Progress on Intelligent Guidance and Control for Wind Shear Encounter

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Low-altitude wind shear poses a serious threat to air safety. Avoiding severe wind shear challenges the ability of flight crews, as it involves assessing risk from uncertain evidence. A computerized intelligent cockpit aid can increase flight crew awareness of wind shear, improving avoidance decisions. This presentation outlines the primary functions of a cockpit advisory expert system for wind shear avoidance. It also introduces computational techniques being implemented to enable these primary functions.

WTA Wind Shear Probability Guidelines

The Wind Shear Training Aid contains a set of Microburst Wind Shear Probability Guidelines to assist flight crews in determining the risk of possible wind shear encounter. These guidelines relate various types of evidence that might be available in the cockpit to a discrete-valued "probability of wind shear encounter." When evaluating combinations of evidence, flight crews are instructed to combine the individual "probabilities" according to the rule, "LOW + MEDIUM = HIGH." If available evidence results in a "high probability of windshear encounter," the Wind Shear Training Aid states that a decision to avoid is appropriate. If the evidence results in a "medium probability of windshear encounter," then precautions are considered appropriate. The guidelines specify that the evidence must apply in the airport vicinity, during the intended time of operations, and along the low-altitude portion of the intended flight path. The Wind Shear Training Aid also supplies a set of Weather Evaluation Exercises to demonstrate the use of the guidelines. More importantly, the Wind Shear Training Aid states that the use of the guidelines "should not replace sound judgment in making avoidance decisions."

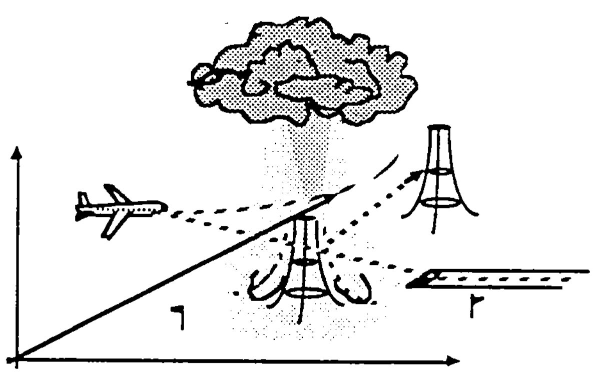
OBSERVATION	PROBABILITY OF WINDSHEAR
PRESENCE OF CONVECTIVE WEATHER NEAR INTENDED FLIGHT PATH:	
- With localized strong winds	HIGH
- With heavy precipitation	HIGH
- With rainshower	MEDIUM
- With lightning	MEDIUM
- With virga	MEDIUM
- With moderate or greater turbulence	MEDIUM
- With temperature/dew point spread between 30 and 50 degrees F	MEDIUM
ONBOARD WIND SHEAR DETECTION SYSTEM ALERT (Reported or observed)	HIGH
PIREP OF AIRSPEED LOSS OR GAIN:	
- 15 knots or greater	HIGH
- Less than 15 knots	MEDIUM
LLWAS ALERT/WIND VELOCITY CHANGE:	
-20 knots or greater	HIGH
- Less than 20 knots	MEDIUM
FORECAST OF CONVECTIVE WEATHER	LOW

Clues are cumulative: LOW + MEDIUM = HIGH

Decision Making for Wind Shear Avoidance

Wind shear is a spatial or temporal variation of the air about an aircraft that causes a deviation of the aircraft from its intended flight path. The hazard posed by severe low-altitude wind shear has prompted considerable study of the wind shear problem by meteorologists and aircraft engineers. A primary objective still being addressed is developing systems for improved flight crew capability to avoid severe wind shear.

A decision to avoid wind shear must be based on predictions made from available information. New and improved sensor systems under development could provide direct evidence of the presence of wind shear, but they will not be available in all circumstances. Wind shear avoidance must be based on indirect meteorological evidence when accurate sensors to determine the presence of wind shear are unavailable. A decision process based on a combination of meteorological evidence can provide better reliability than a decision process based on a single source.



•Avoidance can enhance safety

•Avoidance involves prediction

Make predictions from current measurements

Interpret predictive information

•Avoidance involves uncertainty

Wind inputs must be inferred

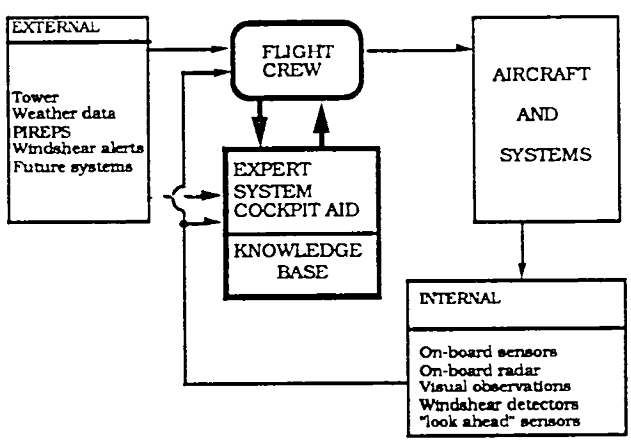
Uncertain knowledge of wind shear meteorology

Indirect evidence can increase reliability

Intelligent Advisor for Wind Shear

Cockpit automation provides an opportunity to assist flight crews with decisions critical to avoiding low-altitude wind shear. The primary goals of a cockpit aid for wind shear avoidance are to increase the likelihood that the flight crew makes an avoidance decision when severe wind shear actually will be present and to decrease the likelihood of a decision to avoid when one is not called for. Technology from the rapidly-growing field of artificial intelligence provides a basis for a wind-shear-avoidance cockpit aid. In an intelligent system for decision aiding, the merits of possible decision alternatives are determined by a machine reasoning process that is rational and sound, producing results in an intuitive and meaningful manner. This means that the system is capable not only of recommending actions but of explaining why those actions are being recommended. An intelligent cockpit aid can summarize relevant information from a variety of sources and recommend actions, improving avoidance decisions.

An expert system for wind shear avoidance, dubbed the Wind Shear Safety Advisor, is depicted schematically on this slide. It will operate in real time, accepting evidence from on-board sensors and external evidence (such as pilot reports or PIREPs), perhaps facilitated by a direct data link (represented by a dotted line connecting the external sources to the expert system). It will interact with the flight crew, interpreting their intentions and providing advice and explanations. The development and improvement of the Wind Shear Safety Advisor are subjects of current research.



- Aid awareness, increase decision reliability
  - Summarize a variety of information
  - Meteorological knowledge
  - Real time prediction and estimation
  - Provide step-by-step explanations
  - Facilitated by direct data link

Wind Shear Safety Advisor

Primary Functions and Proposed Solution Methods

Primary functions of the Wind Shear Safety Advisor (WSSA) may be divided into the categories of executive, monitoring, prediction and assessment, and planning. Executive is a process of top-level control, while monitoring is the process of obtaining evidence from sources. Prediction is the process of extrapolating this evidence to the place and time of intended operations, while assessment is the process of considering the impact of evidence on the current flight plan. Planning is the process of altering the flight plan to reduce the risk of wind shear encounter. When operating in real time, these functions are executed in a cyclical fashion, processing evidence continuously. While the architecture currently being developed will facilitate real-time implementation, real-time implementation is a follow-on to the current study.

Declarative rule-based techniques and structured data base techniques have been used extensively in the development of the WSSA to provide a modular and explicit program structure. To deal with the uncertainty inherent to prediction and assessment, methods for probabilistic Bayesian inference are being incorporated. Algorithms for interpreting wind data based on stochastic flight path prediction are also being developed for risk assessment and planning.

- EXECUTIVE - Top-level control

  Rule-based techniques

- MONITORING - Observe sensors, receive reports, alerts, warnings

  Rule-based techniques

  Structured data bases

- PREDICTION AND ASSESSMENT - Make predictions from reports, assess risk of continuing with nominal flight plan

  Probabilistic inference

  Stochastic error prediction

- PLANNING - consider flight path revisions and precautions, receive flight plan revisions

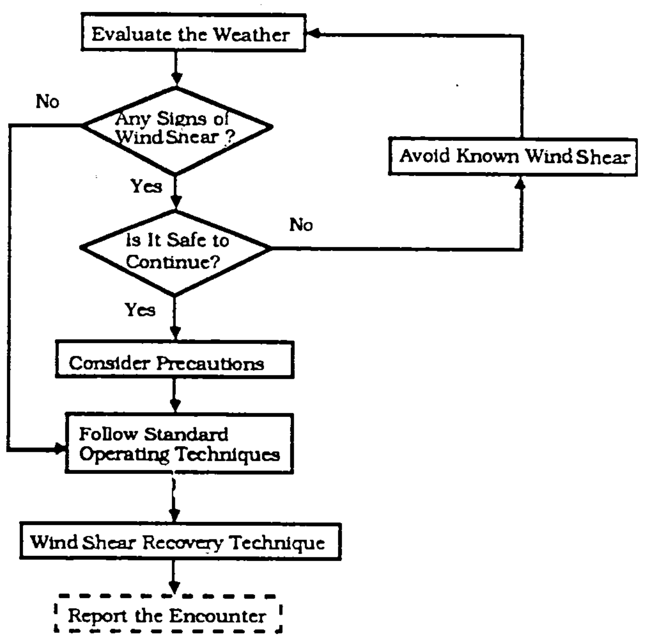
  Decision analysis

  Rule-based techniques

  Stochastic error prediction

Wind Shear Training Aid
Model of Flight Crew Actions

The FAA Wind Shear Training Aid has been a primary source of knowledge for the Wind Shear Safety Advisor. The two-volume Wind Shear Training Aid document, prepared with the support of the Integrated FAA Wind Shear Program, was written by a team from the airframe industry that interacted with airlines, government, and academia. The Wind Shear Training Aid is a comprehensive training manual for flight crews that describes the hazards of wind shear and details precautionary and recovery procedures to help escape inadvertently-encountered wind shear.



Probability Theory for Risk Assessment

Developing a representation of these guidelines for the Wind Shear Safety Advisor that incorporates sound judgment is complicated by uncertainty surrounding wind shear meteorology and the subjective terms used in the guidelines. Use of the guidelines in real situations requires combined judgments involving uncertainty that the qualitative levels of probability and combination rule can not represent. Probability theory provides a set of sound and consistent axioms that are understood throughout the scientific community. Probability theory produces results consistent with ordinary logic and stochastic prediction and estimation. Bayesian belief network representation, which has been developed primarily by Judea Pearl [12], provides an efficient means to represent uncertain knowledge and to reason in a manner consistent with these axioms, provided some assumptions are made.

- F.A.A. Wind Shear Training Aid (1986)
  - Example training program for flight crews
  - Logical model of flight crew actions
  - Windshear avoidance guidelines
- Combined judgments involving uncertainty
  - "Convective weather near flight path"
  - "LOW," "MEDIUM," and "HIGH" Risk
  - "LOW + MEDIUM = HIGH"
- Probability and decision theory
  - Understood by scientific community
  - Relates to logic, stochastic estimation
  - Can incorporate statistical results
  - Efficient implementation using Bayesian network representation

Logical Expert System Techniques

Logical expert system techniques common to expert systems have been used for initial versions of the WSSA, as was previously reported. With rule-based techniques, knowledge pertinent to wind shear avoidance is transcribed as a set of statements of the form "If *premise* is true, then *consequent* follows." The expert system's data base is structured by defining a hierarchy of object structures, called *frames*. Structuring the data base adds modularity to rules and permits clearer explanations to be generated during execution.

Execution of the rule base is controlled by an *inference engine*. Forward- and backward- chaining searches, described in an earlier presentation, select rules to evaluate and update the data base through a process of logical deduction. As a side-effect of search, quantitative algorithms may be called as necessary. A recent implementation of the WSSA on a Symbolics 3670 LISP machine consists of over 200 rules.

- Declarative knowledge representation
  - "IF-THEN" rules
  - Symbolic parameters, LISP functions
  - Data base structured with frames
- Inference engine controls rule evaluation
  - Forward- and backward- chaining
  - Quantitative algorithms called conditionally as side-effects of search
- Symbolics 3670 LISP Machine
  - 212 "IF-THEN" rules
  - 78 numerical and symbolic parameters
  - 15 frame structures
  - 80 functions (& Common LISP)

Elements of Probabilistic Reasoning

In a probabilistic model of reasoning, such as a Bayesian network, reasoning is a process of conditioning the probabilities of hypotheses on the evidence. Bayes's rule is used to accomplish this. To illustrate the fundamentals of probabilistic reasoning, let H represent a hypothesis that wind shear is on the intended flight path, and let E1 represent a piece of evidence, such as a wind shear detection system alert. From a prior probability that wind shear is on the intended flight path, $Pr\{H\}$, the posterior probability is computed using Bayes's rule. To use Bayes's rule, we must provide the probability of detection of the detection system, $Pr\{E1 \mid H\}$. The prior probability of receiving the evidence, $Pr\{E1\}$, must also be specified; however, it is usually easier to provide $Pr\{E1 \mid \neg H\}$, the probability of false alarm (the symbol $\neg$ denotes logical negation), and compute $Pr\{E1\}$. These equations provide a basis for more general probabilistic reasoning, but additional assumptions must first be made.

To see why this is so, suppose that a second detection system alert, E2, is received. Use of Bayes's rule requires the computation of $Pr\{E1, E2 \mid H\}$, a joint probability distribution. In general, the computation of joint probability distributions is a cumbersome process. To simplify the process, we assume that wind shear is the cause of the alerts and that the alerting systems operate independently of each other. Thus, if wind shear is present, the probability of receiving the second alert is not changed by the arrival of the first alert. This assumption is known as *conditional independence*, and we say that the effects are *conditionally independent given the cause*. The assumption of conditional independence simplifies Bayes's rule, permitting efficient computation of the posterior probability of H, based on the probability of detection and false alarm rate of the individual systems.

- Condition probabilities of hypotheses on evidence: Bayes's rule

  Hypotheses of wind shear (H)

  Reports of wind shear (E1 and E2)

  $Pr\{H \mid E1,E2\}=Pr\{E1,E2 \mid H\}Pr\{H\}/Pr\{E1,E2\}$

- Conditional independence assumption: reports independent consequents of wind shear

$Pr\{H \mid E1,E2\} = Pr\{E2 \mid H\}Pr\{H \mid E1\}/Pr\{E2 \mid E1\}$

- Required statistics:

  Prior probability of wind shear, $Pr\{H\}$

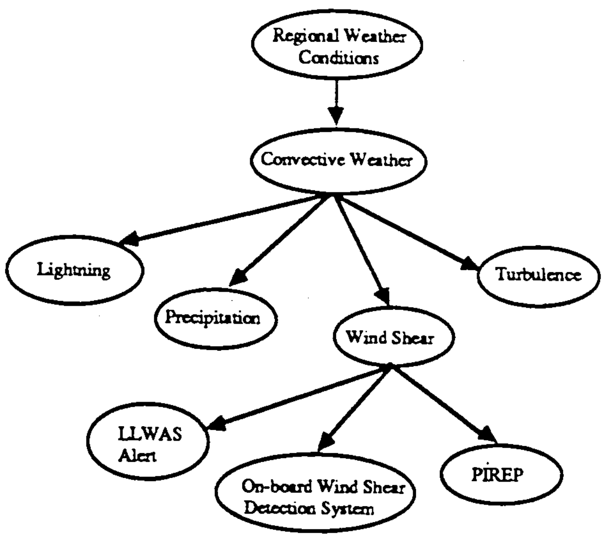
  Probability of detection, $Pr\{E1 \mid H\}$

  Probability of false alarm, $Pr\{E1 \mid \neg H\}$

Bayesian Network Interpretation of Wind Shear Probability Guidelines

A Bayesian network is a probabilistic model of a system. Bayesian networks use graphical representations of dependency, where a set of discrete random variables are represented as nodes and where uncertain relationships between the variables are represented as links. Cause-effect relationships are represented graphically by adding arrows to the links, pointing from cause to effect. A graphical model of dependencies surrounding the meteorology of wind shear, constructed from the Microburst Wind Shear Probability Guidelines and extended to include the prediction, is shown here. Elements of the guidelines are represented as random variables, which can take one of a set of exhaustive and mutually-exclusive values.

Network representations enable efficient probabilistic reasoning because all of the dependencies between variables are specified by the links. In Bayesian networks, nodes that are "effects" or manifestations of the same cause are assumed to be conditionally independent given the cause. With this assumption, all of the information necessary to condition the probability distribution at any particular node can be obtained from the nodes to which it is directly linked. If reasoning is simulated by sequential processing, the probability distribution at each node can be updated step by step, permitting explanations to be generated at each step. Alternatively, the network could be implemented on a set of identical processors, permitting several steps to occur concurrently.

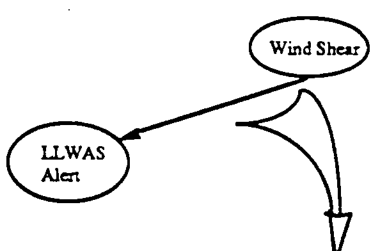


Graphical representation of dependency
Probabilities stored at each node
Nodes updated using Bayes's rule, axioms

Requirements for Probabilistic Representation

The construction of a Bayesian network begins with the construction of a graphical model of dependency, such as the previous slide. After constructing the graphical representation, and determining a set of values for each variable, the knowledge base is augmented by the definition of conditional probabilities associated with each link. For example, completing the link between node Wind Shear and node LLWAS Alert (which represents the state of the Low Level Wind Shear Alert System) requires the estimation of the probabilities shown. Reliability statistics for this link were derived from data obtained for the enhanced LLWAS and incorporated into the network. For each of the other links of the network, a set of conditional probabilities must be defined. These sets of probabilities are called link matrices. The network definition is completed by the definition of prior probability distributions at every node in the network.

There are no statistics available for some of the wind shear link matrices, such as the link between Precipitation and Convective Weather, indicating specific areas where additional meteorological research is required. Definition of these probabilities is aided by qualitative information in the Wind Shear Training Aid and other sources, but the actual values must be assigned subjectively at this time. This is less than desirable, for it adds a degree of subjectivity to some of the probabilities generated by the system during reasoning. Nevertheless, the subjectivity of the values can be reduced by the acquisition of more knowledge. Subjective language contained in the Microburst Wind Shear Probability Guidelines and other sources invites the developer to consider more detailed definitions for the concepts, guiding the search for additional meteorological knowledge and statistical data.



LLWAS Alert (LA)	Wind Shear (WS)	
	Severe wind shear on flight path (WS1)	No severe wind shear on flight path (WS2)
LLWAS Alert of Severe Wind Shear (LA1)	Pr{LA=LA1 | WS=WS1} = 0.714	Pr{LA=LA1 | WS=WS2} = 0.027
LLWAS Alert of Moderate Wind Shear (LA2)	Pr{LA=LA2 | WS=WS1} = 0.095	Pr{LA=LA2 | WS=WS2} = 0.554
No LLWAS Alert (LA3)	Pr{LA=LA3 | WS=WS1} = 0.191	Pr{LA=LA3 | WS=WS2} = 0.419

Conditional and prior probabilities

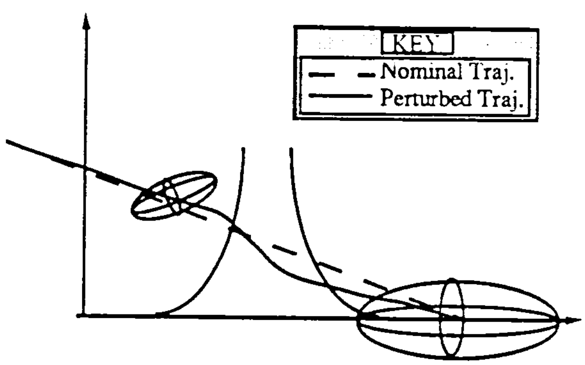
Statistical data incorporated

Some values assigned subjectively

Flight Path Error Prediction With Wind Statistics

If direct measurements of the winds are available, wind shears that are truly hazardous to the aircraft can be distinguished from less hazardous shears. A reasonable approach to distinguish hazardous wind shears using wind measurements is based on flight path deviations from the aircraft's nominal flight path. A hazardous wind shear can be distinguished by determining whether or not a perturbed trajectory lies outside a critical region in space. A perturbation model of the aircraft and control law provides an efficient means to compute trajectory deviations.

Providing a means of distinguishing hazardous wind shear is complicated by errors in wind measurements. For example, devices based on the doppler effect can detect only the radial component of winds; vertical winds that can affect the aircraft's flight path cannot be detected. Stochastic prediction techniques provide a means of computing stochastic trajectory errors, such as touchdown dispersion or mean square glide slope error, given uncertain but statistically defined data from wind sensors.



- Flight path deviations through wind shear
  - Wind profile, nominal trajectory, control law
  - Perturbation model, control saturation
- Covariance propagation
  - Error statistics of wind data
  - Correlation of horizontal and vertical winds
  - Correlation with meteorological parameters
- Stochastic error function computation
  - Touchdown error, impact velocity
  - Errors in glideslope, altitude, energy rate

Conclusions

Cockpit automation provides the opportunity to aid flight crew decisions relevant to wind shear and improve flight safety, but the decision-making process involves the management of uncertainty. Bayesian belief network techniques provide a means to represent this subjective meteorological knowledge so that the knowledge can be used in cooperation with more accurate wind shear detection systems. With the probabilistic representation of the Microburst Wind Shear Probability Guidelines, the door is open for the incorporation of a wider variety of meteorological expert knowledge. This means of representation also facilitates the incorporation of more reliable wind shear detection systems.

Stochastic prediction algorithms provide a means of interpreting uncertain but statistically-defined wind data. An error prediction algorithm would incorporate error models of wind sensors. Stochastic prediction of a trajectory error can provide the basis for an avoidance decision, once a suitable error metric is defined.

- Bayesian networks provide a means to interpret Wind Shear Training Aid avoidance guidelines

  Based on probability theory

  Enables incorporation of statistical data

  Suggests additional meteorological studies

- Stochastic prediction techniques provide a means to incorporate wind data

  Base decisions on error analysis

  Requires error model of wind sensors

  Requires definition of error metric