Probabilistic Reasoning for Intelligent Wind Shear Avoidance

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Avoiding severe wind shear challenges the ability of flight crews because it involves assessing risk from uncertain evidence. A computerized intelligent cockpit aid can increase flight crew awareness of wind shear, improving avoidance decisions. A primary task in the development of such a cockpit aid is providing a means of assessing risk from evidence of wind shear from sources with varying reliability. The Federal Aviation Administration's Windshear Training Aid provides guidelines for assessing the risk of wind shear encounter from meteorological evidence. Use of these guidelines in the cockpit is complicated by uncertainty surrounding meteorological knowledge of wind shear. Bayesian network representation is discussed as a means of modeling this uncertain knowledge in a computer. A probabilistic model of the Windshear Training Aid guidelines using Bayesian network representation is presented. This model combines evidence from sources of varying reliability and incorporates results from meteorological studies of wind shear. The probabilistic model can provide flight crews with meaningful estimates of risk to aid their decisions, using evidence from a variety of sources and a base of meteorological knowledge.

Introduction

LOW-ALTITUDE wind shear poses a serious threat to air safety, as wind-shear-related accidents caused nearly 500 fatalities from 1964 to 1982.[1] Wind shear is defined as a spatial or temporal variation of the air about an aircraft that causes a deviation of the aircraft from its intended flight path. Flight-path deviations resulting from moderate wind shear, such as those arising during the passage of a cold front, are not typically hazardous if the pilot takes corrective action; however, severe wind shears such as downbursts can produce significant flight-path deviations even with corrective pilot actions, potentially resulting in disaster if the shear is encountered at low altitude. The hazard posed by low-altitude wind shear has prompted considerable study of the wind shear problem by meteorological and aviation communities. This has resulted in improved flight crew training programs for wind shear avoidance and escape,[2] improved knowledge of wind shear and its causes,[3] and improved piloting strategies for escaping wind shear.[4-7] 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 indirect meteorological evidence when accurate sensors to determine the presence of wind shear are unavailable. The Federal Aviation Administration (FAA) has provided guidelines for flight crews to help them establish the possible presence of wind shear in the terminal area.[2] Using the guidelines in real situations requires making subjective judgments from the available evidence. In this paper, a probabilistic model of the FAA guidelines using Bayesian network representation[8] is shown to approximate the subjective judgments required to establish the possible presence of wind shear. The Bayesian network model described in this paper incorporates additional meteorological knowledge beyond that provided in the Windshear Training Aid, including statistical results from the NIMROD,[3] JAWS,[3,9,10] and FLOWS[11] studies.

New and improved sensor systems under development[12-15] could provide direct evidence of the presence of wind shear, but they will not be available in all circumstances. The Bayesian network model provides a framework for combining direct evidence of wind shear from these sensors with indirect meteorological evidence if both are available, providing better reliability than either direct or indirect evidence alone. Sensor reliability statistics may be incorporated into the network directly, so that evidence from multiple sensor systems can be weighed according to their relative reliability. The Bayesian network model is capable of assessing the risk of wind shear encounter and explaining in a step-by-step manner how the result is obtained. It will serve as an important component of an expert-system cockpit aid for wind shear avoidance.

Expert System for Wind Shear Avoidance

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. 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 decision alternatives, improving avoidance decisions.

Technology from the rapidly growing field of artificial intelligence provides a basis for a wind-shear-avoidance cockpit aid. Expert systems have successfully modeled the judgment of experts in several fields (e.g., Ref. 16), making this judgment available to decision makers. Real-time expert-system cockpit aids are being developed for decision support in military applications.[17] An expert system for wind shear avoidance, dubbed the Wind Shear Safety Advisor (WSSA),[18] is depicted schematically in Fig. 1. It will be able to operate in real time, accepting evidence from onboard 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

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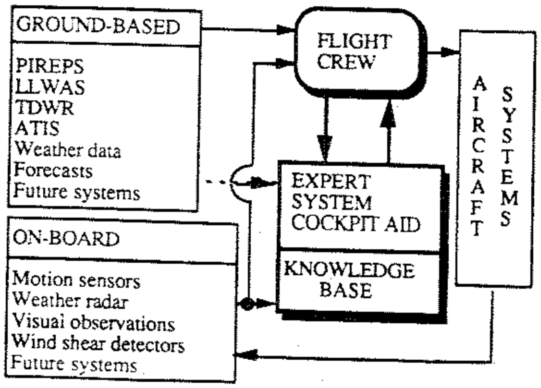


Fig. 1 Wind Shear Safety Advisor schematic diagram.

explanations. The development and improvement of the WSSA are subjects of current research.

Primary functions of the WSSA may be divided into the categories of monitoring, prediction, risk assessment, and planning, as shown in Fig. 2. When operating in real time, these functions are executed in a cyclical fashion, processing evidence continuously. *Monitoring* is the process of obtaining evidence from sources, whereas *prediction* is the process of estimating the impact of the evidence at the place and time of intended operations. *Risk 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 interpreting evidence, the expert system must take the transient nature of wind shear phenomena into account. The relevance of incoming evidence depends on its relationship to the place and time of intended terminal operations. The expert system makes predictions that account for the spatial and temporal differences between evidence and intended flight paths. To assess risk, the expert system must apply knowledge of the meteorology of wind shear to these predictions, but considerable uncertainty surrounds this meteorological knowledge. The development of a risk assessment procedure for the WSSA that can incorporate uncertain knowledge is the focus of this paper.

Windshear Training Aid

The FAA Windshear Training Aid[2] has been a primary source of knowledge for the WSSA. The two-volume Windshear 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 Windshear 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.

The Windshear Training Aid contains a set of microburst windshear probability guidelines, reproduced here as Table 1, to assist flight crews in determining the risk of possible wind shear encounter. Table 1 relates various types of evidence that might be available in the cockpit to evaluate a qualitative probability of wind shear encounter. When evaluating combinations of evidence, flight crews are instructed to combine the individual probabilities according to the rule,

$$\text{LOW} + \text{MEDIUM} = \text{HIGH} \tag{1}$$

If available evidence results in a high probability of windshear encounter, the Windshear 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. More importantly, the Windshear Training Aid states that the use of the Microburst Windshear Probability Guidelines should not replace sound judgment in making avoidance decisions. Clearly, the authors of the Windshear Training Aid recognize that sound judgment must entail more than Table 1.

The Windshear Training Aid also supplies a set of weather evaluation exercises to demonstrate the use of the microburst Windshear Probability Guidelines. These examples give important information about the intended use of these guidelines. For example, when using the guidelines, users must first answer the question, "Is convective weather near the intended flight path?" Exercises are presented where items such as lo-

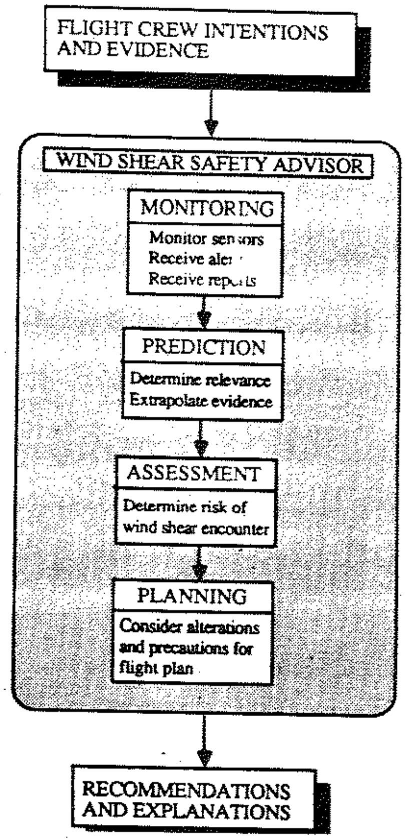


Fig. 2 Functions of the Wind Shear Safety Advisor.

Table 1 Windshear Training Aid Microburst Windshear Probability Guidelines[2]

Observation	Probability of windshear
Presence of convective weather near intended flight path:	
With localized string 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°F	Medium
Onboard wind shear detection system alert (reported or observed)	High
PIREP of airspeed loss or gain:	
15 kt or greater	High
Less than 15 kt	Medium
LLWAS[a] alert/wind velocity change:	
20 kt or greater	High
Less than 20 kt	Medium
Forecast of convective weather	Low

[a]LLWAS = Low-Level Windshear Alert System.

calized, strong winds or virga (rain that evaporates before reaching the ground) are used to justify a "yes" answer to this question. Additionally, other evidence, such as moderate wind variation, is sometimes used to justify a "yes" answer to this question. Determining whether convective weather is near the intended flight path appears to be a subjective judgment based on a combination of evidence, such as wind variability and weather features.

Developing a representation of these guidelines for the Wind Shear Safety Advisor is the focus of the following sections. Bayesian belief network representation, which has been developed primarily by Pearl,[8] is a probabilistic technique for representing uncertain knowledge that is particularly attractive for this application. Probability theory provides a set of sound and consistent axioms that are understood throughout the scientific community. Bayesian belief networks provide an efficient means to represent uncertain knowledge and to reason in a manner consistent with these axioms, provided some assumptions are made. Following a description of how Bayesian network representation and reasoning work, the features of a Bayesian network representation for wind shear avoidance are discussed and demonstrated.

Elements of Probabilistic Reasoning

Bayes's Rule and Conditional Independence

Reasoning is a process of drawing conclusions from evidence by applying knowledge. In a probabilistic model of reasoning, such as a Bayesian network, reasoning is a process of conditioning the probabilities of hypotheses on the evidence. A familiar formula from probability theory known as 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 directly supporting the hypothesis, 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:

$$\Pr\{H|E1\} = \frac{\Pr\{E1|H\}}{\Pr\{E1\}}\Pr\{H\} \tag{2}$$

To use Bayes's rule, we must provide the probability of detection of the detection system $\Pr\{E1|H\}$. The prior probability of receiving the evidence, $\Pr\{E1\}$, also must be specified; however, it usually is easier to provide $\Pr\{E1|\neg H\}$, the probability of false alarm (the symbol $\neg$ denotes logical negation), and to compute $\Pr\{E1\}$ using

$$\Pr\{E1\} = \Pr\{E1|H\}\Pr\{H\} + \Pr\{E1|\neg H\}\Pr\{\neg H\} \tag{3}$$

Equations (2) and (3) provide a basis for more general probabilistic reasoning, but additional assumptions first must be made.

To see why these assumptions must be made, suppose that a second detection system alert, $E2$, is received. Applying Bayes's rule, we obtain

$$\mathrm{PR}\{H|E1,E2\} = \frac{\Pr\{E1,E2|H\}}{\Pr\{E1,E2\}}\Pr\{H\} \tag{4}$$

Use of this equation requires the computation of $\Pr\{E1,E2|H\}$, 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 definitely present, the probability of receiving the second alert is not changed by the arrival of the first alert. This relationship is represented by

$$\Pr\{E2|H,E1\} = \Pr\{E2|H\} \tag{5}$$

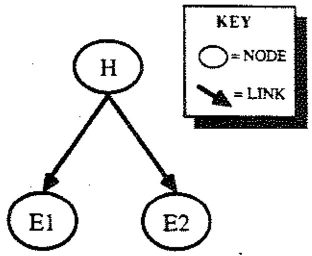


Fig. 3 Graphical representation of dependency (H = hypothesis; $E1$, $E2$ = evidence).

This assumption is known as *conditional independence*, and we say that the evidence is conditionally independent given the cause. The assumption of conditional independence simplifies Eq. (4), permitting efficient reasoning. Since evidence $E1$ and $E2$ is conditionally independent given cause H, we may write

$$\Pr\{E1,E2|H\} = \Pr\{E1|H\}\Pr\{E2|H\} \tag{6}$$

Equation (6) allows Eq. (4) to be rewritten as

$$\Pr\{H|E1,E2\} = \frac{\Pr\{E1|H\}\Pr\{E2|H\}}{\Pr\{E1,E2\}}\Pr\{H\} \tag{7}$$

Using Eq. (2), Eq. (7) may be rewritten as,

$$\Pr\{H|E1,E2\} = \frac{\Pr\{E2|H\}}{\Pr\{E2|E1\}}\Pr\{H|E1\} \tag{8}$$

where $\Pr\{E2|E1\}$ may be computed from the equation

$$\Pr\{E2|E1\} = \Pr\{E2|H\}\Pr\{H|E1\} + \Pr\{E2|\neg H\}\Pr\{\neg H|E1\} \tag{9}$$

With the assumption of conditional independence, the probability of wind shear can be updated in a step-by-step process, using the probabilities of detection and false alarm of the individual alert systems. The conditional independence assumption may be visualized with the aid of the graph depicted in Fig. 3. Here, the wind shear hypothesis and the evidence are represented as circles or *nodes*, and the fact that the wind shear causes the alerts to sound is represented by arrows or *links* that point from the cause to the effects. Notice that the only connection between the two evidence nodes is through the link node. This indicates that they are conditionally independent given the wind shear hypothesis. The assumption of conditional independence of the two alerting systems is valid only when the systems do not exchange information. If alerting systems exchange information, then the more complicated form of Bayes's rule, Eq. (4), must be used.

Conditional Dependence and Causal Hierarchies

Additional conditional independence assumptions may be used to account for indirect evidence more realistically. For example, measurements of lightning and precipitation support the possible presence of wind shear, but they are not independent given wind shear. Even if wind shear were known to be present on the flight path, an observation of lightning near the flight path would still increase the chances that precipitation would be measured. However, severe wind shears such as microbursts are caused by convective weather that also causes lightning and precipitation. Thus lightning, precipitation, and wind shear can more realistically be assumed to be conditionally independent given the presence of convective weather near the flight path. With this assumption, the probability of wind shear encounter can be conditioned on measurements of lightning and precipitation in an efficient step-by-step process as before.

In Eq. (2), the prior probability of wind shear encounter, $\Pr\{H\}$, is a summary of the support for the hypothesis of a wind shear encounter. If the presence of convective weather near the flight path, CW, is given, then the probability of encountering wind shear prior to receiving $E1$ or $E2$ is given by $\Pr\{H|CW\}$, which is established on the basis of observational meteorological studies. If the presence of convective weather is not given, but the possible presence of convective weather is established by an indicator such as lightning near the flight path, L, then the probability of wind shear encounter given the indicator L may be computed by the relationship

$$\Pr\{H|L\} = \Pr\{H|CW\}\Pr\{CW|L\} + \Pr\{H|\neg CW\}\Pr\{\neg CW|L\} \tag{10}$$

where the conditional independence of wind shear and lightning given convective weather is assumed. Conditional independence assumptions such as this are used to define a simple physical model of convective storms used in this paper. This model, which is motivated by the Windshear Training Aid's guidelines, neglects any direct dependence of wind shear on weather indicators, such as lightning. If statistical studies establish a causal relationship between lightning and wind shear, the model can be extended to take this dependence into account. If both lightning and a wind shear alert $E1$ are given, then Eq. (2) takes the modified form

$$\Pr\{H|L,E1\} = \frac{\Pr\{E1|H\}}{\Pr\{E1|L\}}\Pr\{H|L\} \tag{11}$$

where $\Pr\{E1|L\}$ may be computed from the equation

$$\Pr\{E1|L\} = \Pr\{E1|H\}\Pr\{H|L\} + \Pr\{E1|\neg H\}\Pr\{\neg H|L\} \tag{12}$$

These equations may now be generalized to define a probabilistic reasoning procedure that can be applied to risk assessment for wind shear avoidance.

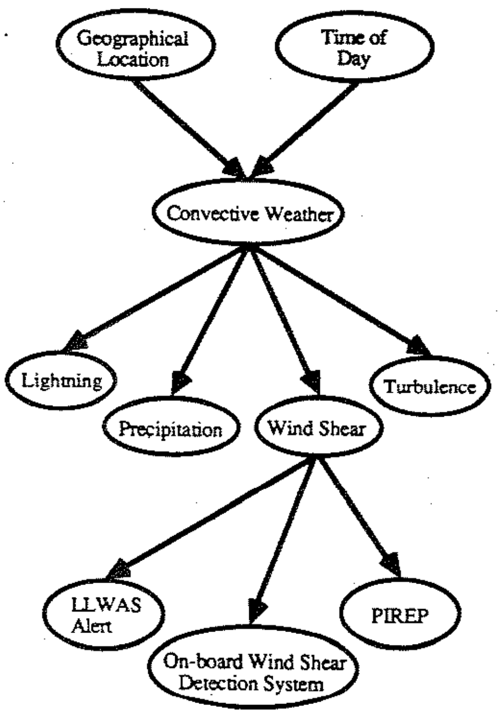


Fig. 4 Graphical representation of dependencies for risk assessment.

Probabilistic Reasoning with Bayesian Networks

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 Windshear Probability Guidelines, is shown in Fig. 4. Elements of the guidelines are represented as random variables, which can take one of a set of exhaustive and mutually exclusive values. The variables and values associated with them are listed in Table 2, along with abbreviations for the variables and values. For example, the state of wind shear along the flight path is represented by the random variable $\boldsymbol{WS}$ (random variables are denoted by boldface characters), which can take on the value WS_1, severe level of wind shear on flight path during terminal operations; the value WS_2, moderate level of wind shear on flight path during terminal operations; or the value WS_3, little or no wind shear on flight path during terminal operations. For each random variable, a probability distribution is assigned, consisting of a set of probabilities for each value of each variable. For example, the probability distribution describing random variable $\boldsymbol{WS}$ is given by the three probabilities $\Pr\{\boldsymbol{WS} = WS_1\}$, $\Pr\{\boldsymbol{WS} = WS_2\}$, and $\Pr\{\boldsymbol{WS} = WS_3\}$.

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 proba-

Table 2 Nodes and nodal values for a Bayesian network for risk assessment

Geographical location (G)	
G_1	High plains location (JAWS)
G_2	Midsouth location (FLOWS and NIMROD)
G_3	All other locations (mean statistics)
Time of day (TD)	
TD_1	Morning (12 p.m.–12 a.m.)
TD_2	Afternoon (12 a.m.–6 p.m.)
TD_3	Evening (6 p.m.–12 p.m.)
Convective weather near flight path (CW)	
CW_1	Frontal or air mass storms (wet microburst producers)
CW_2	Stratocumulus clouds (dry microburst producers)
CW_3	No convective weather near flight path
Wind shear on flight path (WS)	
WS_1	Severe level of wind shear during terminal operations
WS_2	Moderate level of wind shear during terminal operations
WS_3	Little or no wind shear during terminal operations
Precipitation near flight path (P)	
P_1	Heavy precipitation near flight path
P_2	Rain showers near flight path
P_3	Virga (rain not reaching the ground) near flight path
P_4	No precipitation or virga near flight path
Turbulence (T)	
T_1	Moderate or greater turbulence on fight path
T_2	No moderate to severe turbulence on flight path
Lightning (L)	
L_1	Lightning strikes near flight path
L_2	No lightning strikes near flight path
LLWAS alert (LA)	
L_1	Microburst advisory relevant to intended flight path
L_2	Wind shear advisory relevant to intended flight path
L_3	No wind shear alert relevant to flight path
PIREP (PI)	
PI_1	PIREP of severe flight path deviations due to wind shear
PI_2	PIREP of moderate deviations due to wind shear
PI_3	No PIREP of wind shear
Onboard wind shear detection system (WD)	
WSA_1	Wind shear alert during terminal operations
WSA_2	Cautionary alert during terminal operations
WSA_3	No wind shear alert during terminal operations

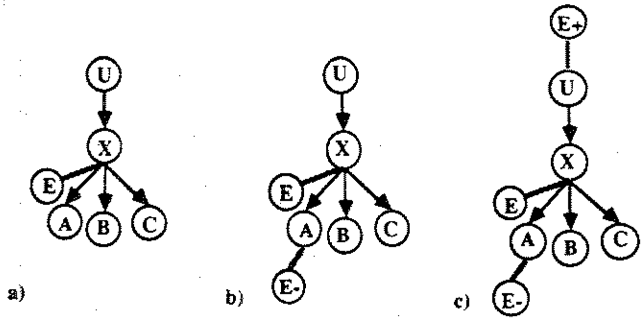


Fig. 5 Probabilistic reasoning in a typical Bayesian network.

bility 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.

With no evidence, the network is in a consistent state with a prior probability distribution assigned at each node. Evidence may be submitted to any node, initiating a sequence of probabilistic conditioning. To submit evidence to a node, probabilities that the evidence would be received must be provided. When the network is integrated into the WSSA, these probabilities will be determined during the process of prediction. From these probabilities, the probability distribution at the node is conditioned on the evidence using Bayes's rule. This is followed by the conditioning of the probability distributions of the other nodes. Probabilistic reasoning in a Bayesian network proceeds from cause to effect and from effect to cause during the conditioning process.

Consider the fragment of a typical Bayesian network representation depicted in Fig. 5a, with a set of nodes associated with random variables U, X, A, B, and C, and with evidence E submitted directly to random variable X. The submitter provides, for each value X_i, a numerical value for $\Pr\{E|X=X_i\}$, weighing the probability that this evidence would be received if variable X had the value X_i. The posterior probability that X takes the value X_i is then computed through the use of Bayes's rule,

$$\Pr\{X=X_i|E\} = \frac{\Pr\{E|X=X_i\}}{\Pr\{E\}} \Pr\{X=X_i\} \tag{13}$$

Applying Eq. (13) to each value of X conditions the probability distribution of X given E. Reasoning proceeds back to U and forward to A, B, and C, updating the entire causal tree.

Bayes's rule also is used while reasoning from effect to cause. For example, suppose evidence $E-$ is submitted at or below variable A, as depicted in Fig. 5b. After A's probability distribution is conditioned on $E-$, the probability that X takes the value X_i can be found using Bayes's rule,

$$\Pr\{X=X_i|E,E-\} = \frac{\Pr\{E-|X=X_i\}}{\Pr\{E-|E\}} \Pr\{X=X_i|E\} \tag{14}$$

where $\Pr\{E-|X=X_i\}$ is computed from the equation

$$\Pr\{E-|X=X_i\} = \sum_k \Pr\{E-|A=A_k\}\Pr\{A=A_k|X=X_i\} \tag{15}$$

Reasoning then proceeds back to U and forward to B and C. Conditional probabilities such as $\Pr\{A=A_k|X=X_i\}$ must be defined as part of the Bayesian network representation, as discussed in the next section.

To illustrate the method of reasoning from cause to effect, suppose evidence $E+$ is submitted somewhere at or above U, as shown in Fig. 5c. After U's probability distribution has been conditioned on $E+$, the probability that X takes the value X_i is updated according to the equation

$$\Pr\{X=X_i|E,E-,E+\} = \sum_k \Pr\{X=X_i|U=U_k\}\Pr\{U=U_k|E,E-,E+\} \tag{16}$$

After X's values are updated, nodes A, B, and C are updated. The reasoning process then continues down the causal tree. Figure 6 summarizes the three possible ways of computing the posterior probability distribution of a random variable X.

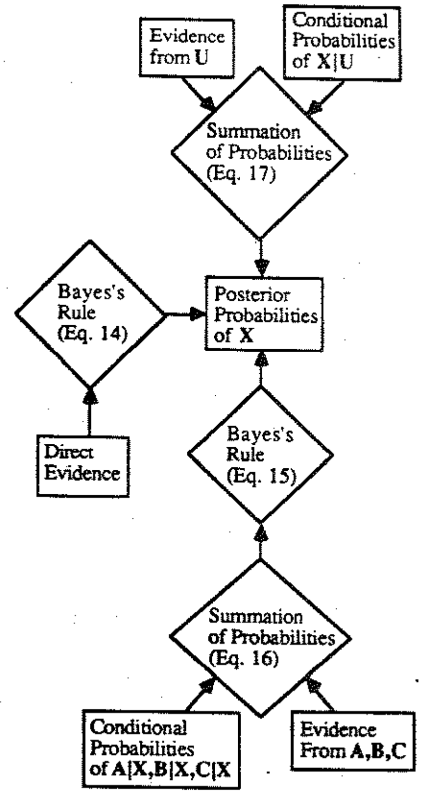
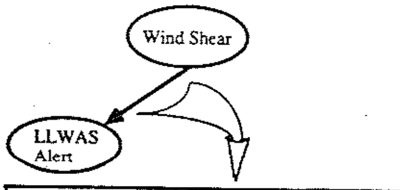


Fig. 6 Diagram of probabilistic reasoning process.

Developing the Bayesian Network Representation

The construction of a Bayesian network begins with the construction of a graphical model of dependency, such as Fig. 4. After constructing the graphical representation, a set of values are assigned for each variable. For example, values of random variable CW are taken from Ref. 3, which details convective weather types associated with microburst wind shears. In this model, diurnal and regional variations of the frequency of wind shear observed by Refs. 3, 9, and 10 are attributed to variations in convective weather frequency; that is, the probability of wind shear encounter is conditionally independent of the time of day given the presence of convective weather near the intended flight path.

As it is with the Windshear Training Aid guidelines, establishing the presence of convective weather near the intended flight path with this Bayesian network representation is a judgment based on a combination of evidence; however, yes-or-no commitment to convective weather's presence is not required. Additionally, by recognizing the cause-effect relationships between convective weather, wind shear, and wind shear alerting systems, wind shear alerts are directly associated with wind shear and will bear directly on the likelihood of wind shear encounter. More indirect indicators such as precipitation and lightning are limited in their ability to affect the likelihood of wind shear encounter because these indicators are seen only as possible manifestations of the convective weather that may



Given the level of wind shear on flight path is:	Severe	Moderate	Light
Probability of LLWAS Microburst Advisory is:	0.65	0.082	0.026
Probability of LLWAS Wind Shear Advisory is:	0.22	0.81	0.25
Probability of no LLWAS Advisory is:	0.13	0.11	0.73

Fig. 7 A set of conditional probabilities for risk assessment.

independently cause wind shear. By distinguishing more reliable information and avoiding yes-or-no judgments, the Bayesian network development facilitates the application of the guidelines in real situations.

After defining variables and dependencies, the representation 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 Windshear Alert System) requires the estimation of the conditional probability distribution of LLWAS Alert given each level of wind shear, as shown in Fig. 7. Reliability statistics for this link were derived from data given in Ref. 13 for the enhanced LLWAS and have been incorporated into the network. For each of the other eight links of the network of Fig. 4, a set of conditional probabilities must be defined. These sets of probabilities are called link matrices. In addition to the link matrices, a prior probability distribution for each node must be provided. For example, probabilities for node Wind Shear are derived from the statistical results from the NIMROD, JAWS, and FLOWS studies.

Additional meteorological data are still being acquired for some of the link matrices, such as the link between Turbulence and Convective Weather. Definition of these probabilities is aided by qualitative information in the Windshear 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 uncertainty to some of the probabilities generated by the system during reasoning. Nevertheless, the uncertainty of the values can be reduced by the acquisition of more knowledge. Subjective language contained in the Microburst Windshear Probability Guidelines and other sources encourages the consideration of more precise definitions for the concepts, guiding the search for additional meteorological knowledge and statistical data. Sufficient data were available to prepare the demonstration of probabilistic reasoning that follows, and

Table 3 Evidence from Windshear Training Aid weather evaluation exercise 6

ATIS information

"This is Stapleton information November, 1710 Zulu, twelve thousand scattered, visibility 40, temperature 92, dewpoint 54, wind 340 variable 030, 15 gusting to 25, altimeter 29.96, departing runways 35 left and 35 right."

LLWAS alert, reported by tower

"Windshear alert, Centerfield wind 040 degrees at 13 knots, gusting 26 knots. North boundary wind 160 degrees at 18 knots. Southeast boundary wind 010 degrees at 12 knots."

Observations

Windsock at the approach end of runway 35L to be indicating approximately 050 degrees at over 20 knots and gusting. There is virga 5 miles northeast of the airport.

Pilot report

A B-727 [that] just departed on runway 35R reported a 10 knot loss in airspeed at 200 feet.

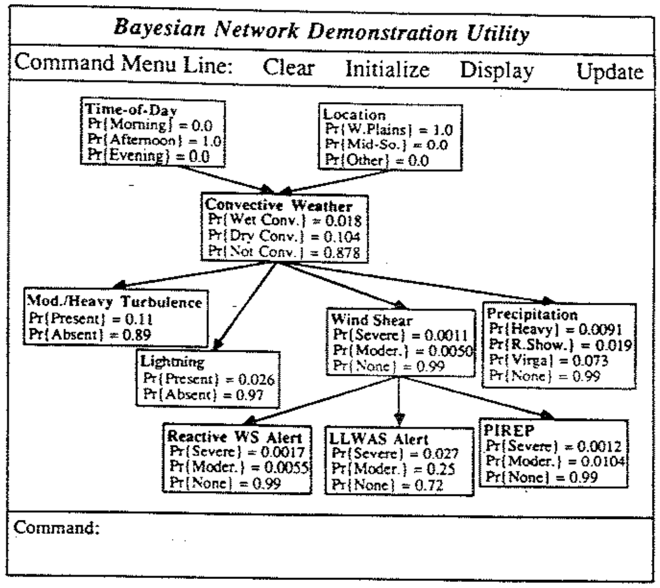


Fig. 8 Bayesian network demonstration utility.

ongoing meteorological research should further enhance the accessibility of statistics to refine the knowledge base.

Demonstration of Probabilistic Reasoning

To illustrate the use of the probabilistic model just presented, the probability of encountering severe wind shear is predicted for 12 weather evaluation exercises presented in the Windshear Training Aid. Each exercise describes a hypothetical situation where various types of evidence are presented. For example, the evidence presented in the sixth weather evaluation exercise is reproduced here as Table 3. The probability of encountering severe wind shear is conditioned on the evidence using the Bayesian Network Demonstration Utility, shown in Fig. 8. This utility is intended to display only the network's results and not the entire WSSA described earlier. The utility is not intended to serve as a realistic flight crew interface; providing satisfactory interfaces between expert system cockpit aids and their operational environment is an important consideration remaining to be addressed. Probabilities shown in this demonstration have been derived from information in Refs. 2, 3, and 9–11. Although the probabilities shown here will be subject to further refinement and validation, the values are representative.

The Bayesian Network Demonstration Utility is a multiple-window interface developed on the Princeton Laboratory for Control and Automation's Symbolic 3670 LISP machine. Features visible in Fig. 8 include a command menu line and two windows for graphical and text output. In the larger of the two windows, the Bayesian network development for risk assessment is depicted. Each node is represented by a box, with the node's values and corresponding probabilities inside of it. In the smaller of the two windows, commands are entered to manipulate the network.

The example situation takes place shortly before an afternoon takeoff at Denver Stapleton International Airport. Upon receiving Automated Terminal Information System (ATIS) information indicating a large spread between the airport's temperature and dew point and wind variability, the probability of convective weather being near the intended flight path is increased. After a sequence of probabilistic reasoning, the probability of wind shear encounter and other probabilities are increased, as shown in Fig. 9a.

Upon receiving an LLWAS alert, the probability of a microburst advisory is increased to 1, and the probability of wind shear encounter increases substantially, as shown in Fig. 9b. The probability of encounter with severe wind shear has increased from approximately 1 in 1000 initially to nearly 1 in 10.

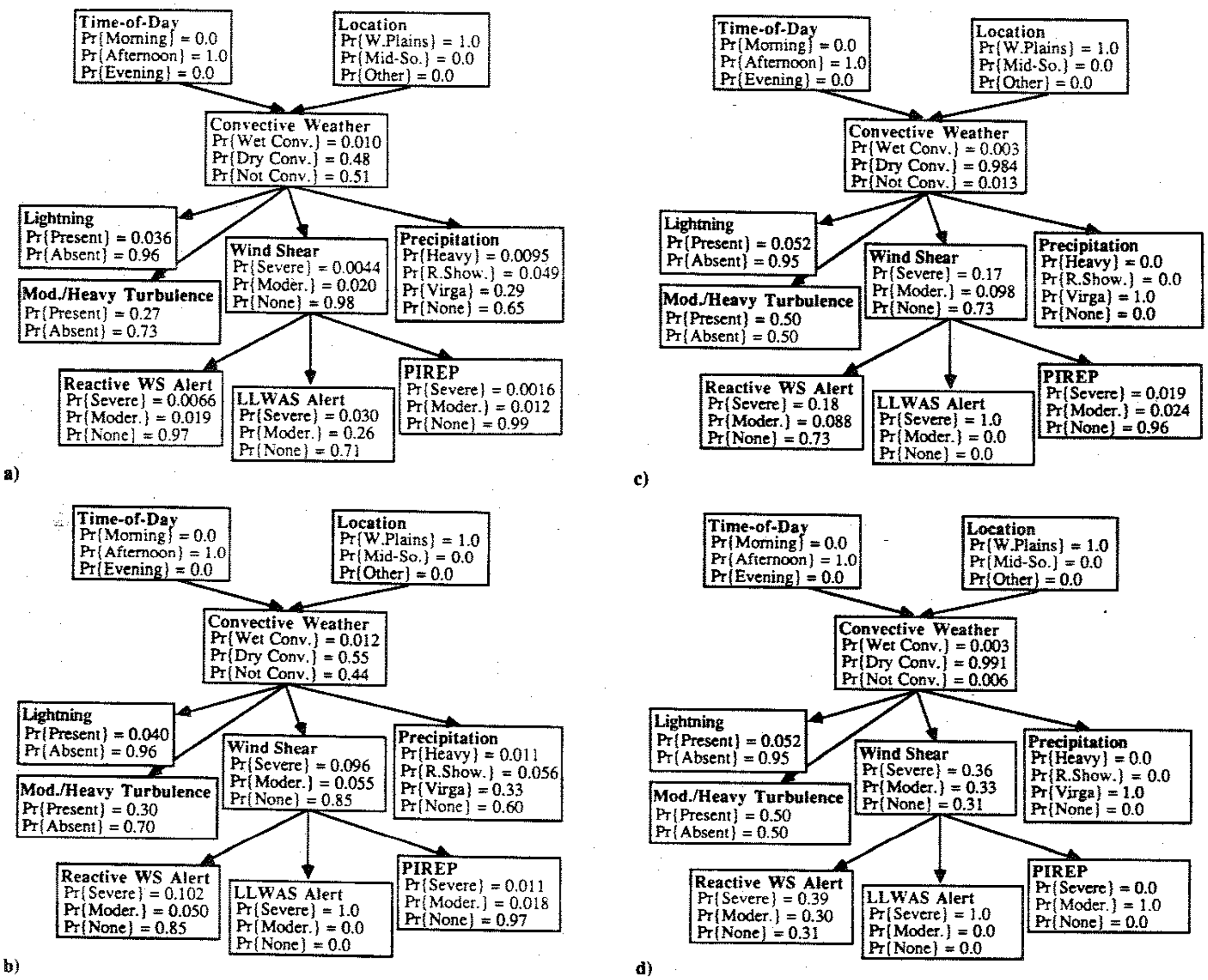


Fig. 9 Example of probabilistic reasoning.

Note that the Windshear Training Aid Microburst Windshear Probability Guidelines (Table 1) indicate high probability of wind shear encounter given the LLWAS alert alone. Upon observation of virga 5 miles from the airport, the probability of virga being near the flight path is increased to 1, further increasing the probability of wind shear encounter as shown in Fig. 9c. A pilot report of moderate speed loss on the takeoff path increases the likelihood of wind shear encounter still further, as shown in Fig. 9d. The Windshear Training Aid discussion of this exercise, located on pages E-57 and E-58, indicates that avoidance is appropriate in this situation. Considering the dangerous consequences of encountering microburst wind shear, the chance of encountering wind shear—approximately 1 in 3 flights—is quite significant.

In this demonstration, the probability of virga near the intended flight path was increased to 1, assuming that the virga 5 miles from the airport was certainly near enough to produce wind shear along the intended flight path during the intended takeoff. Modeling uncertainty introduced by the spatial and temporal displacement of evidence from the intended flight path would result in a probability assignment between zero and unity, reducing the impact of the evidence on the probability of wind shear encounter.

In a similar manner, the probability of encounter with severe wind shear has been computed for all 12 of the Windshear Training Aid's weather evaluation exercises. Figure 10 summarizes these results, plotting the probability of severe wind shear encounter for each case on a logarithmic scale. Note that the

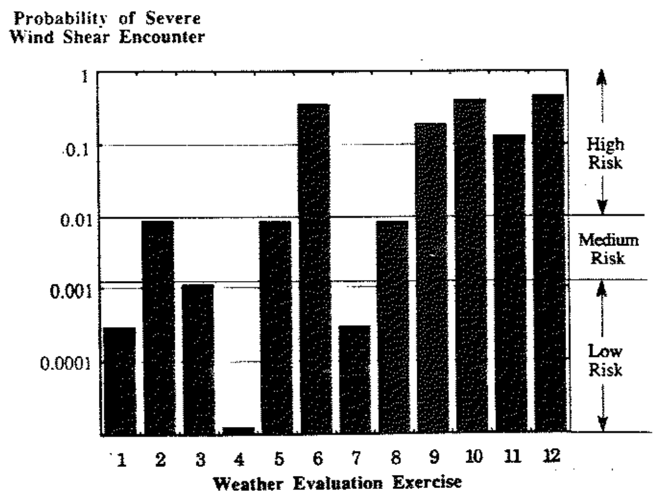


Fig. 10 Risk assessment for 12 weather evaluation exercises.

probabilities in high-risk situations are significantly greater than those in low or medium-risk situations. The results suggest that, in keeping with the Windshear Training Aid guidelines, instances where the probability of severe wind shear encounter exceeds 0.01 should be considered high-risk situations. Penetration of microburst wind shear is comparable to an aircraft failure state requiring considerable pilot compensation to avoid disaster, if it can be avoided at all. A microburst wind shear can rob a jet transport of as much specific excess power as the failure of one or more of its power plants, preventing the pilot from establishing a positive climb rate while at low altitude. Thus, piloting decisions that keep the probability of severe wind shear encounter in the range 0-0.01 are justified.

Conclusions

Bayesian network representation techniques have been presented as a means to assess the risk of encounter with wind shear. Examples of a probabilistic Bayesian network show that the network is capable of approximating the FAA's wind shear avoidance guidelines. The model provides a statistical summary of meteorological knowledge that can be made available to flight crews as a part of an expert system for wind shear avoidance. This knowledge base can be refined and expanded to include new detection systems under development. With probabilities as the components of a wind-shear-avoidance knowledge base, refinement and validation of the knowledge can proceed component by component, reducing the complexity of these processes. The development of a statistical knowledge base for wind shear avoidance creates a basis for interaction between the airframe and meteorological communities, with the refinement of the probabilities serving as the focus for meteorological discussions and observational studies.

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