N93-14854

Wind Shear Related Research at Princeton University

Dr. Robert Stengel, Princeton University

Wind Shear-Related Research at Princeton University

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April 1992

Real-Time Decision Aiding:
Aircraft Guidance for Wind Shear Avoidance

Target Pitch Angle and Optimal Recovery
from Wind Shear Encounter

Dynamic Behavior of an Aircraft Encountering a Wind Vortex

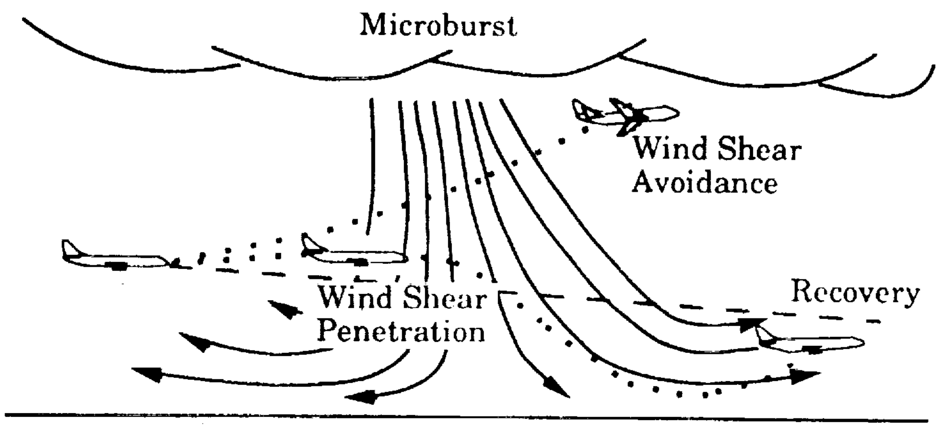
Real-Time Decision Aiding: Aircraft Guidance for Wind Shear Avoidance

D. Alexander Stratton and Robert F. Stengel
Princeton University

Presentation Outline

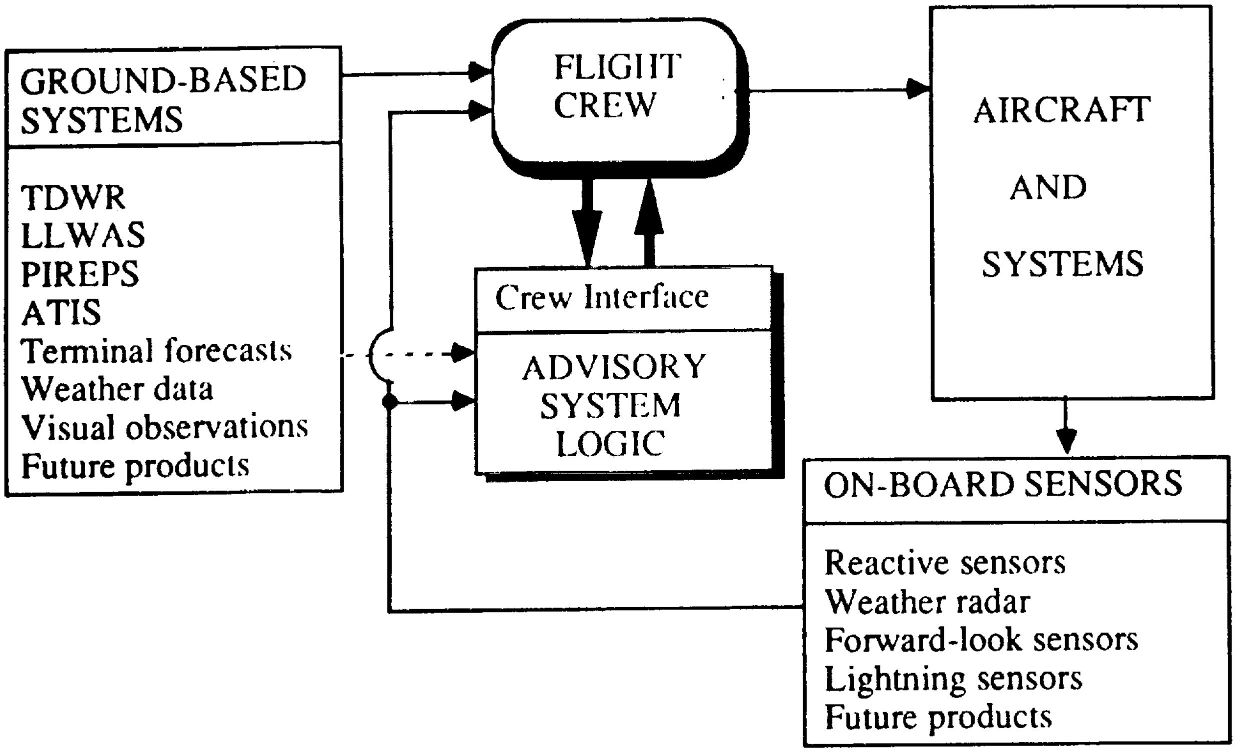
- The Microburst Hazard to Aviation
- Processes of a Wind Shear Advisory System
- Simulated Microburst Encounters

The Low-Altitude Wind Shear Threat



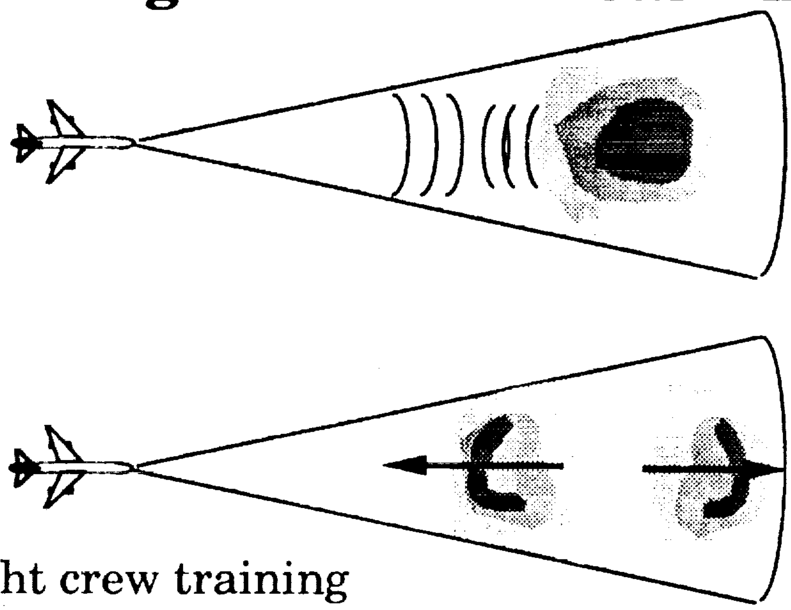
- Microburst phenomenon
  - Short-lived, powerful outflow
  - Aircraft performance, control
- Microburst research
  - Wet, dry environments classified
  - Frequency, characteristics determined
  - Guidance and control strategies

An Advisory System for Wind Shear Avoidance



- Support crew decision reliability
  - Monitoring and estimation, data link
  - Risk assessment
  - Provide decision alternatives
  - Recovery procedures
- Define computational structure
  - Summarize relevant information
  - Incorporate meteorological data
  - Declarative structure, convert to real-time

Reducing the Wind Shear Threat



- Flight crew training
  FAA Windshear Training Aid

- Ground-based detection systems
  LLWAS, TDWR
  Weather services, forecasting

- Airborne detection technology
  Doppler radar, lidar, infra-red
  Radar reflectivity, lightning

- Integration, information transfer

Energy-Based Hazard Model

One-dimensional energy model:

$$E_S(t) = \left(\frac{1}{2g}\right) V_a{}^2 + h$$

$$\frac{dE_S}{dt}(t) = P_s - \mathcal{F}(t)V_a$$

- $\mathcal{F}$ - "F-factor" (Bowles)

$$\mathcal{F}(t) = \left(\frac{1}{g}\right)\frac{dw_X}{dt}(t) - \frac{w_h(t)}{V_a}$$

Specific excess power (P_s) variation

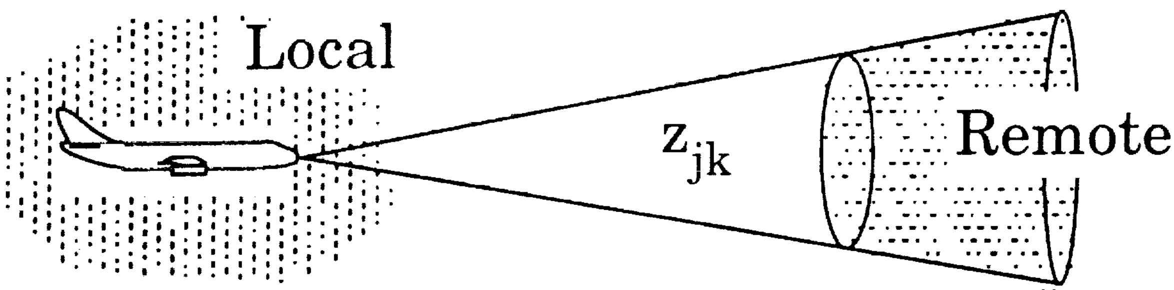
Airspeed variation

NASA Langley – 0.1 average $\mathcal{F}$ over 1 km

- Energy deviation across shear

$$\Delta E_S = -\mathcal{F}_{ave}\Delta x = -\frac{V_{an}}{g}\Delta w_X + \frac{w_{h_{ave}}}{V_{an}}\Delta x$$

Forward-Look Sensor Measurement of Wind Shear



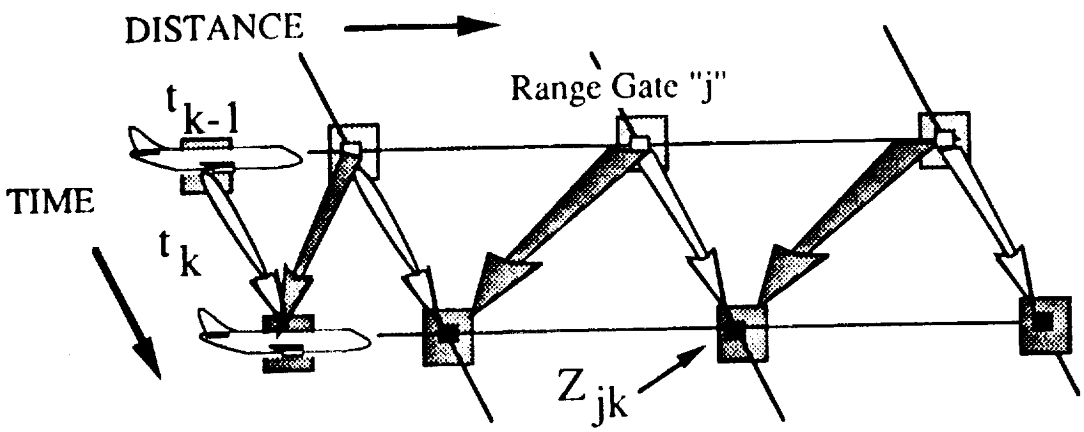
Relative Speed of the Air Masses	=	Remote Wind Speed with respect to Aircraft	–	Aircraft Speed with respect to Local Air Mass

$$\Delta w_{jk} = z_{jk} - V_a$$

- Aircraft Specific Energy Loss

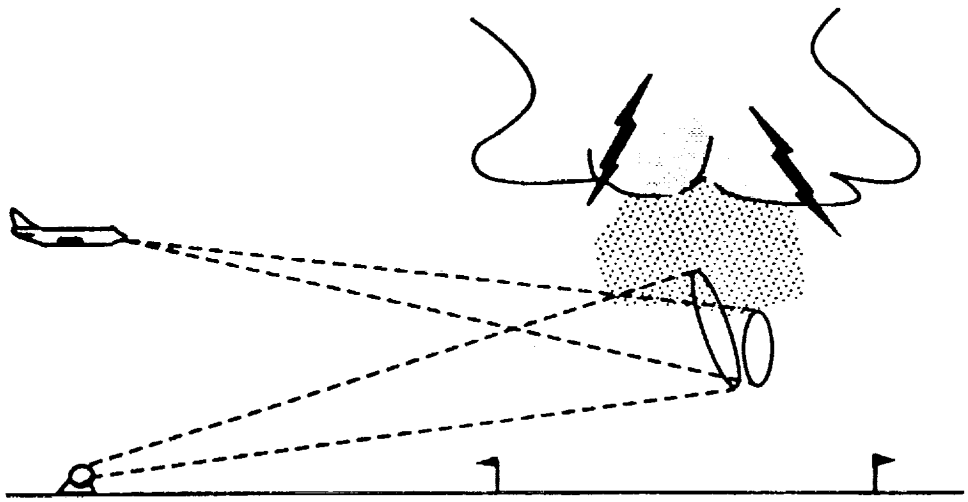
$$\Delta E_S = -\mathcal{F}_{ave}\Delta x = -\frac{V_{an}}{g}\Delta w_x + \frac{w_{h_{ave}}}{V_{an}}\Delta x$$

Stochastic Prediction Algorithm



- Coupled Kalman filters
  - "Random walk" stochastic model
  - Sensor platform motion - state propagation
  - Parallel processing
  - Optimize design gain parameter
- Coupled predictive-reactive detection
- Positive detection - threshold exceedence

Probability-Based Decision Strategy



- Predictive measurements $\mathbf{z_p}(t)$

- Probability-based decision-making

$$\Pr\{\exists t_i \in [t,t_f]: \mathbf{w}(t_i) \in \mathcal{U} \mid \mathbf{z_p}(t), u_d(t) = u_{d1}\} < T \Rightarrow u_d(t) = u_{d1}$$

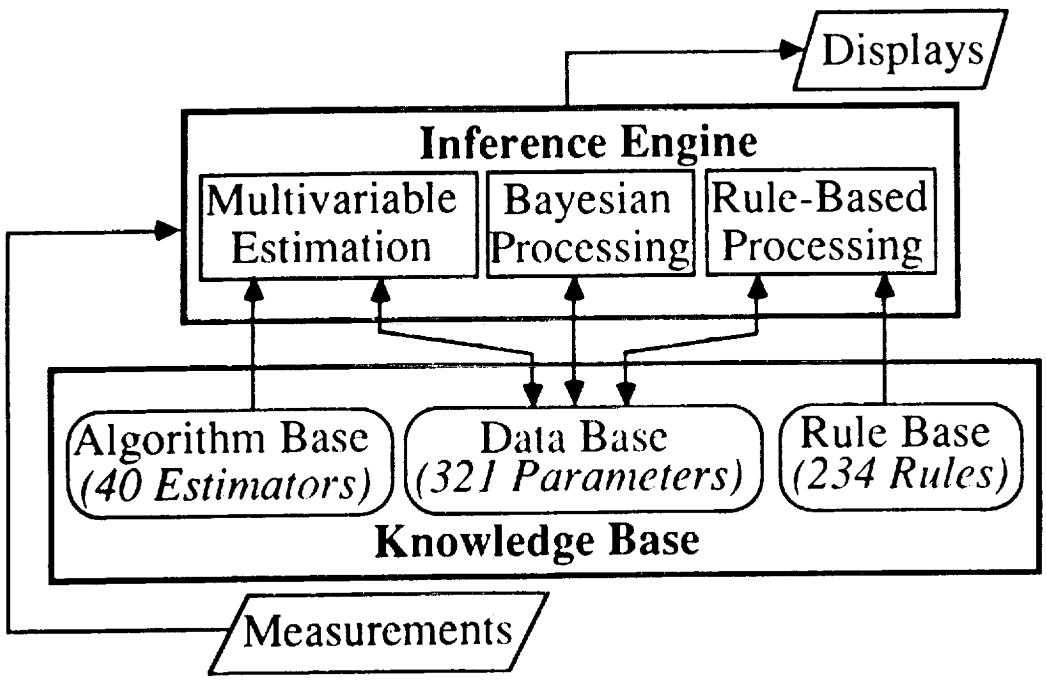
- Bayesian inference

$$\Pr\{H \mid \mathbf{z_p}(t)\} = \frac{\Pr\{\mathbf{z_p}(t) \mid H\}}{\Pr\{\mathbf{z_p}(t)\}} \Pr\{H\}$$

- Joint probability computation

Computational Processes for Decision Aiding

- Identify Knowledge, Structure



- Rule-Based Logic

  Declarative, back-chaining inference

  Top-level monitoring, assessment, planning, guidance functions

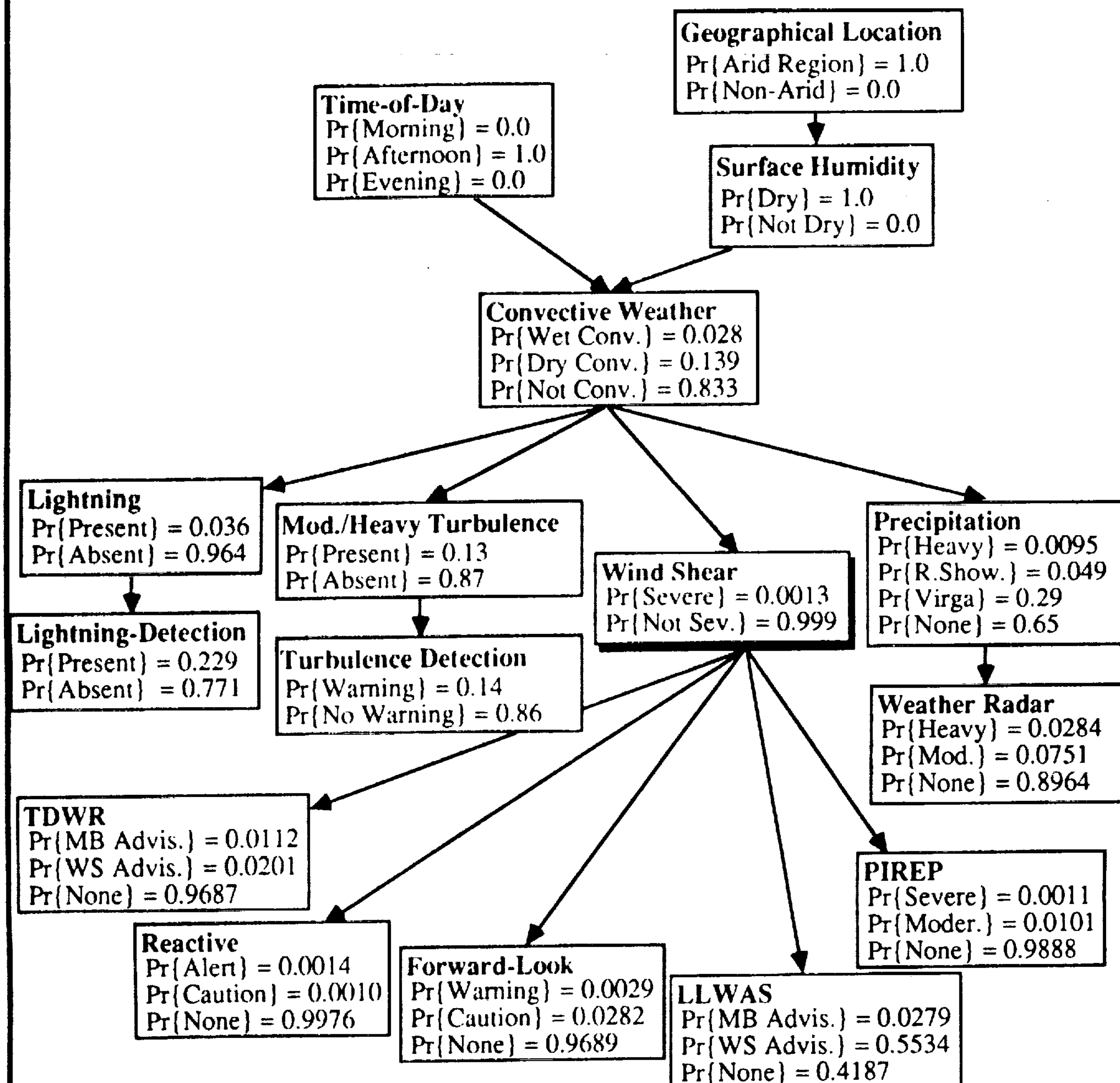
- Bayesian Logic

  Statistical model, data-driven inference

- Multivariable Estimation

  Stochastic model

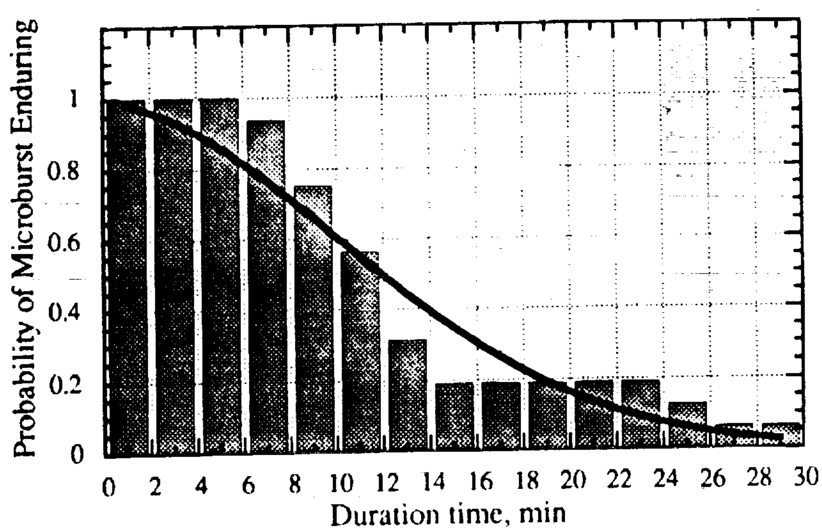
Bayesian Network Risk Assessment



- Assign link probabilities, priors
- Probabilities updates, Bayes's theorem

Spatial and Temporal Factors

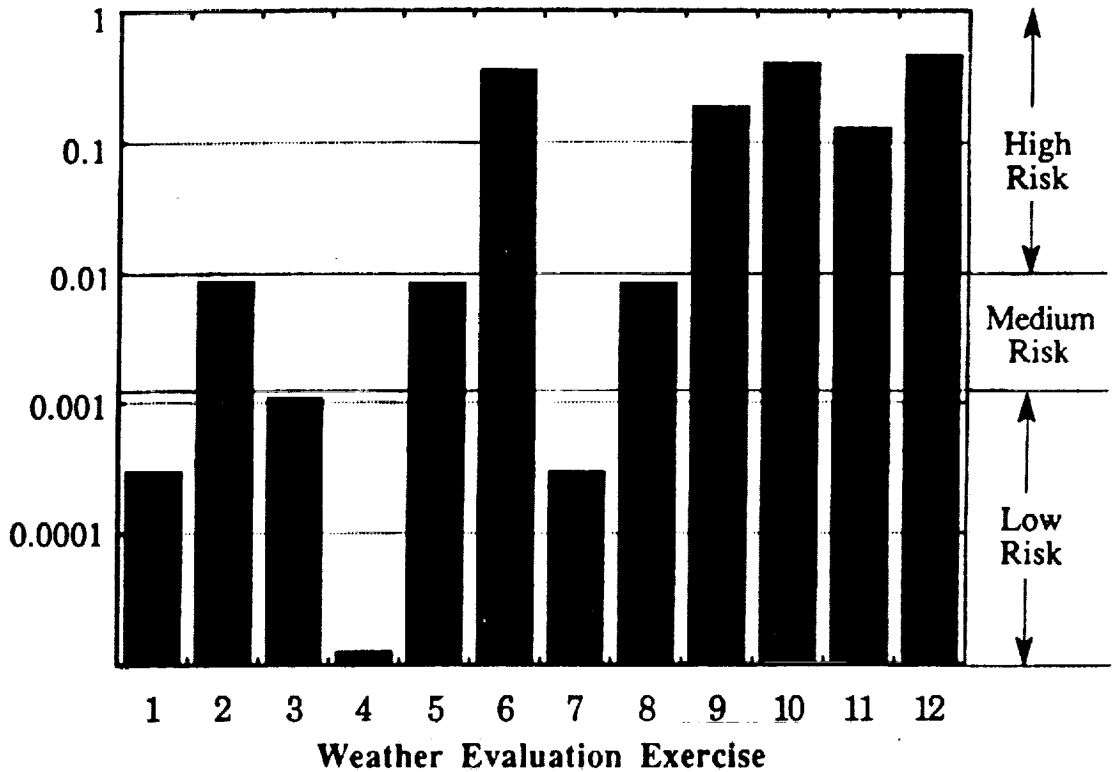
- Likelihoods weigh timeliness, nearness
  - Dual-doppler data (Hjelmfelt, 1988)



- Network time-dependant, re-initialize

- Repeated evidence, downgrade relevance

Risk Assessment Benchmarks



- Windshear Training Aid Guidelines
  - 12 Weather Evaluation Exercises
  - Risk Assessed by WTA authors

    Example: moderate convection results in Medium risk

- Bayesian Network Calculations
  - Monotonic relationship
  - Subjective levels assigned

Robustness of Predictive Wind Shear Detection

- Robustness issues

  Variation in microburst structure

  Vertical winds unmeasured

  Bandwidth limitations

- Detection robustness metrics

  Probability of Correct Warning, $\Pr\{A \mid WS\}$

  False Warning Probability, $\Pr\{A \mid \neg WS\}$

$$\Pr\{WS \mid A\} = \frac{\Pr\{A \mid WS\}}{\Pr\{A\}} \Pr\{WS\}$$

$$\Pr\{A\} = \Pr\{A \mid WS\}\Pr\{WS\} + \Pr\{A \mid \neg WS\}[1 - \Pr\{WS\}]$$

- Accuracy metrics

  Mean-Square Prediction Error

  Mean Advance Warning Time

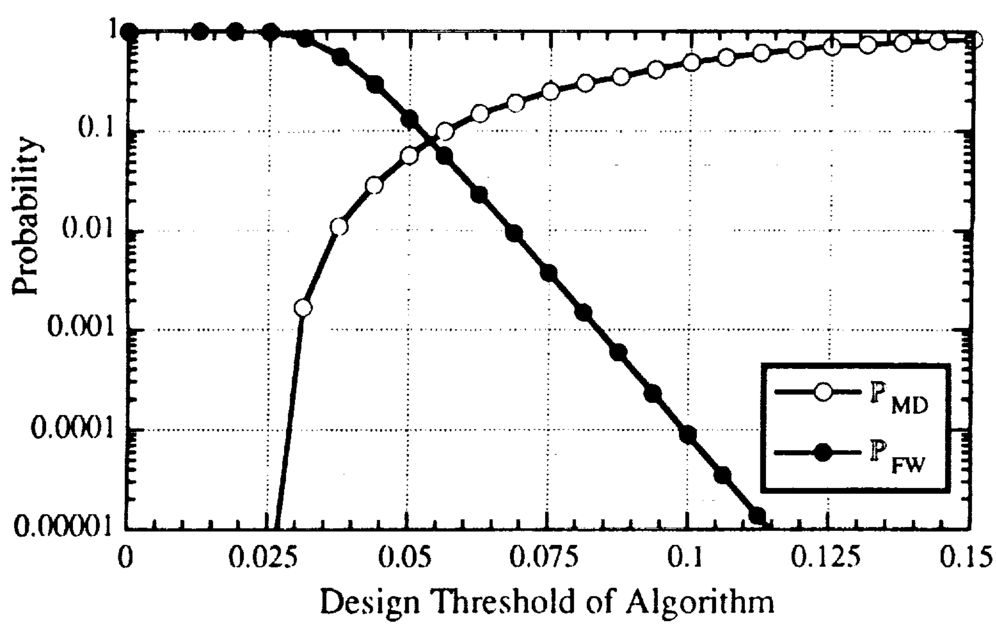
Prediction Algorithm Refinement

- Probability of Correct, Missed Detection
  Monte Carlo analysis

- Design parameter optimization
  Mean-Square Hazard Prediction Error

- False Warning Probability

$$N(T_d) = \frac{\sigma_{\dot{y}}}{2\pi\sigma_y} e^{-\left(\frac{T_d^2}{2\sigma_y^2}\right)}$$



- Benchmark Statistics for Bayesian Network

Selection of Design Threshold

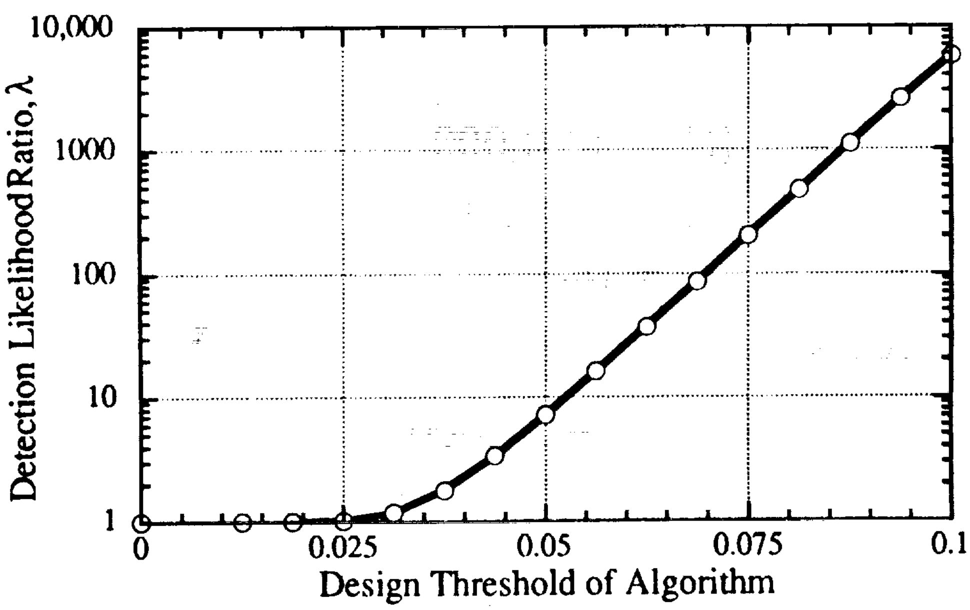
- Fixed design threshold

  Tolerance for false warning rate

  Tolerance for wind shear encounter

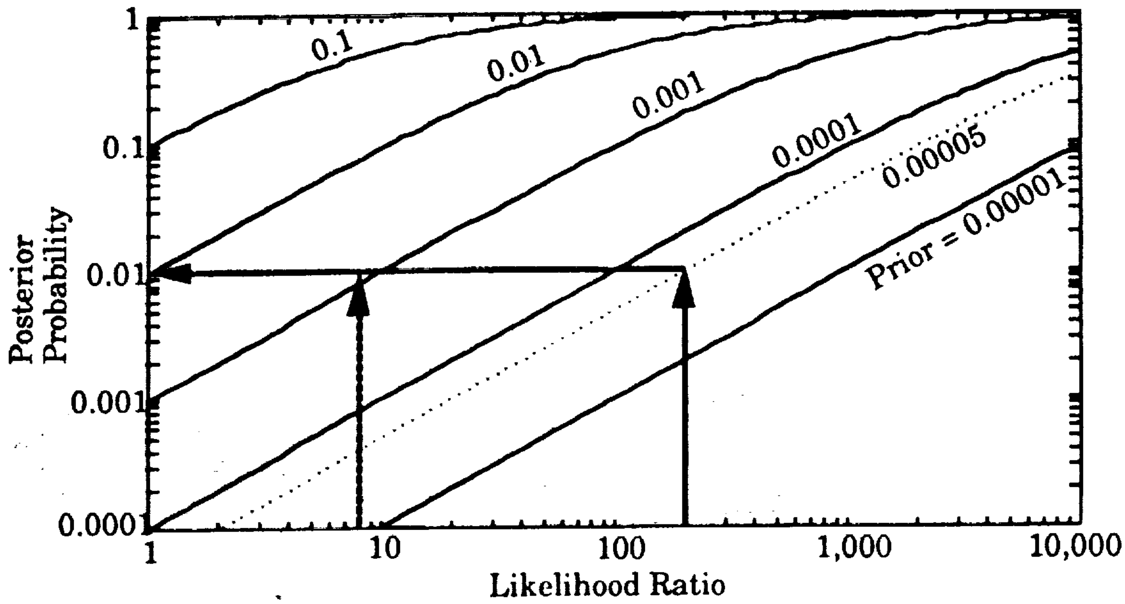
$$\lambda = \frac{\mathbb{P}_{CW}}{\mathbb{P}_{FW}}$$

$$\lambda = \frac{\Pr\{WS \mid A\}}{[1 - \Pr\{WS \mid A\}]} \frac{[1 - \Pr\{WS\}]}{\Pr\{WS\}}$$



- Variable or multiple threshold

Benefit of Integrated Warning



- CASE 1

  Prior Pr{H} = 1/20,000

  Likelihood ratio = 200 (0.075 radial F)

  Posterior = 1/100

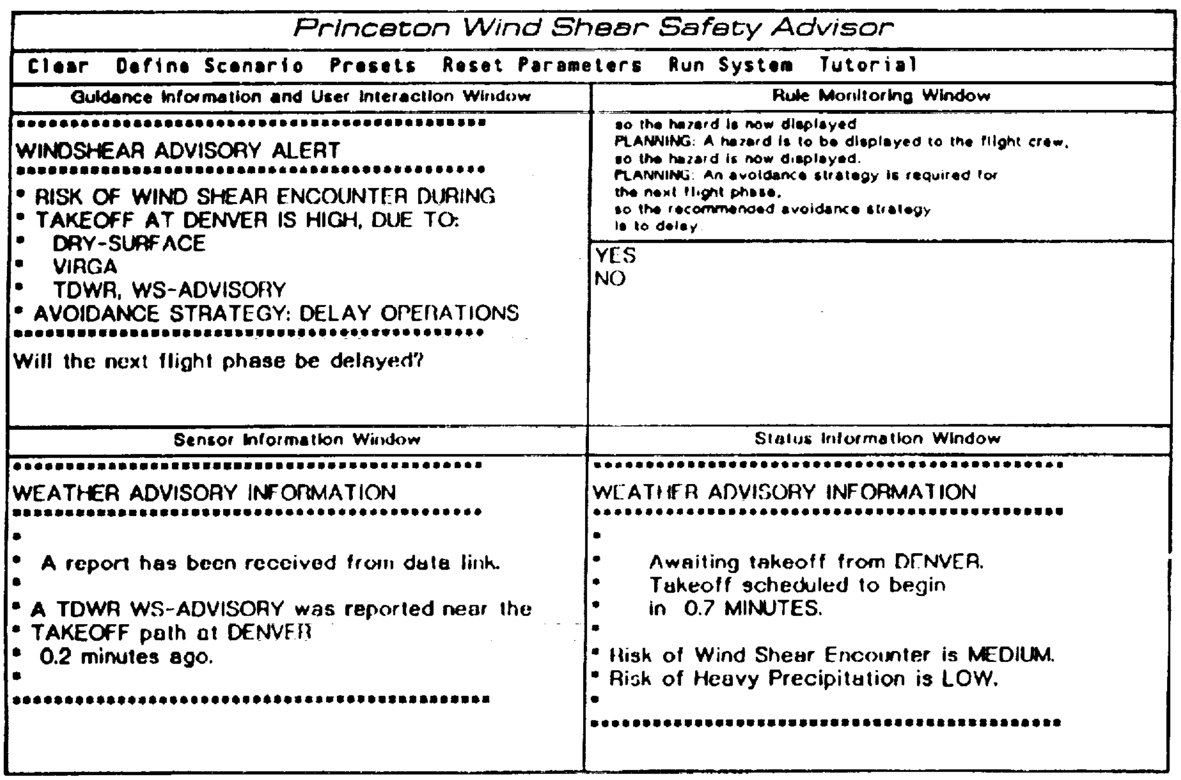
- CASE 2

  Prior Pr{H | E} = 1/1000

  Likelihood ratio = 8 (0.05 radial F)

  Posterior = 1/100

Wind Shear Safety Advisor Determines "High" Risk



Conclusions

- Diverse information aids hazard avoidance

- Explicit models easier to refine, validate
  - explicit conditions
  - statistical data, analysis

- Architecture for strategic decision-making
  - Mission planning, vehicle guidance
  - Failure detection, reconfiguration

- WSSA logic applications
  - Pilot training aid
  - Automated detection, recovery guidance

Reducing the Threat: Manual Recovery Strategies

- After liftoff/on approach technique
  - Aggressive application of thrust
  - Pitch toward 15° attitude
  - "Respect Stick Shaker"
  - Higher attitude, thrust if necessary

- On the runway
  - Aggressive application of thrust
  - Below V_1, abort takeoff
  - Above Vr, rotate toward 15°
  - With less than 2000 ft runway, rotate toward 15° (possible tail scrape)

- Pilot Report

Target Pitch Angle for the Microburst Escape Maneuver

Sandeep S. Mulgund and Robert F. Stengel

Overview

- The Wind Shear Problem
- Previous research
- Effect of wind shear on airplane performance
- Recovery strategies for inadvertent encounters with wind shear
- Present Research
    - Recovery technique for commuter-class aircraft
    - Trajectory Optimization
- Conclusions

Recovery Technique for Inadvertent Encounter

FAA Wind Shear Training Aid

- Apply maximum thrust and rotate aircraft toward initial pitch target of 15°, while respecting "stick shaker"
- Maintain aircraft configuration

Why Constant Pitch?

- Attitude indicator is one of few major aircraft instruments not affected by microburst environment
- Easily recalled in emergency

Why 15° as the target?

- Easily recalled in emergency
- 15° mark on attitude indicator can be targeted even in heavy turbulence
- Provides good recovery performance for *jet transports* in a wide spectrum of shear encounters

Application to Commuter/General Aviation Aircraft

Issues

- Lower takeoff and approach speeds than jet transports
- Lower wing loading
- Lower specific excess power

Objective

- Apply FAA recovery strategy to this class of aircraft
- Methodology for identification of Target Pitch Angle (TPA)

Commuter Aircraft Model

- Simulation model representative of light twin prop - 6300 lb g.w.
- Point Mass dynamics

Maximum Climb Capability in Wind Shear

- Rate of Climb:

$$\dot{h} = V \sin\gamma + w_h$$

- Maximize steady-state rate of climb under an imposed F-Factor

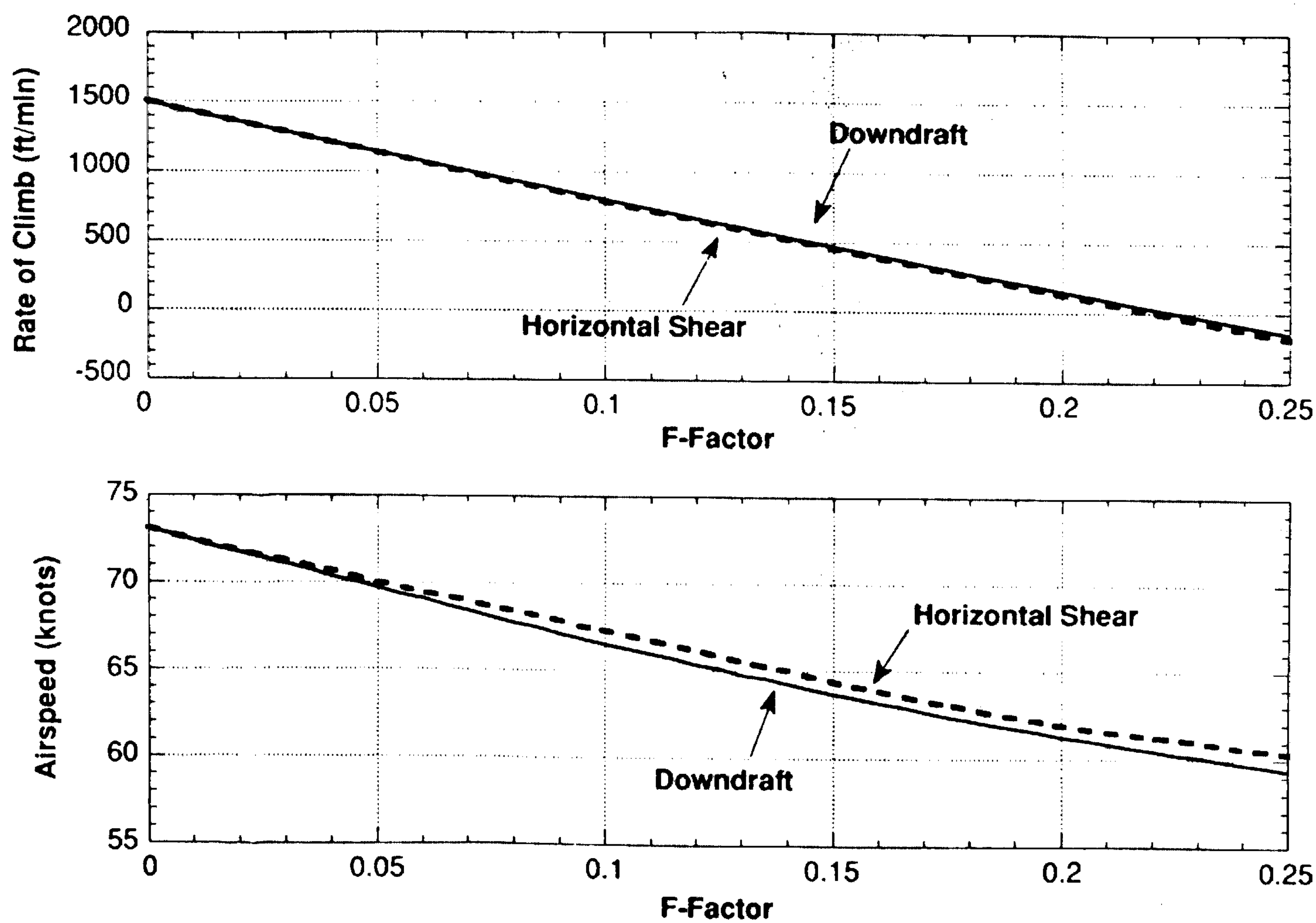
$$F = \frac{\dot{w}_x}{g} - \frac{w_h}{V}$$

$$\text{(a)}\ F = \frac{\dot{w}_x}{g}$$

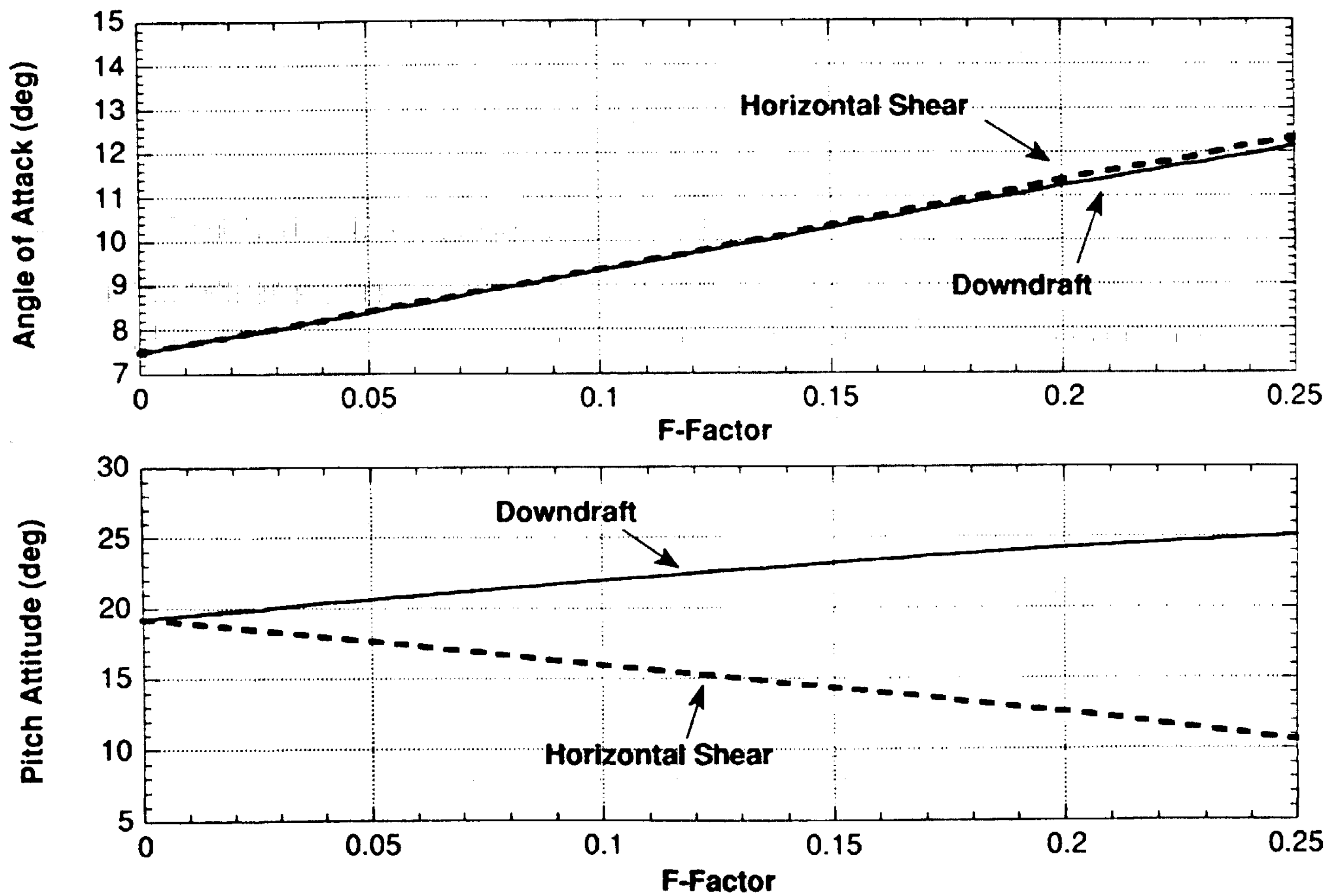
$$\text{(b)}\ F = -\frac{w_h}{V}$$

- Aircraft in initial approach configuration: 45° flaps, gear retracted

Effect of Wind Shear on Maximum Rate of Climb



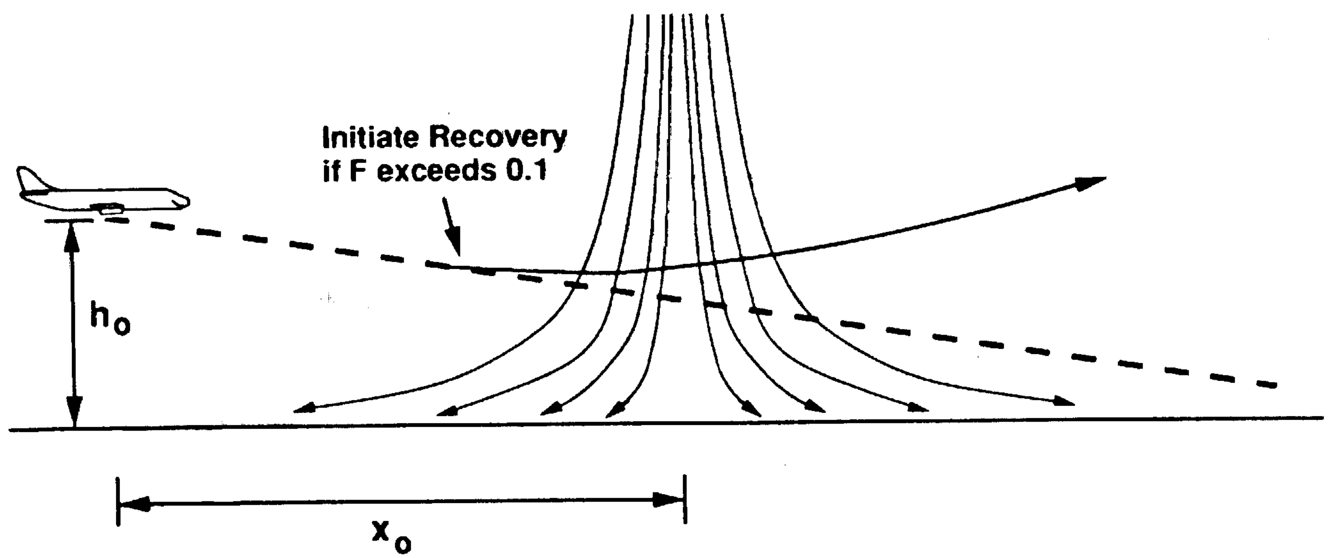
Angle of Attack and Pitch Attitude for Best Climb in Wind Shear



Implications

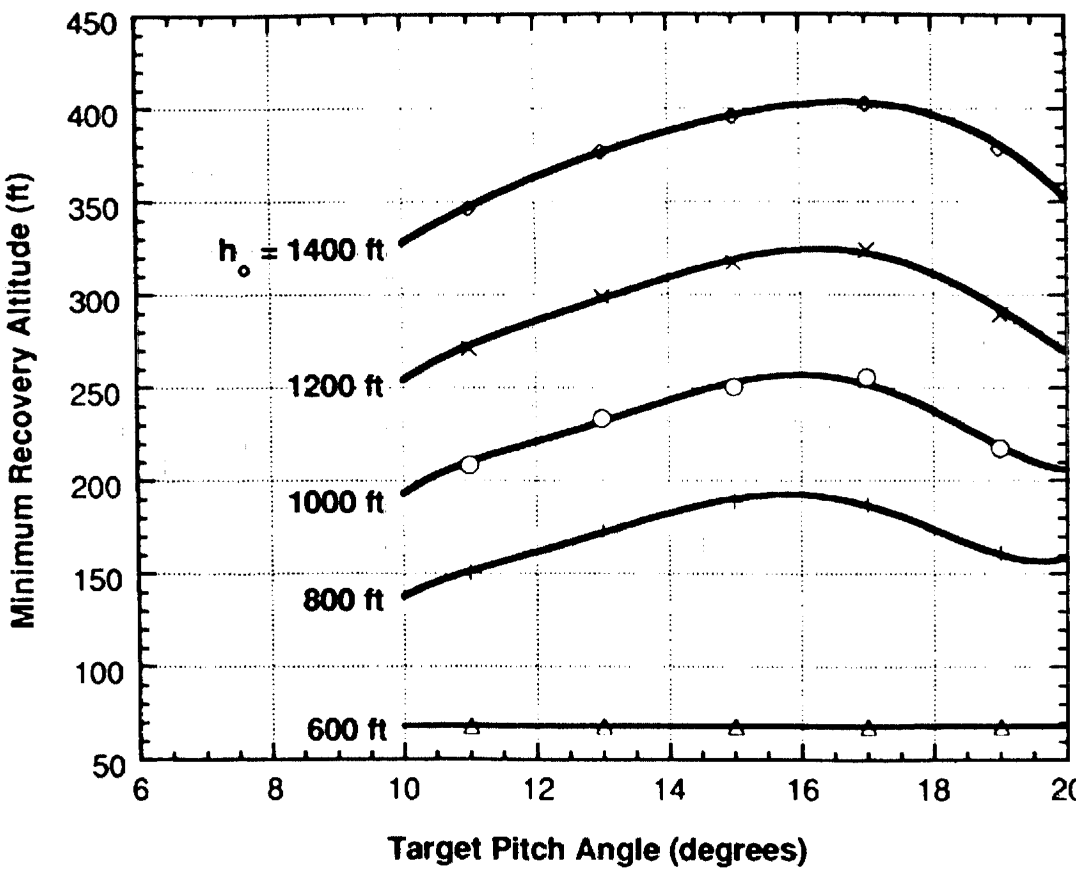
- Pitch attitude for climb rate depends on source of threat
- Actual environment contains regions of both downdraft and horizontal shear
- Single target pitch angle is a compromise
- Nature of trade-off may be ascertained through simulation of microburst encounters
- Require a mathematical microburst model

Simulation of Encounter During Final Approach



- Microburst core placed directly along flight path
- Aircraft tracks glide slope prior to shear entry

Effect of Initial Altitude on Minimum Recovery Altitude



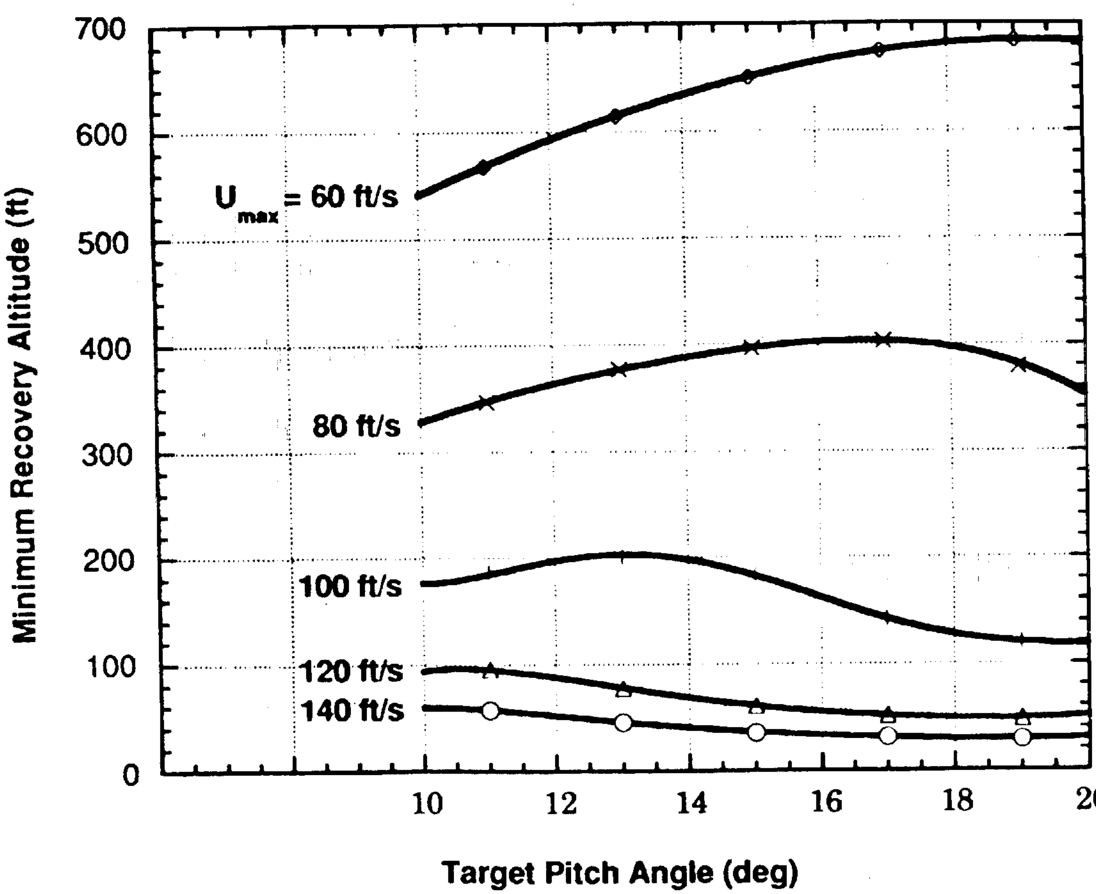
V_o = 95 knots
$\delta F = 45^\circ$

Shear Parameters:

R = 3000 ft
U_{max} = 80 ft/s
Z_{max} = 150 ft

Initial Distance
from Core: 10,000 ft

Effect of Shear Strength on Minimum Recovery Altitude



V_o = 95 knots
δF = 45°
h_o = 1400 ft

Shear Parameters:

R = 3000 ft
Z_{max} = 150 ft

Initial Distance from Core: 10,000 ft

Trajectory Optimization in Wind Shear

- Find $\mathbf{x}(t)$, $\mathbf{u}(t)$ to minimize

$$J = \phi[\mathbf{x}(t_f), t_f] + \int_{t_o}^{t_f} L[\mathbf{x}(t), \mathbf{u}(t), t]\,dt$$

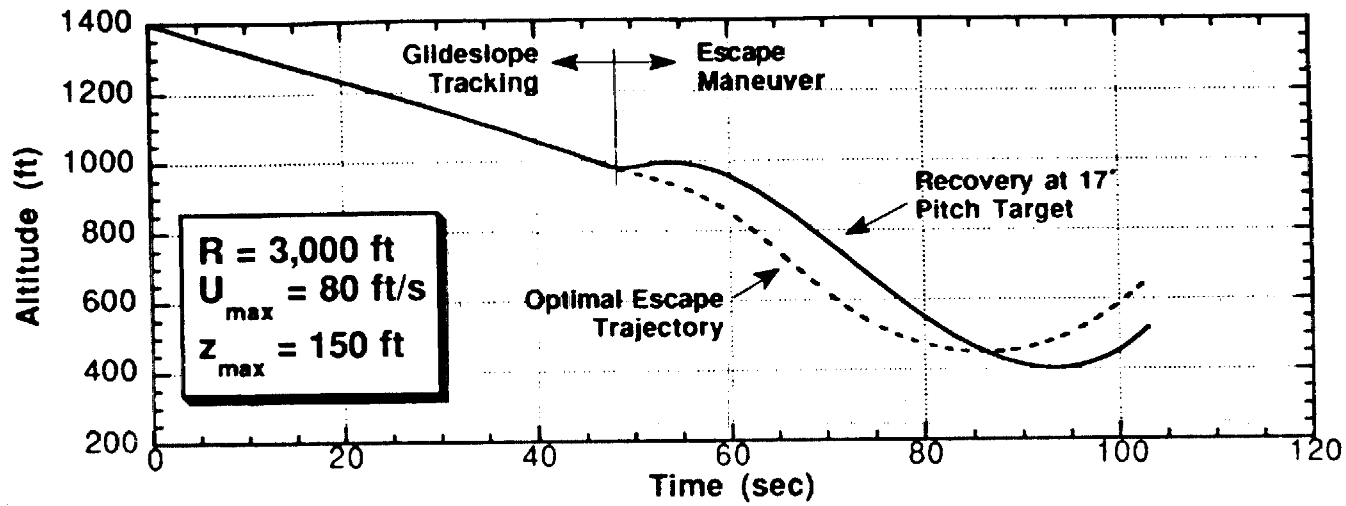
- What is optimal?
- Successful recovery $\Rightarrow$ Avoiding ground impact
- Maximize minimum altitude $\Rightarrow$ Minimize maximum deviation from a high reference altitude: [Miele]

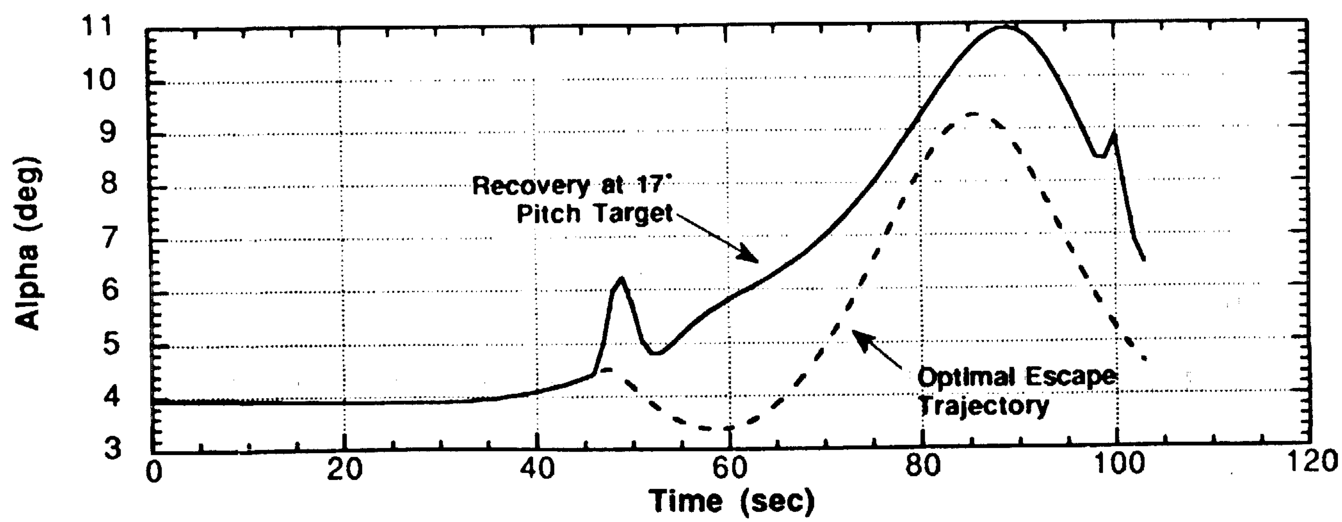
$$I = \max_t (h_{ref} - h(t)) \qquad t_o \le t \le t_f$$

- Equivalent Lagrangian problem:

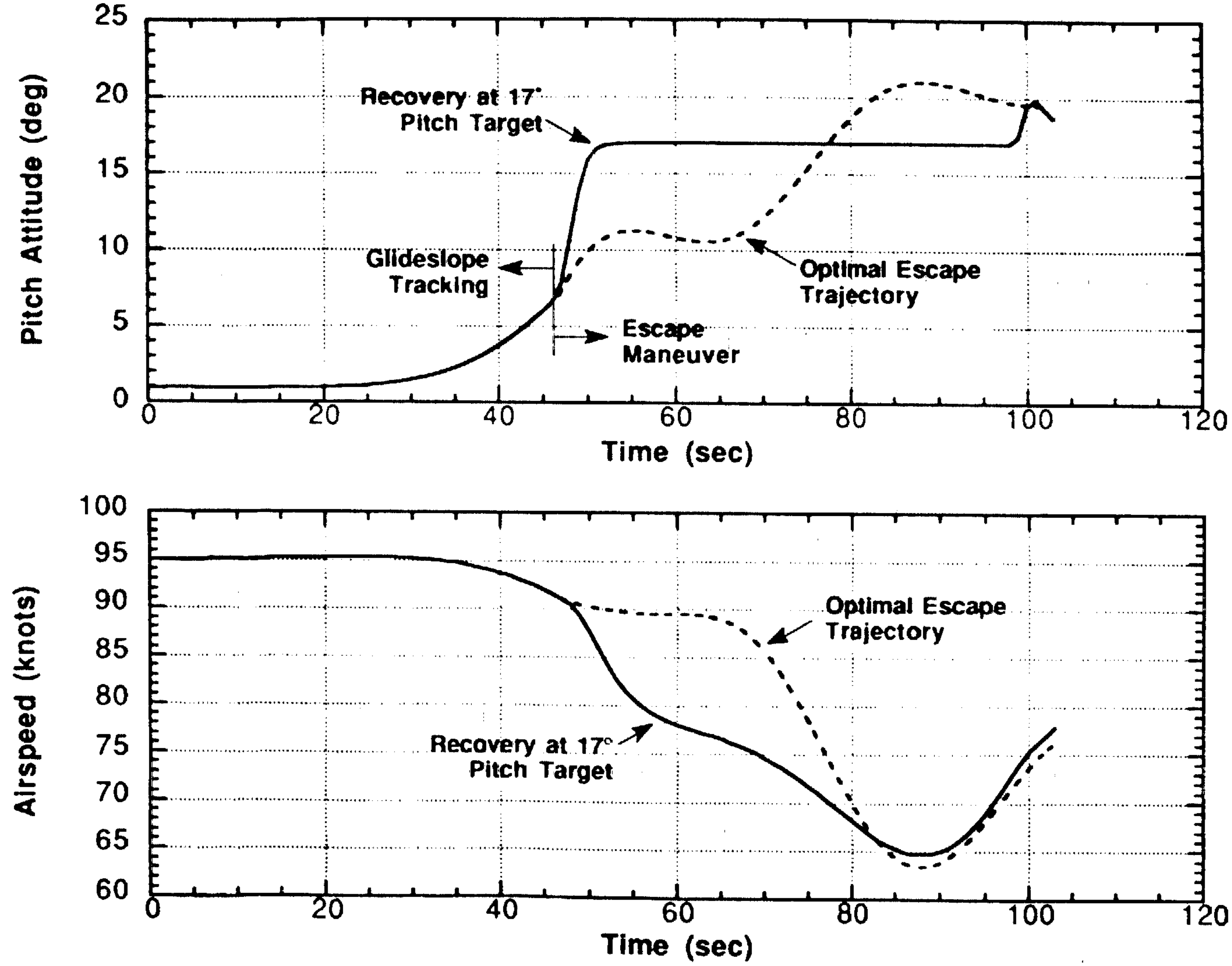
$$J = \int_{t_o}^{t_f} (h_{ref} - h(t))^q\,dt \qquad q >> 2 \text{ and even}$$

Altitude and Angle of Attack vs. Time for TPA and Optimal Recovery





Pitch Attitude and Airspeed vs. Time for TPA and Optimal Recovery



Comparison of Trajectories

- Performance

	TPA Recovery	Optimal Recovery
Min. Altitude (ft)	403	455
Min. E_S (ft)	596	630
Min. Airspeed (kts)	65	63
Max. Alpha (deg)	11.0	9.3

- Qualitative features

  Optimal trajectory involves initial reduction in pitch attitude

  Positive climb rate established earlier in optimal recovery

Conclusions

- Aircraft attitude for best climb rate depends on source of threat
- TPA simulation results - no single attitude stands out
- Optimal trajectory analysis - TPA not optimal, but reasonable

Computation of Optimal Trajectories

- Aircraft subject to two constraints:

$$-20^\circ \le \delta_E \le 20^\circ$$
$$V \ge 125\ \text{knots}$$

- Airspeed constraint imposed using a penalty function:

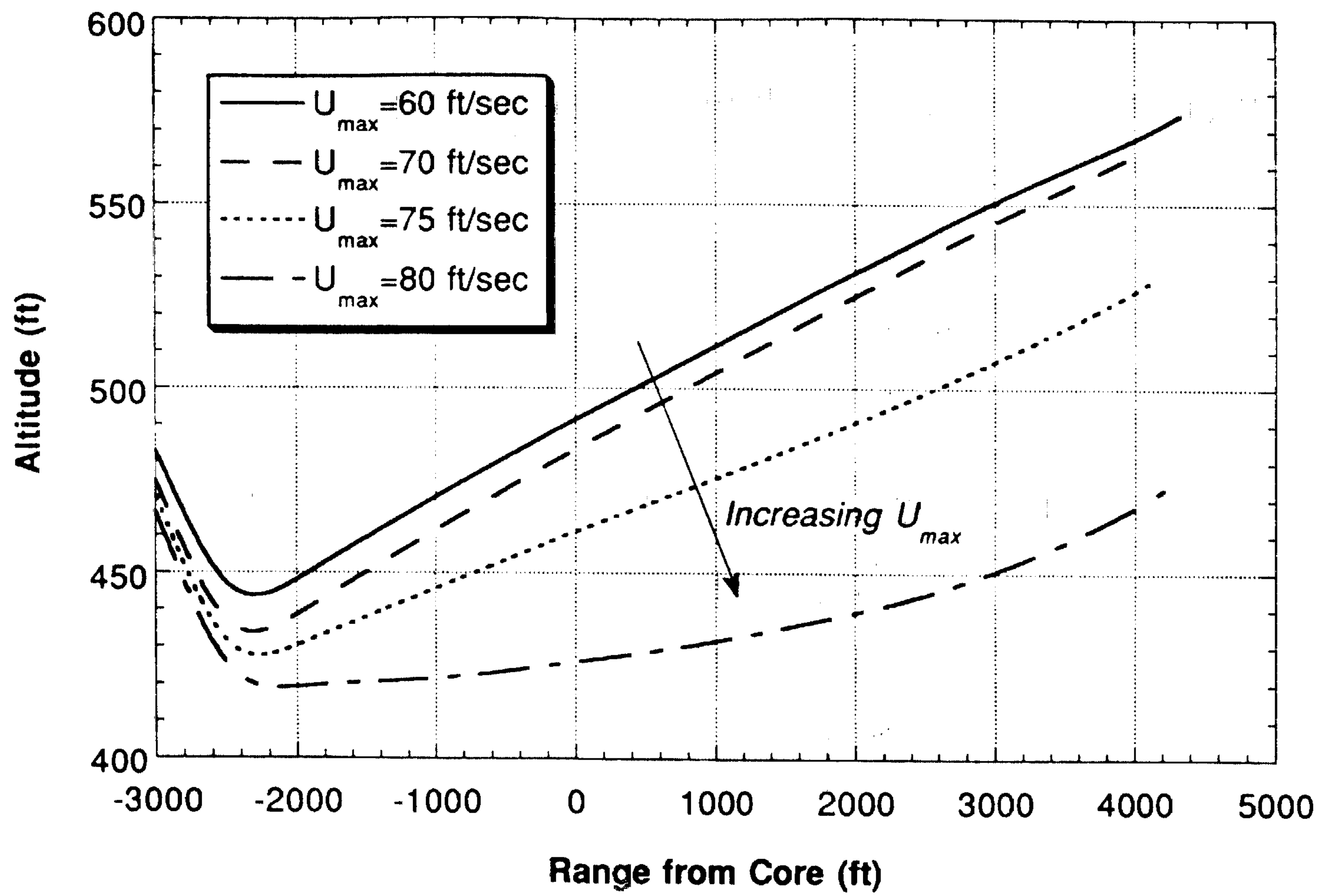
$$L(\boldsymbol{x},\boldsymbol{u}) = L(\boldsymbol{x},\boldsymbol{u}) + L_V(V)$$

where

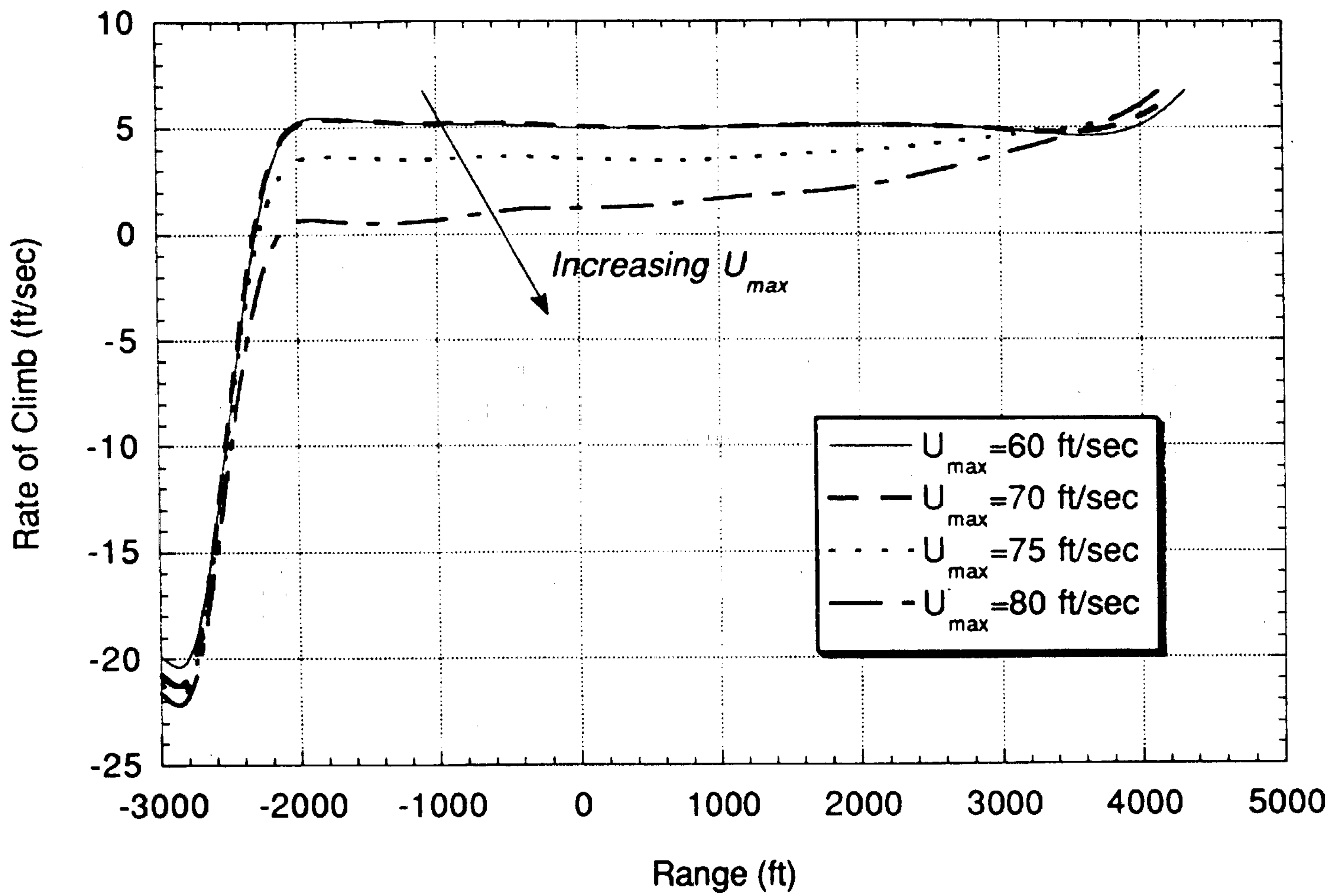
$$L_V(V) = \begin{cases} 0 & V > V_{\min} \\ K_V[V - V_{\min}]^2 & V \le V_{\min} \end{cases}$$

- Contribution of L_V to cost grows quadratically with magnitude of constraint violation

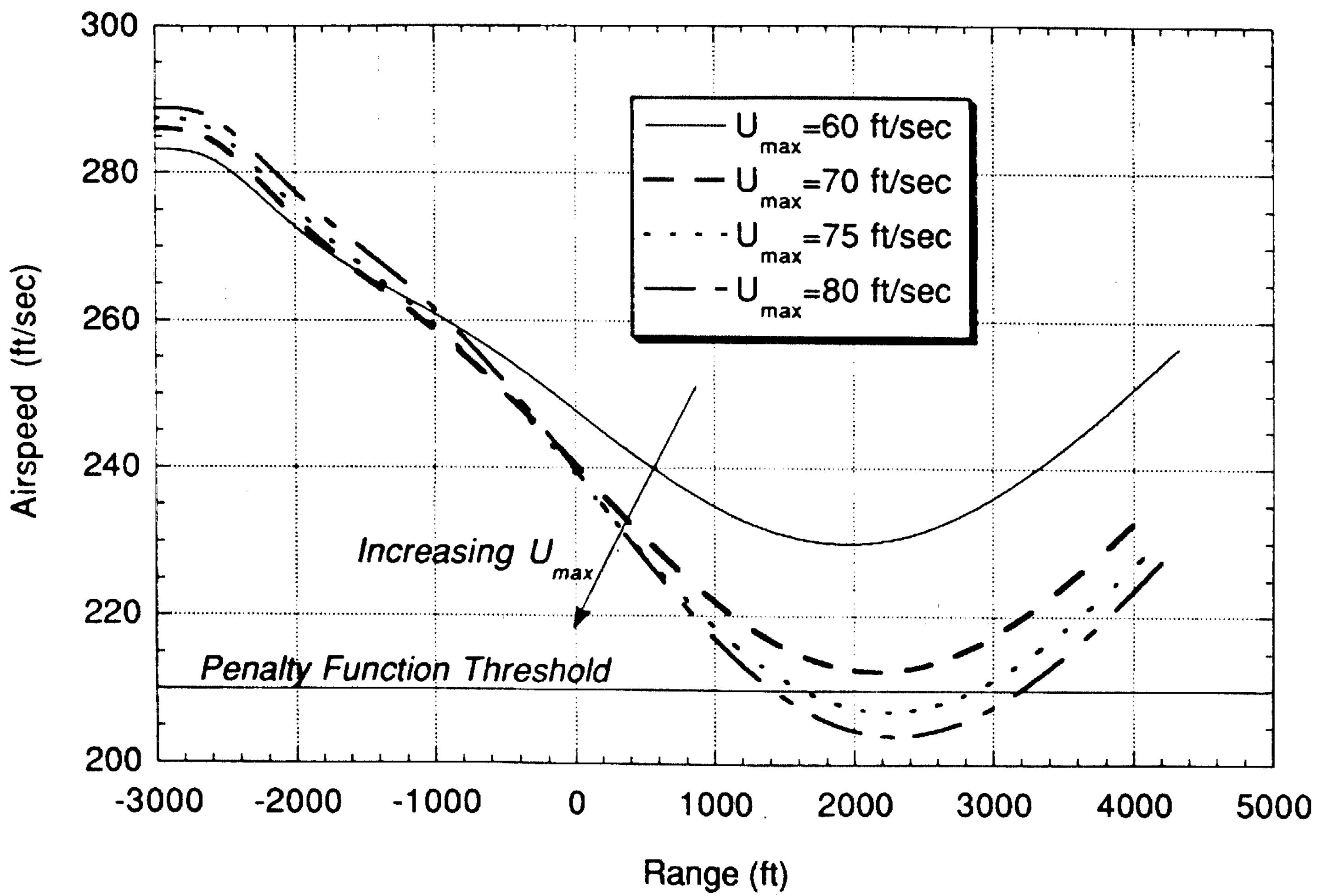
Altitude vs. Time for Optimal Paths through 4 Different Downbursts



Rate of Climb vs. Time for Optimal Paths through 4 different Downbursts



Airspeed vs. Time for Optimal Paths through 4 different Downbursts



Qualitative Features of the Optimal Flight Paths

- Rapid transition from descending to level or ascending flight
- Targeted rate of climb during escape depends on wind shear severity

    Weak to moderate $\Rightarrow$ Aircraft reaches 5 ft/sec climb rate

    Severe to very severe $\Rightarrow$ Aircraft reaches a lower climb rate

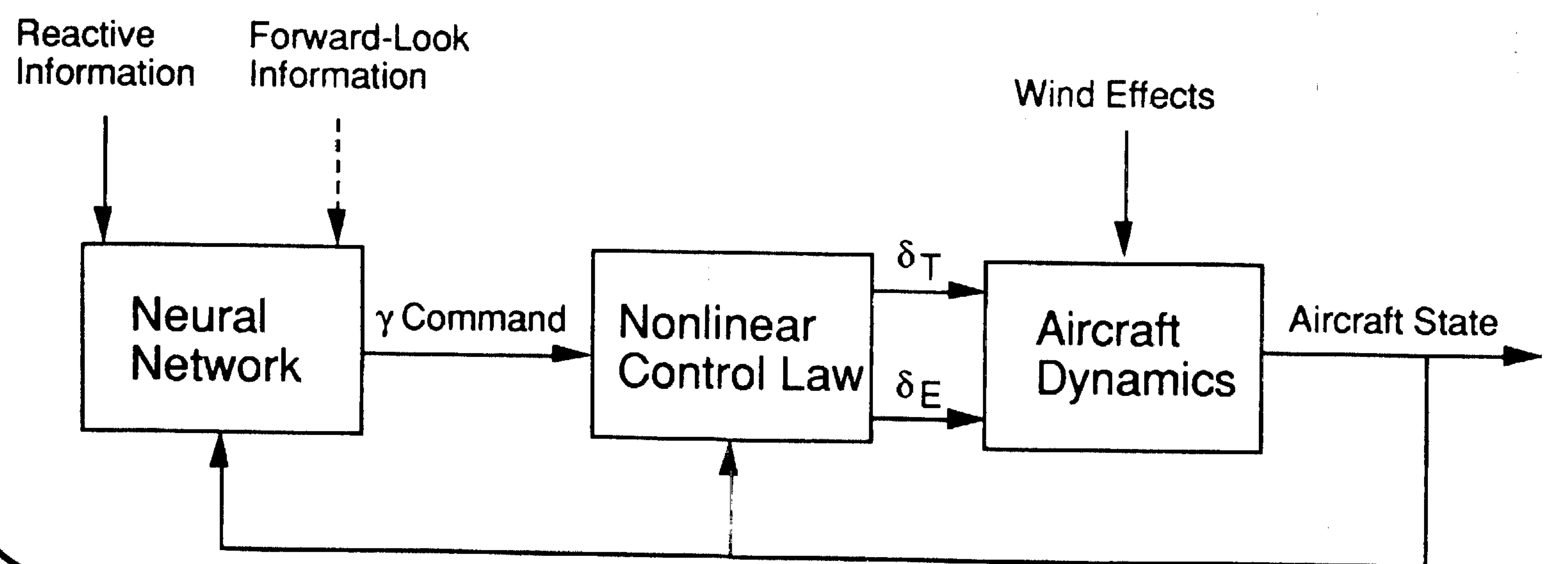
- Lower climb rate in severe microbursts results in reduced violation of minimum airspeed constraint

OK, but...

- Global knowledge of flowfield required for optimization
- Results not immediately applicable to real-time feedback control

Future Work:
Neural Networks for Real-Time Flight Guidance

- Train neural network with results of trajectory optimization
- Can parametrize microbursts according to size and severity
- Network generates flight path angle commands according to position within flow field
- Availability of forward-look information could assist in flight-path planning



Neural Networks for Aircraft Control

Benefits and Limitations of Trajectory Optimization

- Provides insight into the nature of control action required to most effectively achieve a specified goal
- Require global knowledge of microburst
- Optimal performance can only be approximated in real-time

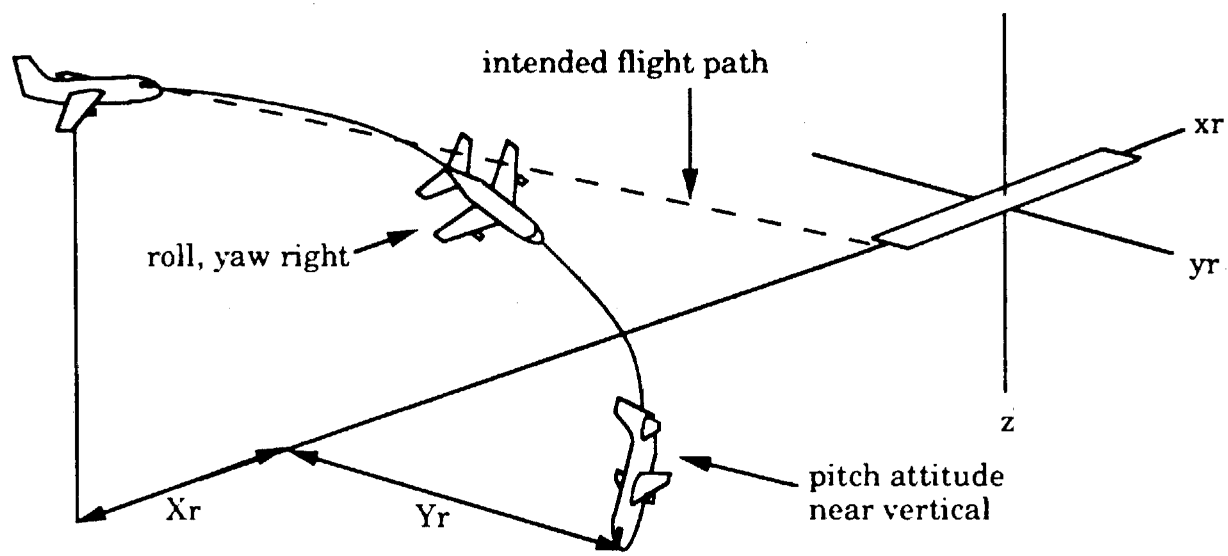
Enter Neural Networks!

- Objective: Teach a neural network to fly an airplane through windshear using the results of trajectory optimization as training data
- Families of optimal trajectories through a broad spectrum of microbursts must be developed
- Robust optimization technique needed - cost functions weights themselves need to be optimized

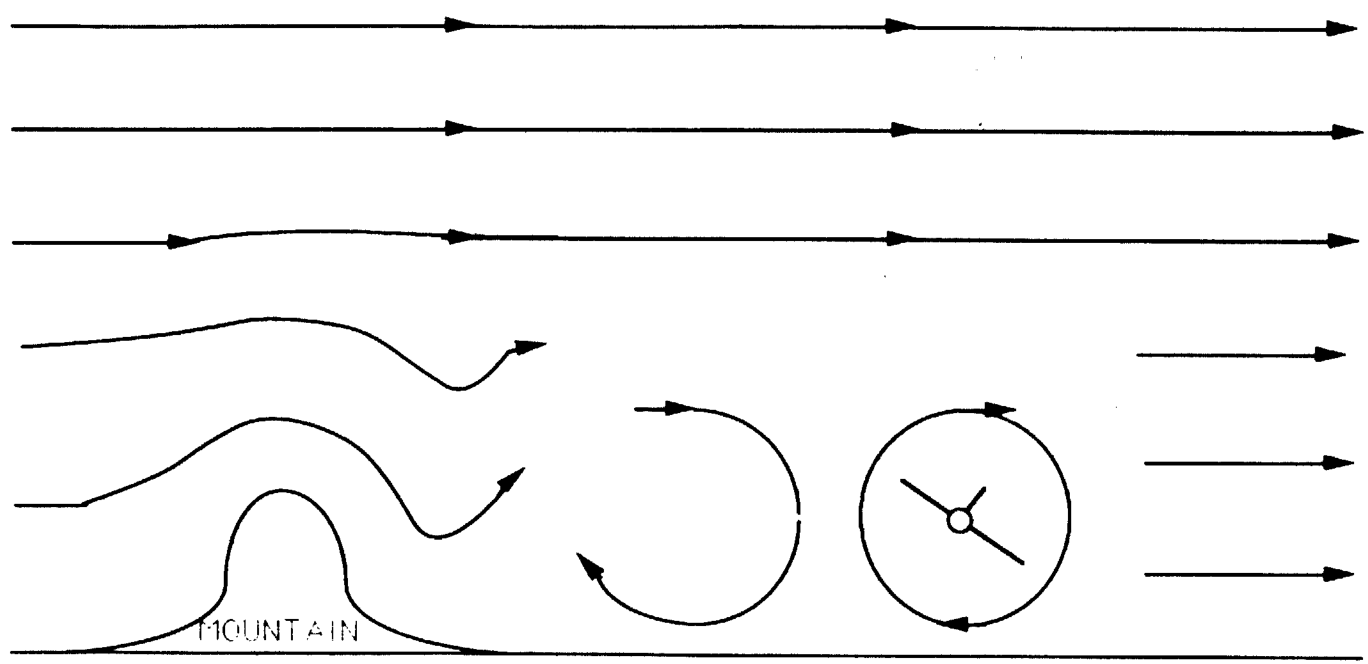
DYNAMIC BEHAVIOUR OF AN AIRCRAFT ENCOUNTERING A SINGLE AXIS VORTEX

Darin R. Spilman

FLIGHT PATH

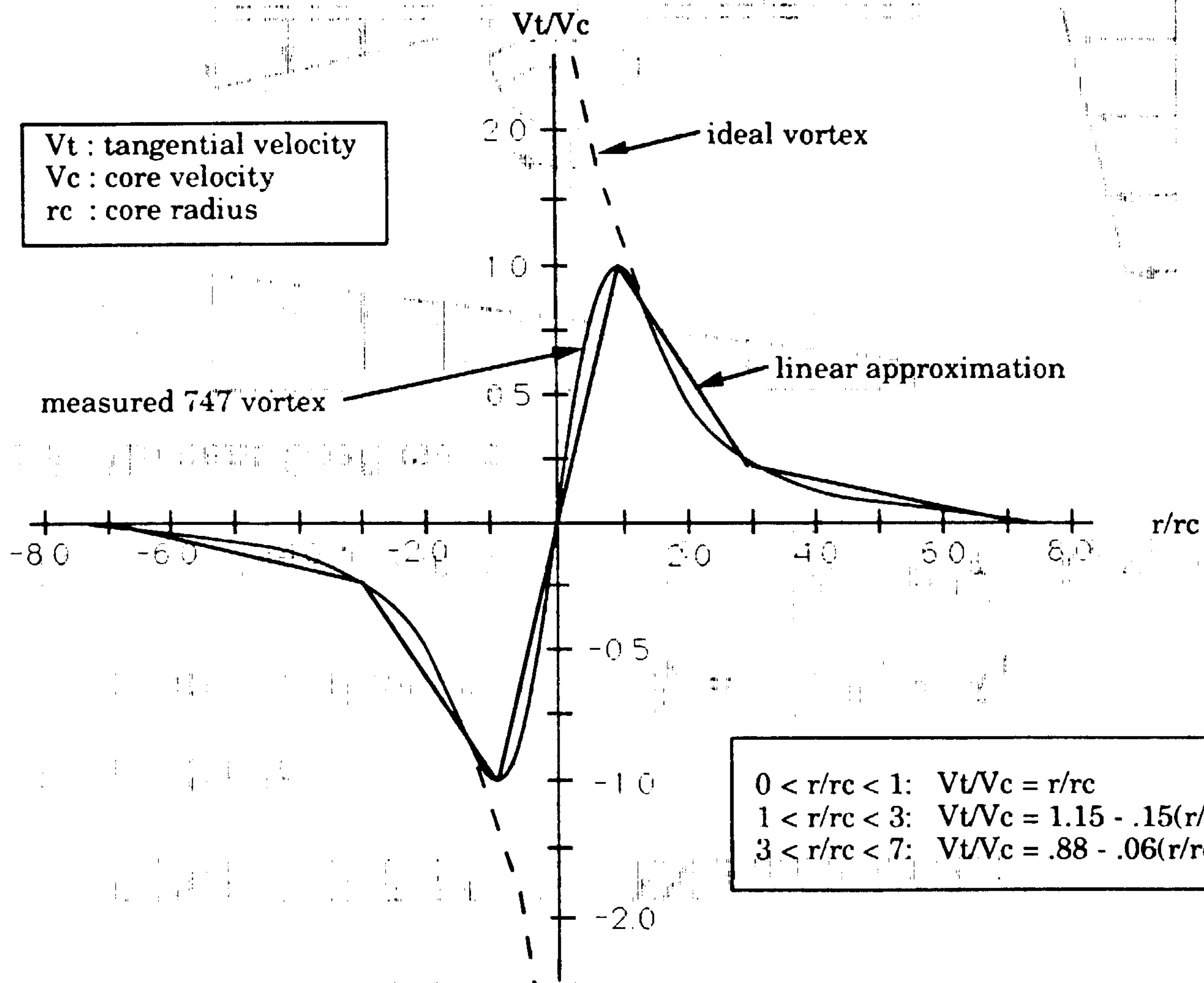

intended flight path
xr
yr
z
roll, yaw right
pitch attitude
near vertical
Xr
Yr

WIND ROTOR FORMATION



WIND ROTOR MODEL

Vt : tangential velocity
Vc : core velocity
rc : core radius



0 < r/rc < 1: Vt/Vc = r/rc
1 < r/rc < 3: Vt/Vc = 1.15 - .15(r/rc)
3 < r/rc < 7: Vt/Vc = .88 - .06(r/rc)

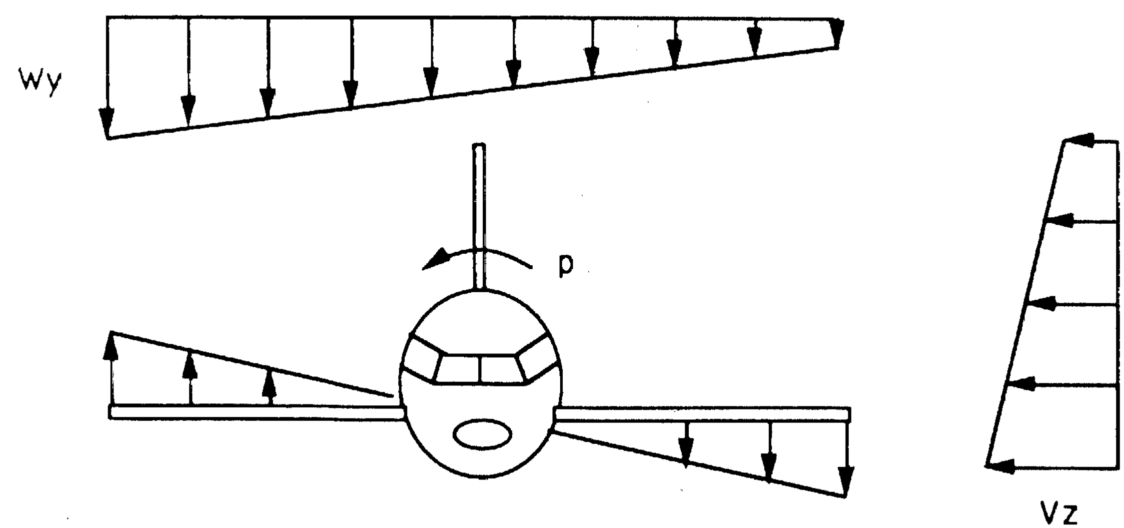
WIND EFFECTS ON AIRCRAFT

1. Equations of Motion

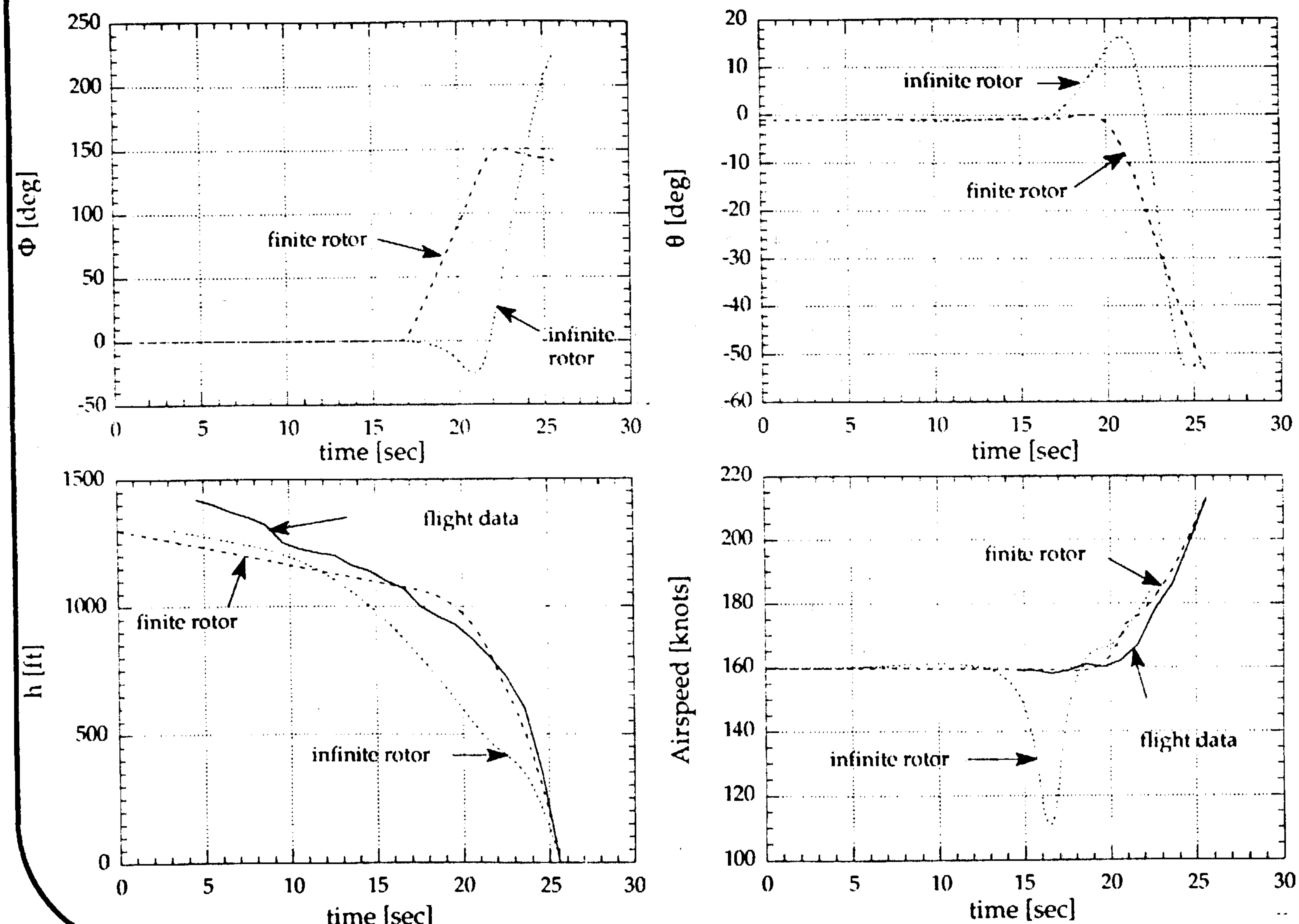
Translational kinematics $\dot{\vec{r}}_E = L_{EB}\vec{v}_B + \vec{w}_E$

Translational dynamics $\dot{\vec{v}}_E = \dfrac{F_B}{m} - H_I^B g - \tilde{w}_B v_B - \dot{\vec{w}}_B$

2. Force & Moment Coefficients



$$(C_{RL})_{ROLL} = (C_{RL_p})p - (C_{RL_{p_{wing}}} + C_{RL_{p_{htail}}})w_Y + (C_{RL_{p_{vtail}}})v_Z$$


Φ [deg]
250
200
150
100
50
0
-50
0
5
10
15
20
25
30
time [sec]
finite rotor
infinite rotor
θ [deg]
20
10
0
-10
-20
-30
-40
-50
-60
0
5
10
15
20
25
30
time [sec]
infinite rotor
finite rotor
h [ft]
1500
1000
500
0
0
5
10
15
20
25
30
time [sec]
flight data
finite rotor
infinite rotor
Airspeed [knots]
220
200
180
160
140
120
100
0
5
10
15
20
25
30
time [sec]
finite rotor
flight data
infinite rotor

CONCLUSIONS?

TBD

Wind Shear Related Research at Princeton University
Questions and Answers

Unknown - I would like to comment that Rob's work is independent of the accident investigation on the Colorado Springs accident which is still far from complete. We appreciate the efforts that they are doing, but you should not leave here with any conclusions based on it.

Rob Stengel (Princeton University) - No certainly and we have not made any conclusions either.

Session XI. Regulation, Certification and System Standards

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