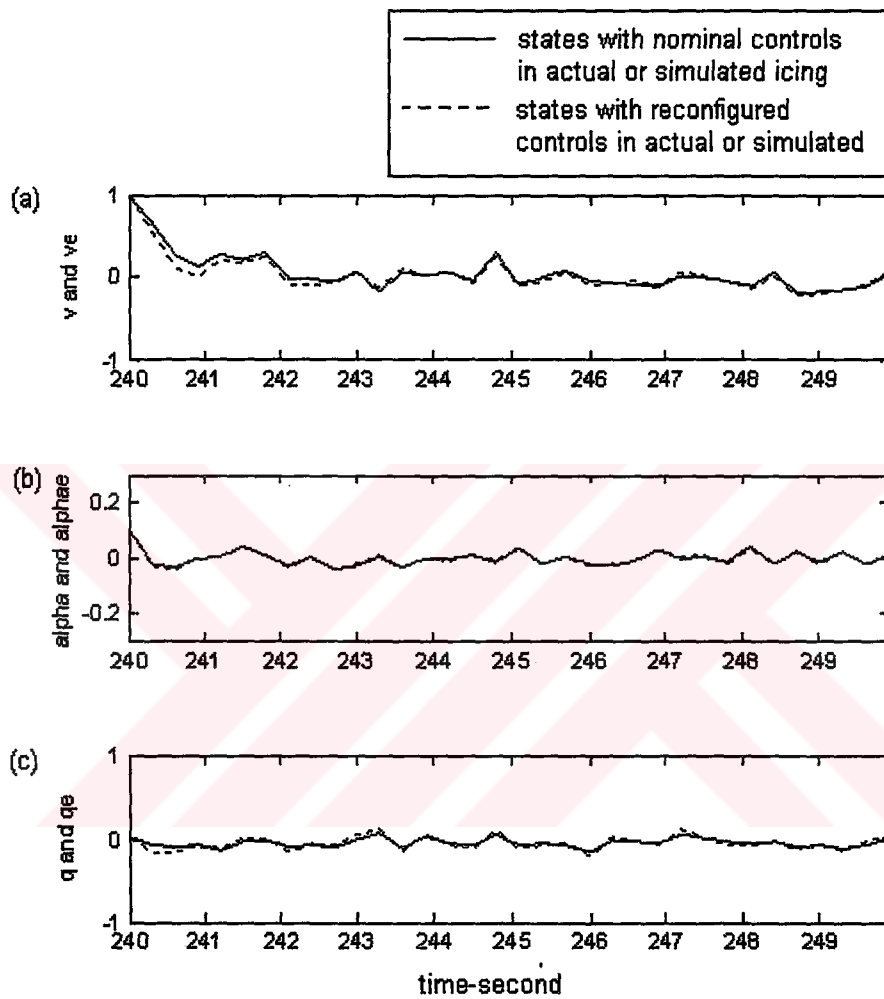


Figure 7.17 States in nominal controls and NN reconfigured control of F16
(a) Aircraft speed, (b) angle of attack, (c) pitch rate

8. CONCLUSIONS AND COMMENTS

This study has proposed a modern automatic ice detection and protection system without using any additional sensors.

In-flight icing affects several aircraft dynamic parameters. In order to evaluate icing effect on aircraft performance variations of these parameters can be tracked. The selected five stability derivatives primarily affected by icing have been used for icing detection, identification and control reconfiguration. By simulating the analytical flight dynamic model of an aircraft in terms of varying stability derivatives, aircraft icing flight model can be represented. The simulation data could be used for training of aircraft neural network model.

Aircraft icing problem has been considered as an FDI problem so that the techniques in the literature can be applied successfully. The KF innovation sequence method that we use has detected icing accumulation, and then the well trained NN model of aircraft flight dynamics could predict the icing parameters in terms of the existing flight conditions and trim values of states and controls of aircraft flight dynamics. The KF has been also used to increase state measurements' accuracy such that the training performance would increase.

This work differs from the other recent studies in this area in many ways. Many previous studies used experimental data. Performing the tunnel tests for icing is difficult and expensive. Instead, the simulations data could be used for training of NN models. So, the proposed method for identification and control of iced model only depends on analytical redundancy, which uses the existing sensors and additional filtering of the KF and identification of the NN.

In system identification, looking at one model structure may not give us a consideration about the correct model structure selected. This is one of the reasons of the application icing to two different aircraft, F16 and A340. The results have showed that icing could be identified on both aircraft in almost the same quality.

A normal operational maneuver such as the initiation of a landing approach descent would generally be more hazardous than icing during steady level flight. This research is concerned with airframe icing that could have accreted prior to the landing. However, the method may be applied to landing or take off.

The proposed method resolving the icing problem may also be applied in the similar manner to some other aircraft failures showing similar effects to icing such as missing part of an aircraft (winglet, fairing, panel, etc.) or a control surface (elevator, rudder, aileron, spoiler, flap, slat, etc.), and engine-out case problems. These may result from lightning strikes, mechanical contact to parts each other or maintenance faults.

Too many numbers of neurons in the NN have decreased the generalization of the network, and also increased noises at the outputs of trained NN. Application and validation samples outside the border of the training data values have had much more errors and resulted in rough estimation of the ice-affected parameters.

The KF estimations as inputs of the NN have produced more efficient training performance. In order to identify in-flight icing by NN, aircraft should have sufficient dynamical properties or certain level model noises. As the models of F16 and A340 have been simulated in a time dependent manner by entering changed stability derivatives, the necessary training samples have been collected, and trained NN has been obtained so that the trained NN have predicted uncertain stability derivatives in relation to icing.

In this research, icing detection based on the KF and reconfiguration based on the NN have been applied for the first time to models of F16 and A340 aircraft. A new automatic control system modified for icing has been considered for the management of the existing ice protection system of Airbus A340 aircraft. This system may allow being the engine performance optimum by controlling the wing anti-ice system valve. This valve is already controlled manually. An automatic system commanding anti ice system valve will be offered. Thus, 3-5 % fuel could be have saved. Additionally, ice detection information is sent to cockpit display for an advisory purpose. Icing sensors mounted to fuselage nose section and hinge moment sensors at control surfaces may be combined with this system. The modified control system can work as long as ice exists.

This research has developed an augmented AFCS for in-flight icing so called ITFCS. As a real application, this work also helps to improve the existing automatic anti-icing system on A340 aircraft by optimizing ice protection system in order to improve flight performance and safety, by minimizing the use of engine hot air, by minimizing missed ice detection and false alarms, and by optimizing the inputs of ice detection systems. Simulation results have showed the good performance and accuracy of the method.

Icing detection by KF innovation approach has worked in both aircraft, F16 and A340. However, the method has been more effective in A340 than in F16. In cruise conditions, the method has detected the certain level icing within 1 minute in A340 and 3 minutes in F16. This means that beta statistics affect the flight dynamics of A340 aircraft more than F16's. On the other hand, the proposed icing identification method based on NN has been more effective in F16 than in A340 in relation to accuracy of the simulated data. The better system dynamical properties are, the better Kalman filter gives results.

In future studies, the new aircraft model with the icing parameters estimated by NN may be investigated in the points of robustness, stability, controllability and observability. Instead of linearly changing ice affects, various type of icing models may be trained so that more capable NN icing identification system may be developed. In order to differentiate icing from other type faults, additional methods may be combined into the proposed method. Icing on empennage, engine intakes, fuselage nose may be evaluated by the similar method. The method may be applied for more than five parameters.

Instead of the use of simulation data of F16 and A340 aircraft analytical model in EKF estimations for detection and NN identification, real flight data downloaded from aircraft computer, called Flight Data Recorder (FDR) or Black Box, will be able to provide more accurate and reasonable results.

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APPENDIX A: COMPUTER PROGRAMS

The proposed method of icing detection, identification and reconfigurable control is applied to two aircraft. Computer programs, **“nnidicf16.m”** and **“nnidica340.m”**, have been used for simulations of F16 and A340 aircraft. They are given in the attached floppy disk.



APPENDIX B – ADDITIONAL FIGURES OF SIMULATIONS

Some examples of figures obtained from the simulations of dynamic models of nonlinear F16 aircraft and linear A340 aircraft were given in Chapter 7. More simulation results are given here.

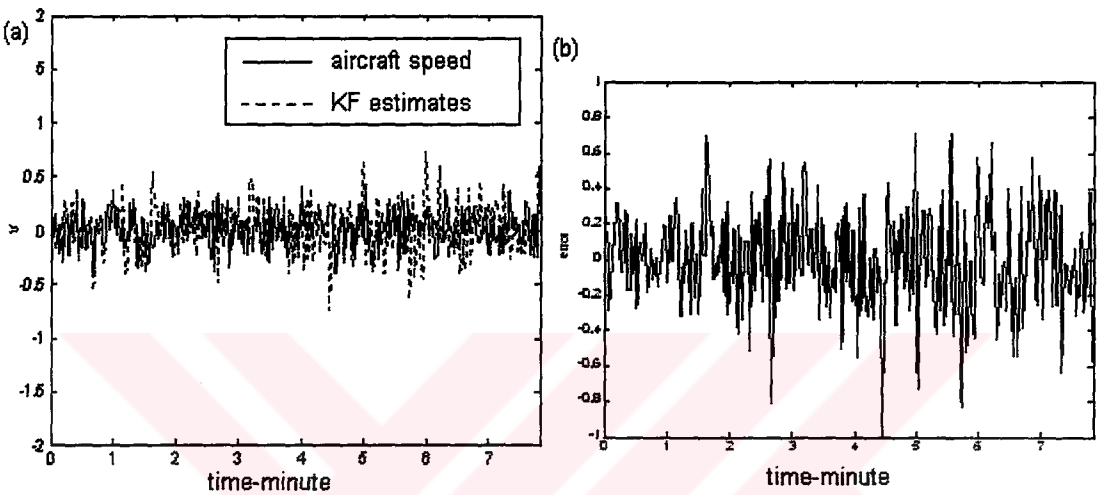


Figure B.1 Speed history of F16 within the simulated time frame, (a) Actual or simulated speed and its Kalman filter estimate, (b) Error between speed estimate and actual speed

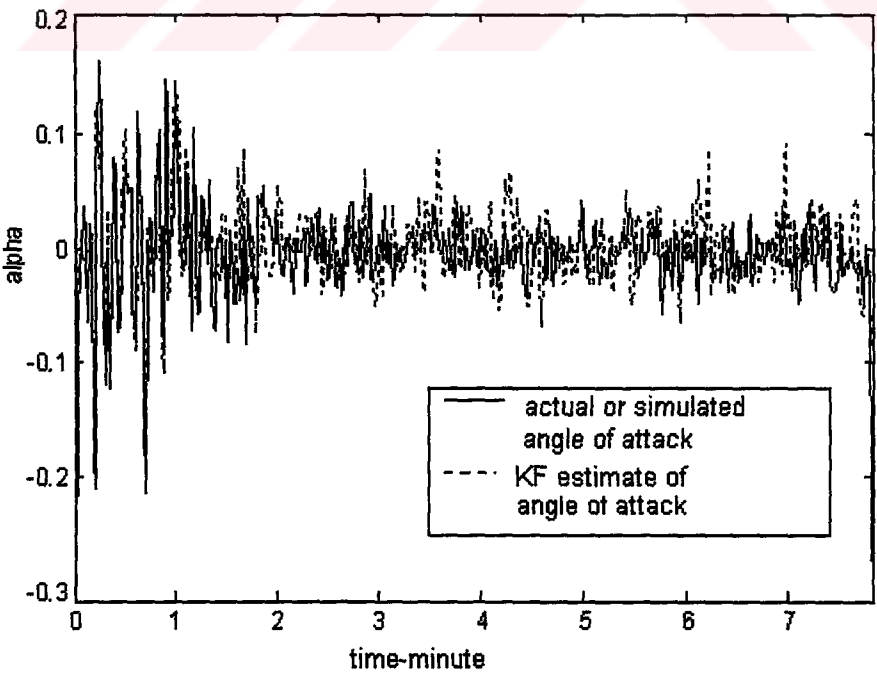


Figure B.2 Angle of attack history of F16 within the simulated time frame

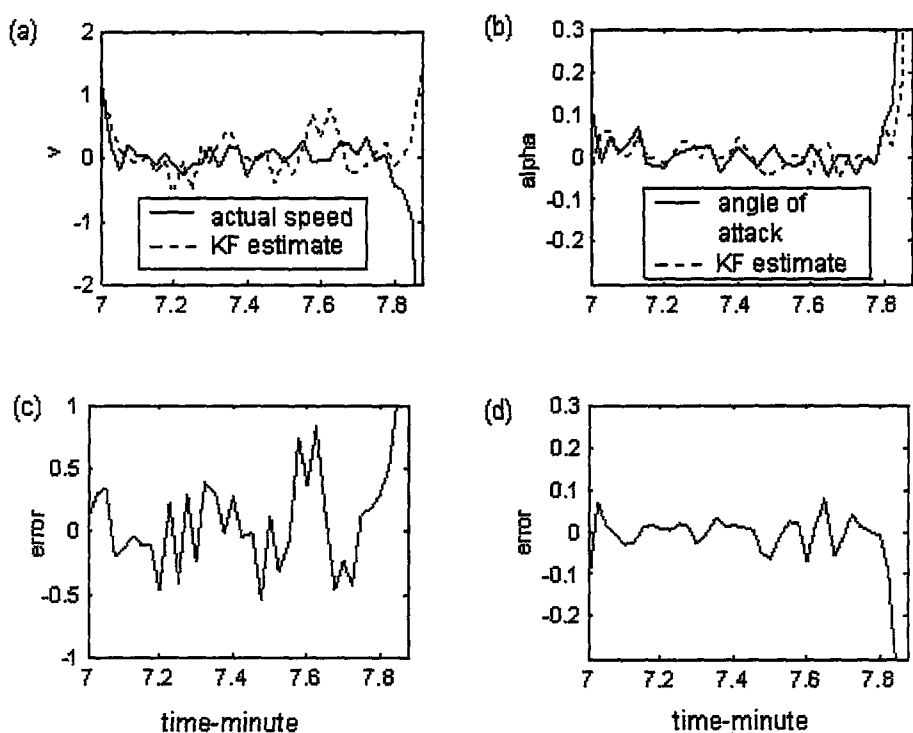


Figure B.3 States, KF estimates and error of KF estimates, focused on the time around unstable flight in F16, (a) aircraft speed and estimate, (b) angle of attack and estimate, (c) error of KF speed estimate, (d) error of KF angle of attack estimate

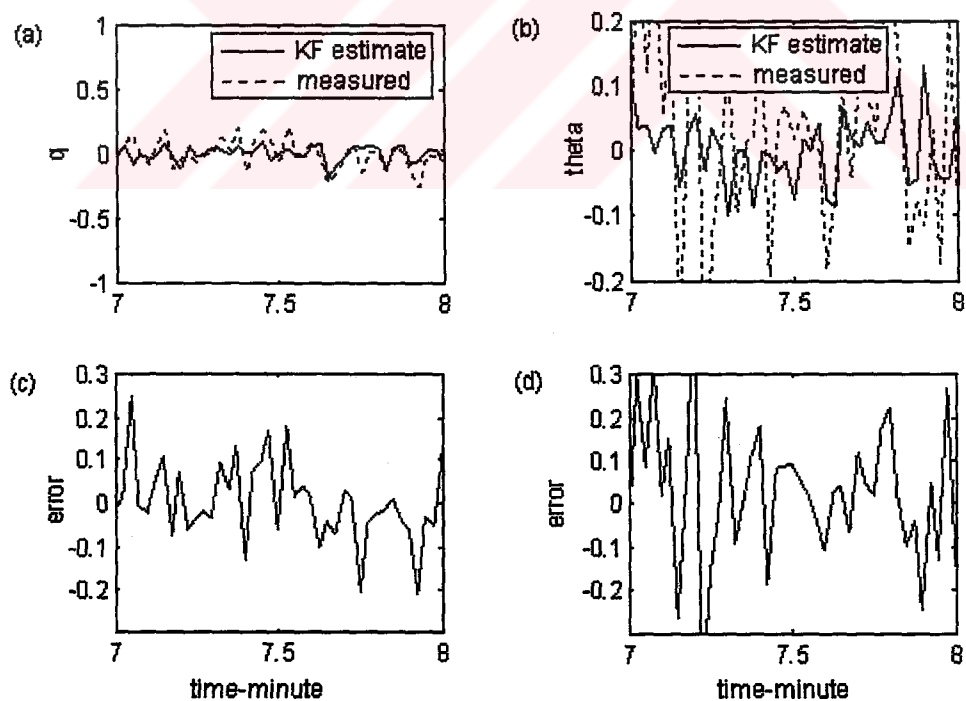


Figure B.4 Measured states, KF estimates and error between them in F16, (a) pitch rate, (b) pitch angle, (c) error between pitch rate measured and pitch rate estimated, (d) error between pitch angle measured and pitch angle estimated.

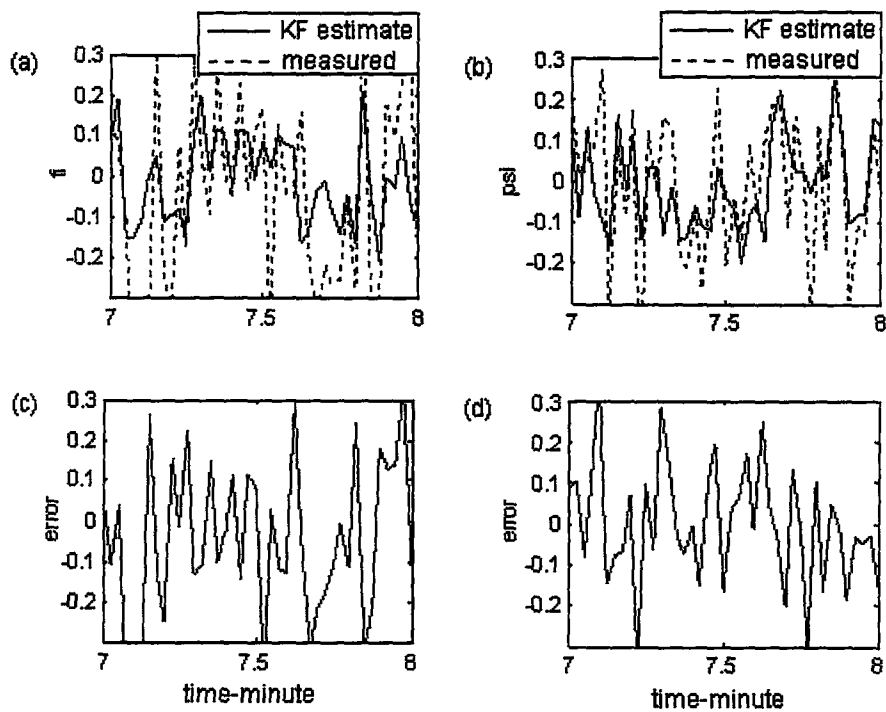


Figure B.5 Measured states and error between measurements and estimates of F16, roll angle, (b) yaw angle, (c) error between roll angle measured and roll angle estimated, (d) error between yaw angle measured and yaw angle estimated.

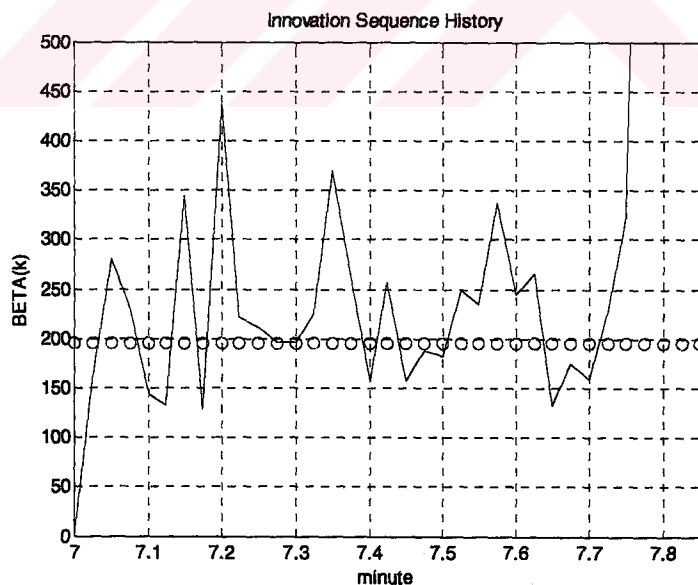


Figure B.6 Beta (β) function of F16 simulation focused on the time around unstable flight.

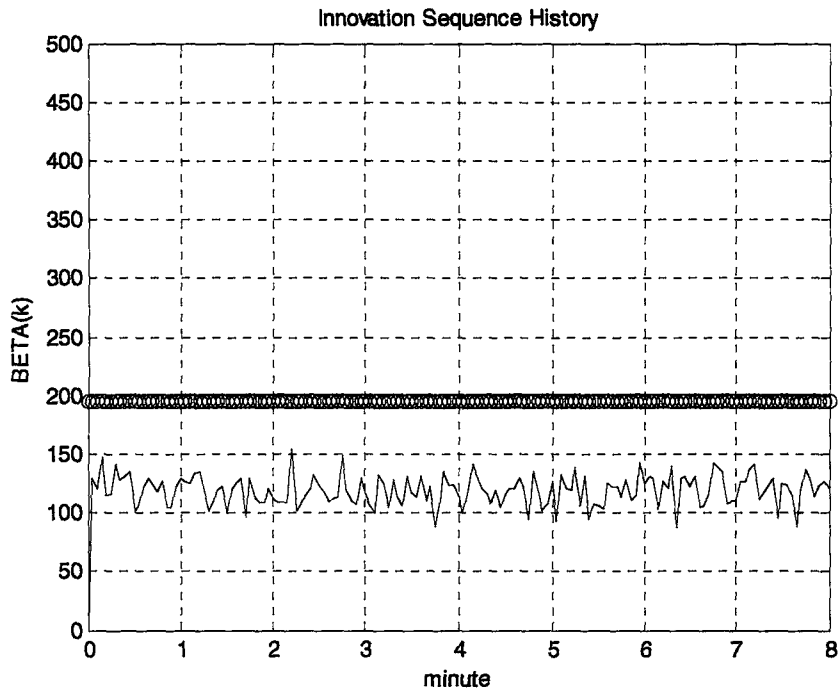


Figure B.7 Beta (β) function history of F16 simulation with reconfigured controls

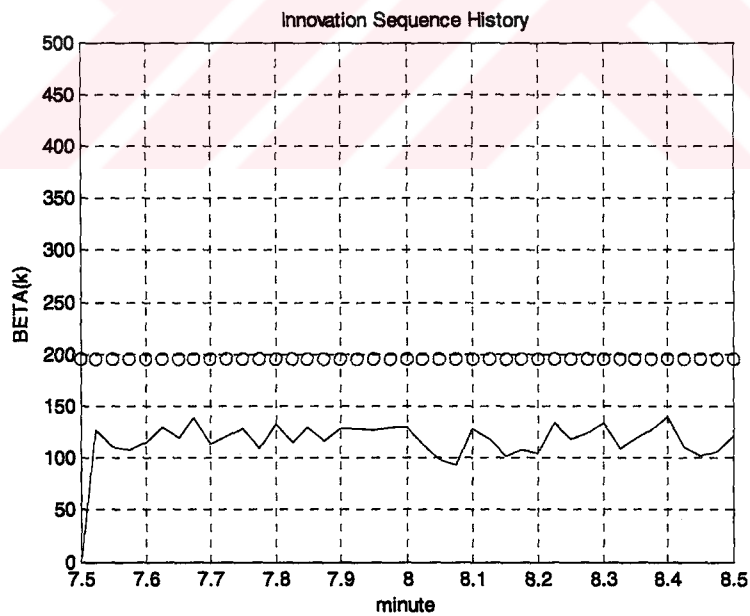


Figure B.8 Beta (β) function history of F16 simulation with reconfigured controls, focused on severe icing conditions

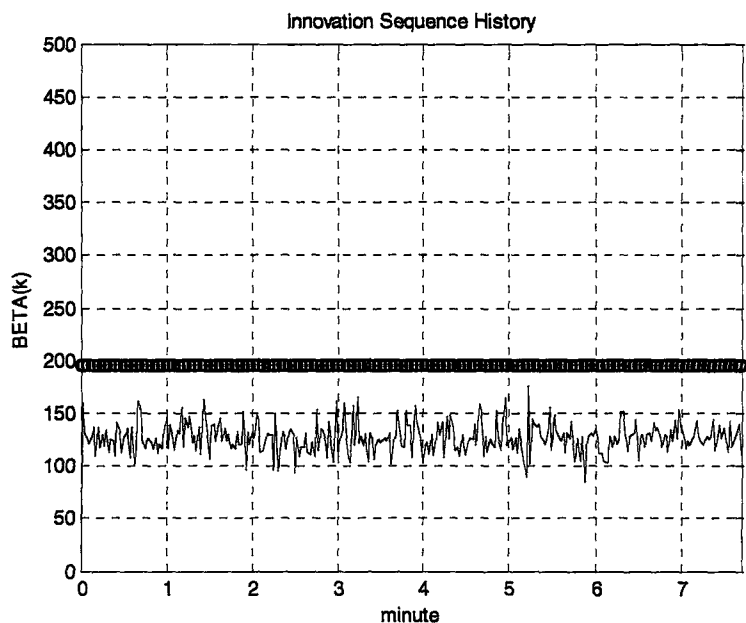


Figure B.9 Beta (β) function history of A340 simulation with reconfigured controls

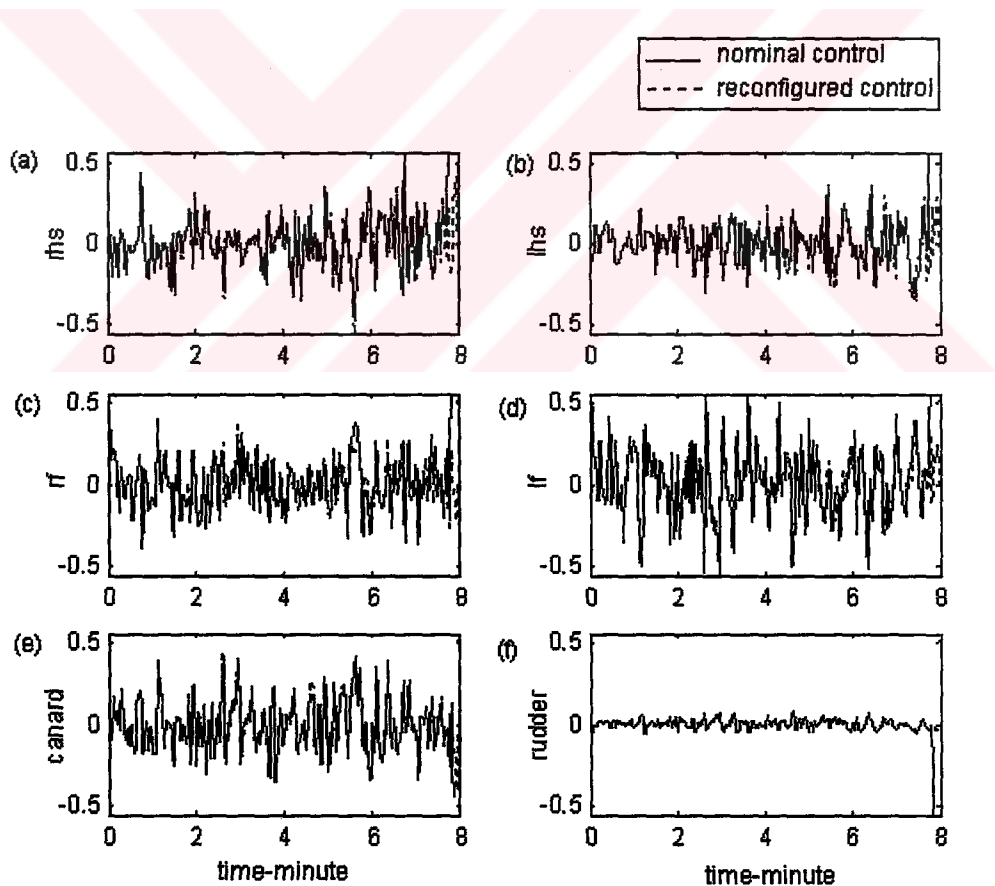


Figure B.10 Nominal and reconfigured control deflections of F16 Aircraft in icing conditions, (a) right stabilizer, (b) left stabilizer, (c) right flap, (d) left flap, (e) canard, (f) rudder

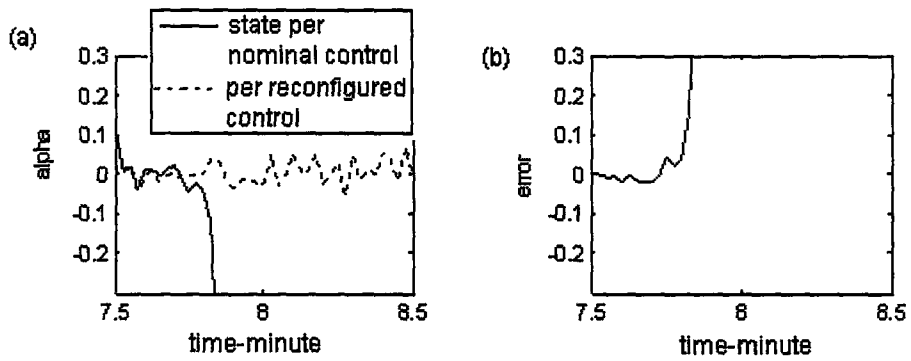


Figure B.11 Angle of attack history of F16, (a) angle of attack per nominal control and reconfigured control, (b) error between states per nominal and reconfigured controls

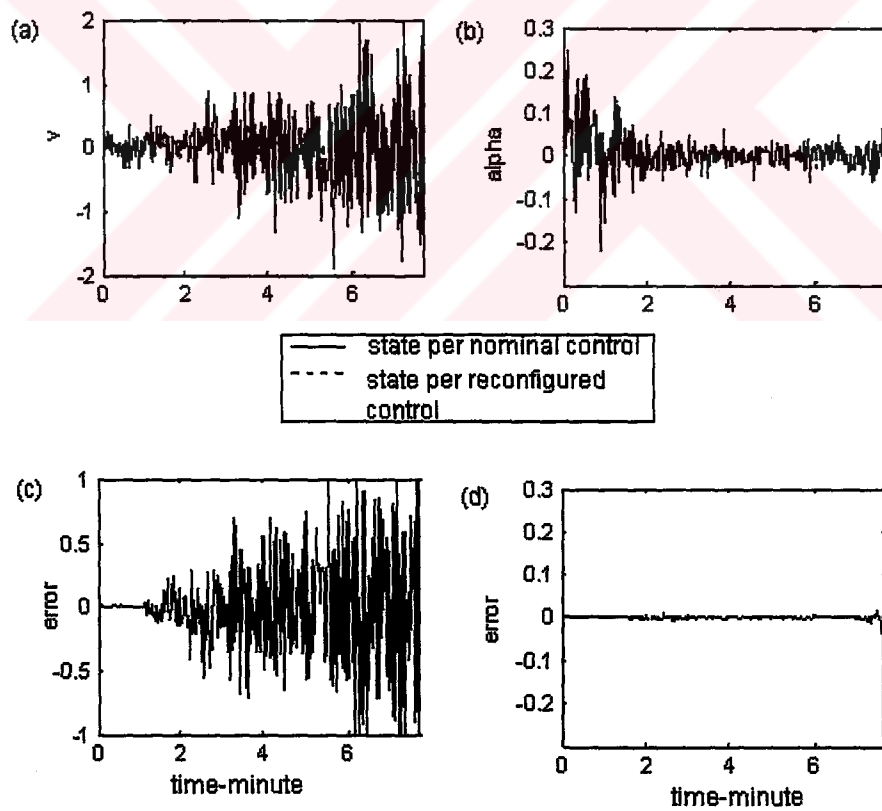


Figure B.12 Speed and angle of attack history of A340, (a) speed, (b) angle of attack, (c) error between speed per nominal and reconfigured control, (d) error between angle of attack per nominal and reconfigured control.

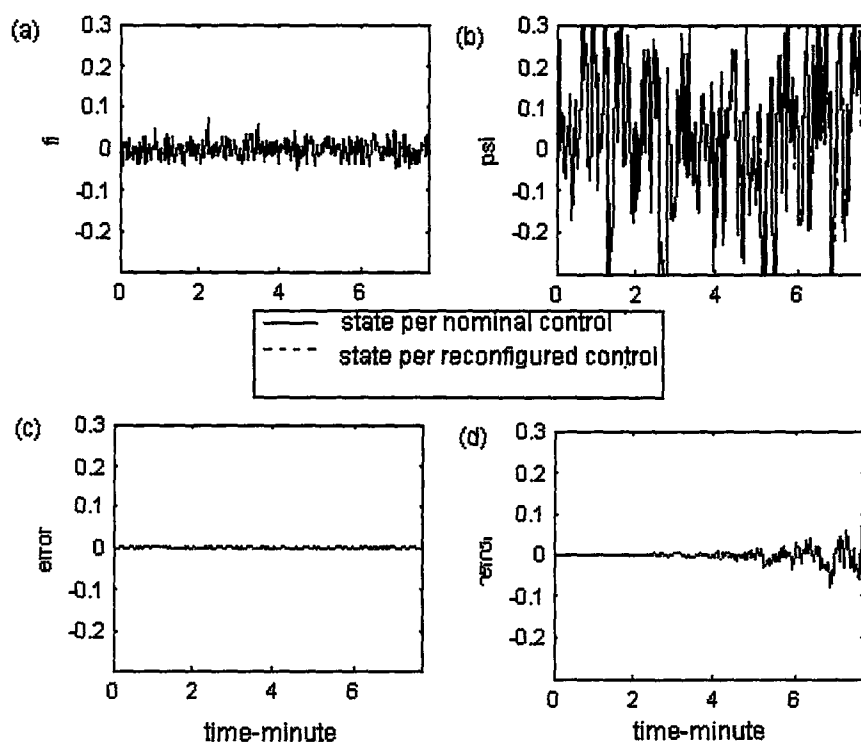


Figure B.13 Roll and yaw angle history of A340, (a) roll angle, (b) yaw angle, (c) error between roll angles per nominal and reconfigured control, (d) error between yaw angles per nominal and reconfigured control

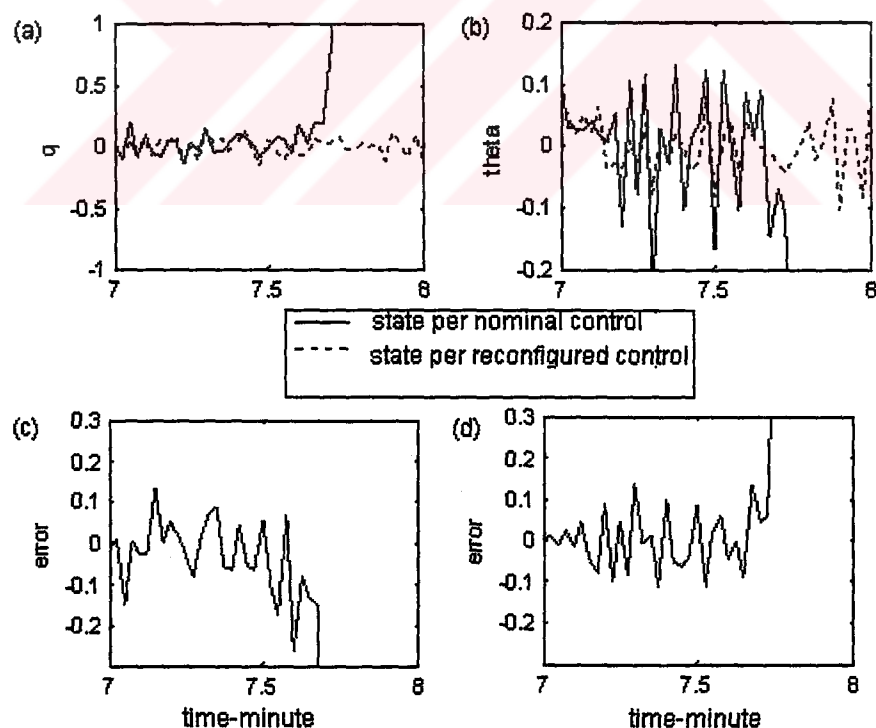


Figure B.14 Pitch rate and angle history of A340, (a) pitch rate, (b) pitch angle, (c) error between pitch rates per nominal and reconfigured control, (d) error between pitch angles per nominal and reconfigured control

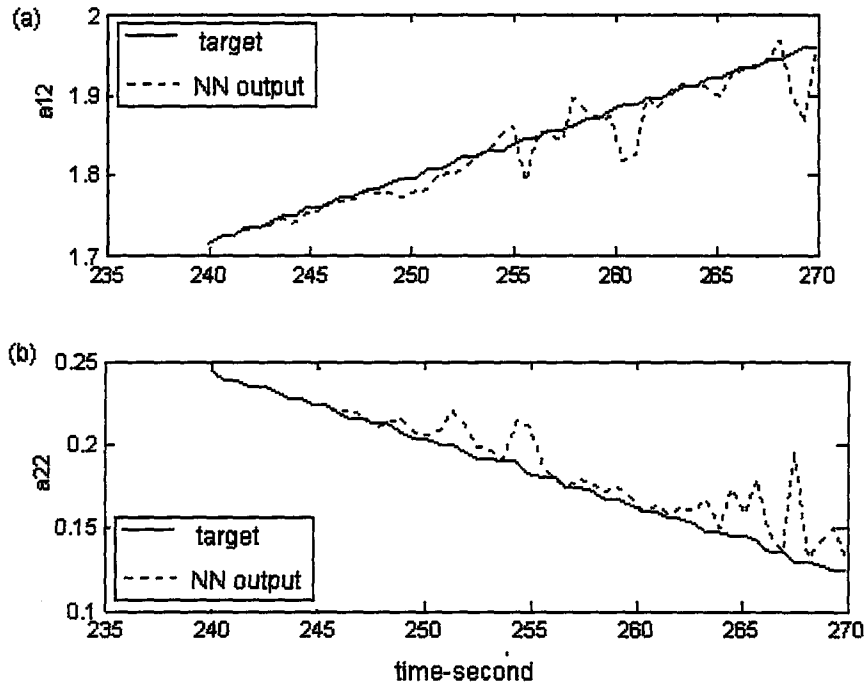


Figure B.15 Training of F16 NN model, (a) parameter a_{12} related to drag-angle of attack, (b) parameter a_{22} related to lift-angle of attack.

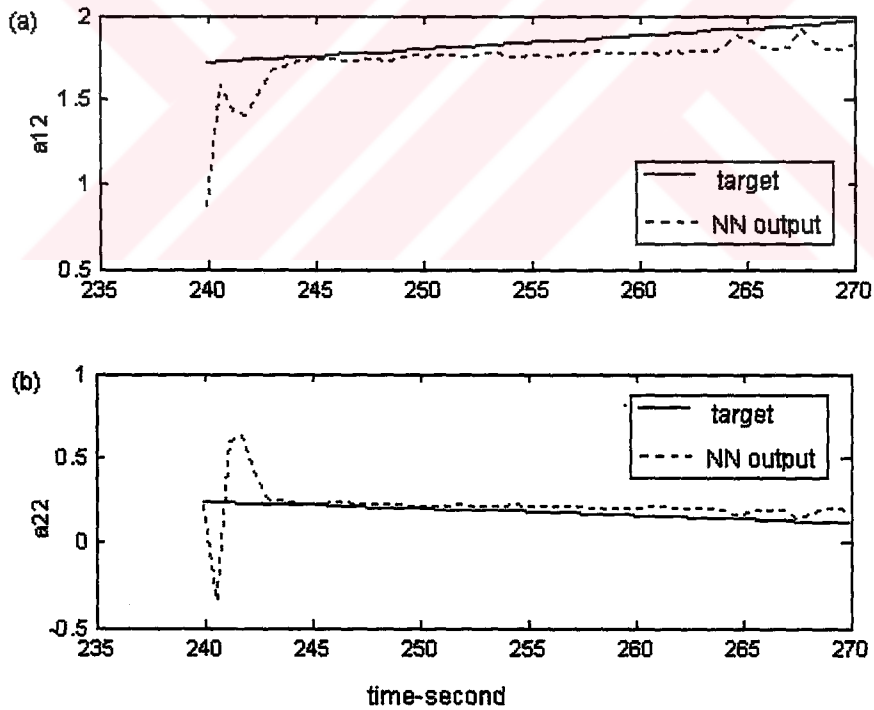


Figure B.16 Validation of F16 NN model, (a) parameter a_{12} related to drag-angle of attack, (b) parameter a_{22} related to lift-angle of attack.

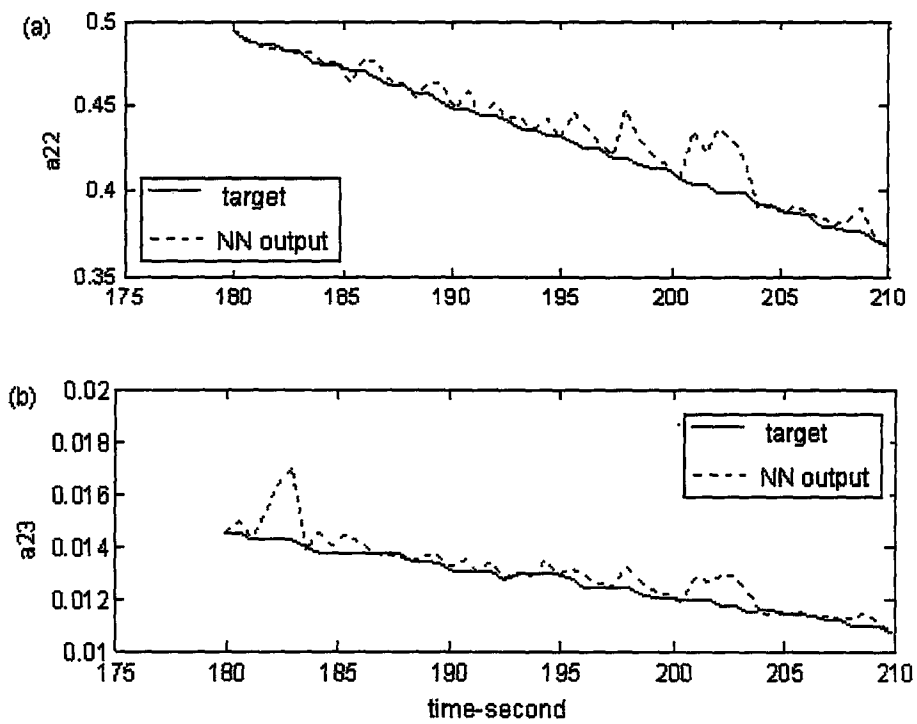


Figure B.17 Training of A340 NN model, (a) parameter a_{22} related to lift-angle of attack, (b) parameter a_{23} related to moment-angle of attack.

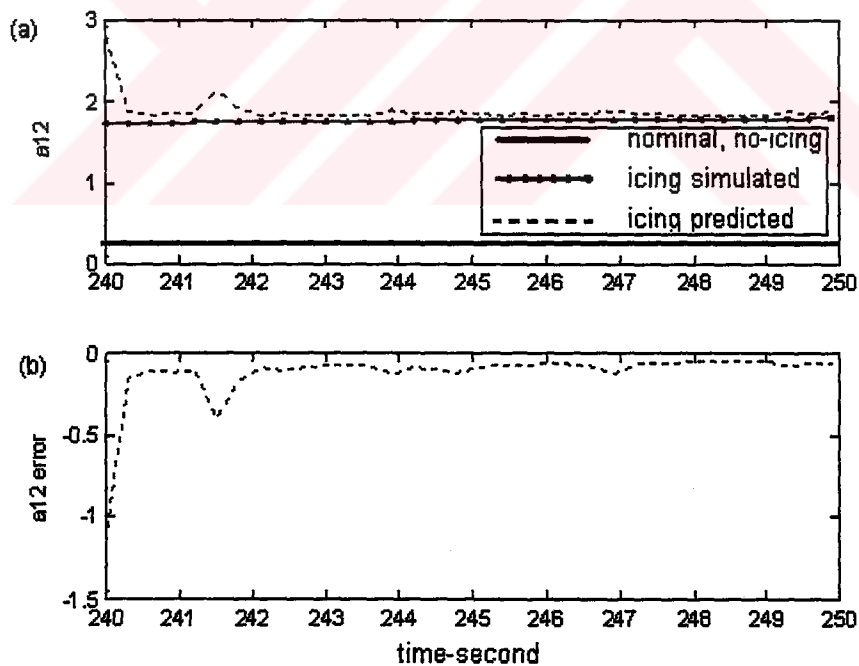


Figure B.18 Parameter a_{12} of F16 with comparison per nominal and simulated icing history, (a) NN output of a_{12} , (b) The error history of predicted output. Other than training and validation data sets are used.

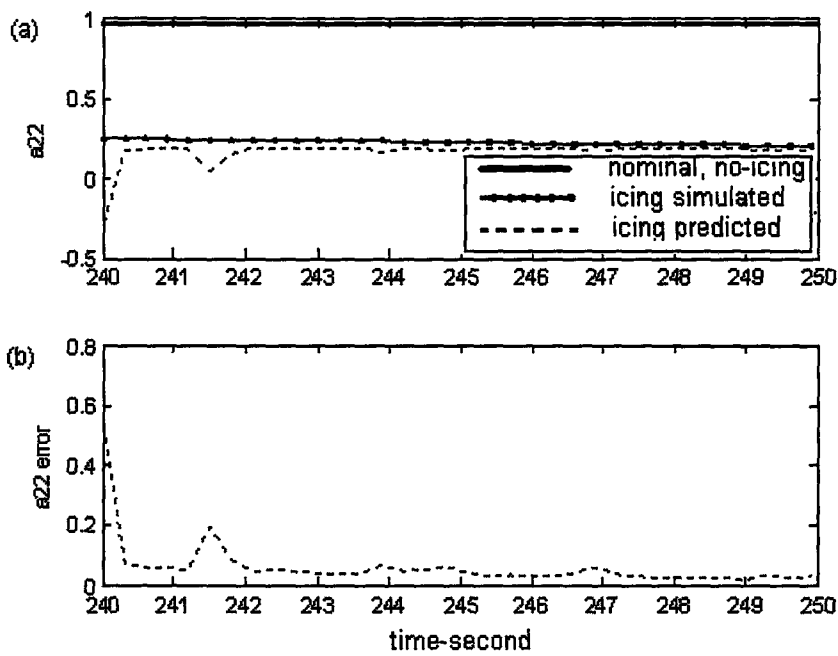


Figure B.19 Parameter a_{22} of F16 with comparison per nominal and simulated icing history, (a) NN output of a_{22} , (b) The error history of predicted output. Other than training and validation data sets are used.

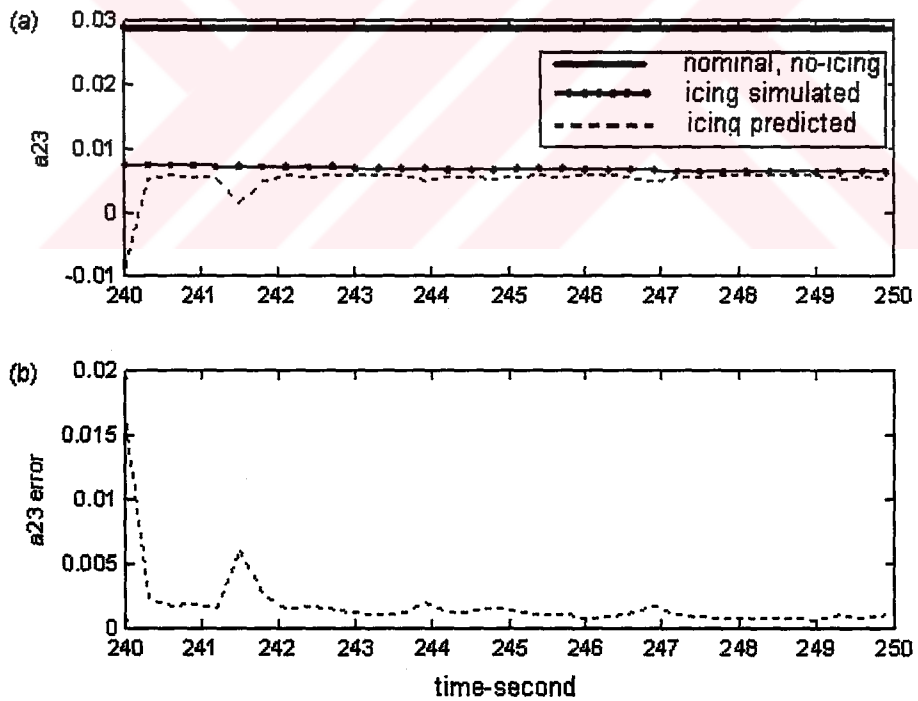


Figure B.20 Parameter a_{23} of F16 with comparison per nominal and simulated icing history, (a) NN output of a_{23} , (b) The error history of predicted output. Other than training and validation data sets are used.

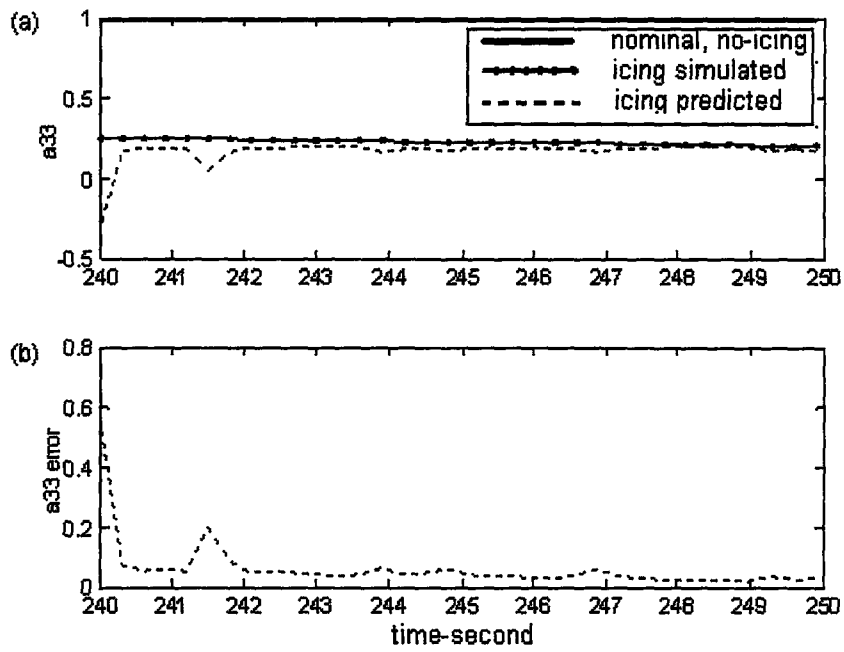


Figure B.21 Parameter a_{33} of F16 with comparison per nominal and simulated icing history, (a) NN output of a_{33} , (b) The error history of predicted output. Other than training and validation data sets are used.

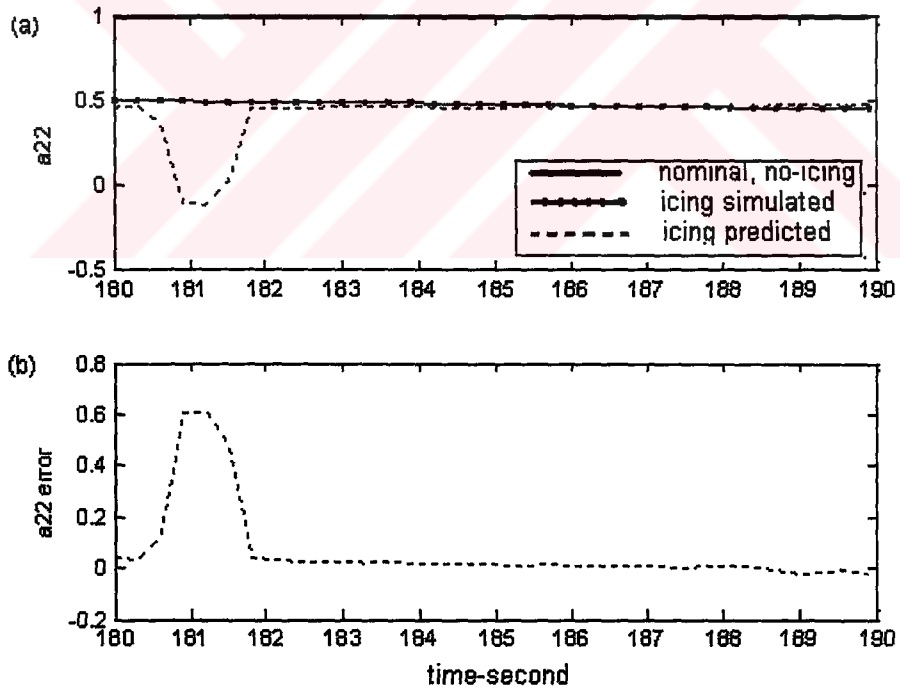


Figure B.22 Parameter a_{22} of A340 with comparison per nominal and simulated icing history, (a) NN output of a_{22} , (b) The error history of predicted output. Other than training and validation data sets are used.

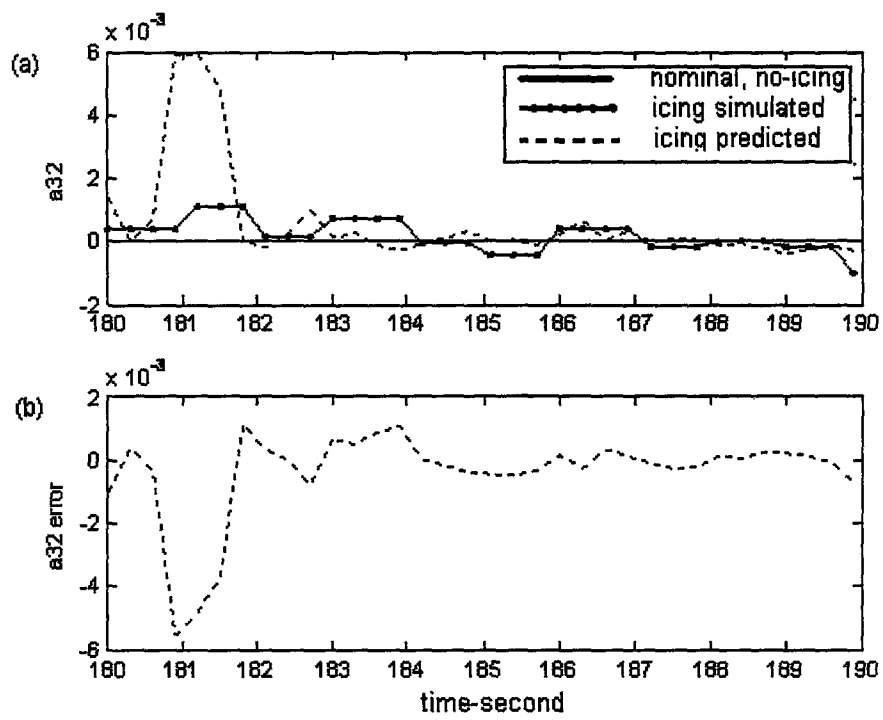


Figure B.23 Parameter a_{32} of A340 with comparison per nominal and simulated icing history, (a) NN output of a_{32} , (b) The error history of predicted output. Other than training and validation data sets are used.

CUIRRICULUM VITAE

The author was born in Yıldızeli, Sivas in 1970. He finished primary and secondary school in his county, Yavru; and high school in Kabataş Erkek Lisesi in Istanbul. He started the study of aircraft engineering in Istanbul Technical University (İTÜ) in 1987. He took the MSc degree, and started PhD studies in the same department in 1997. He has worked for Turkish Airlines as an aircraft engineer since 2000. He has a paper which was issued in a journal of Aircraft Engineering and Aerospace Technology included in Science Citation Index (SCI), seven papers in national and international conferences and meetings. His specialty is aircraft structures and flight dynamics & control. His working subjects currently are aircraft icing, fault detection and isolation based on flight data, system identification, airline engineering, structural repairs and modifications, cargo conversion of passenger aircraft, aircraft wing tank corrosion, design organization procedures, international civil aviation rules (FAR, JAR, EASA). He has been married to a teacher for 6 years. They have two sons with one and five ages.