Pilot Modeling and Decision-Aiding in Adverse Weather Conditions

by

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Abstract

Air traffic congestion has made large-scale, fast-time simulations desirable for testing air traffic management system enhancements. In order to effectively model several sectors, hundreds of aircraft may be required. The use of autonomous agents to control simulated aircraft is one solution to this problem, but requires a model of pilot behavior to ensure that the agents correctly represent the interactions between weather and other aircraft.

Pilot behavior in the presence of weather was assessed using a survey and a set of scenarios involving static tactical encounters between an enroute jet transport aircraft and one or two significant weather cells. The subject pilot planned a new routing, if desired, by interactively designating waypoints on a navigation display with weather depiction. The data was analyzed to determine relationships between a pilot's preferred route and weather size, severity, and distance from the route. A preliminary behavior model was developed based on a Bayesian belief network, taking the route's closest point of approach and distance from weather cells of varying intensities as inputs, and providing a weather threat rating as an output. This output was then used to determine if the current route was acceptable, and if not, what proximity to weather must be achieved in a new route. The model was tuned using the initial pilot behavior data and then validated using a second set of scenario conditions. Performance of the model in terms of generating new routes around weather was consistent with pilot-generated routes for the same situations, suggesting that the method may be viable for driving large-scale traffic simulations. A randomized model is also proposed that may better capture the potential variability in pilot response to a given situation. Finally, recommendations are given to expand the modeling effort to capture variability across different pilots and aircraft types, as well as to manage more complex and realistic weather encounter situations.

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Chapter 1 Introduction

1.0 Introduction

Currently, the capacity of the Air Traffic Control system is being pushed to the limit. To compensate, new tools are needed that can model system interactions and allow validation and testing of system enhancements. System enhancements are focused on improving overall efficiency, with the improved rerouting of aircraft in adverse weather being an area of high potential benefit. However, extensive validation and testing is required since any modification of the air traffic management system must not reduce the current safety level.

Current testing procedures require human pilots, air traffic controllers, and airline operations controllers, which is untractable for a large simulation requiring hundreds of aircraft that contains many sectors of control. One solution to the problem is to use pseudo-pilots where a pilot controls multiple aircraft through a computer workstation. The primary drawback of pseudo-pilots is that simulations would require additional personnel and the scripting of major events. Simulations would also be limited to real-time since human pseudo-pilots cannot operate in "fast-time". One solution to this problem is the development of autonomous agents that simulate at least some subset of pilot and controller behavior. The advantage of using agents are that experiments can be run over a long period of time, repeated continually with subtle changes in parameters, and also be run in "fast time" to get many simulations run in a relatively short time. As shown in Figure 1, the human's behavior is modeled and used in the "fast time" simulation. The simulation is run, but situations may arise that were not well covered in the model and these are referred back to a human during a follow-on simulation study. The model is then updated with the results from the human in the loop simulation and the cycle repeats.

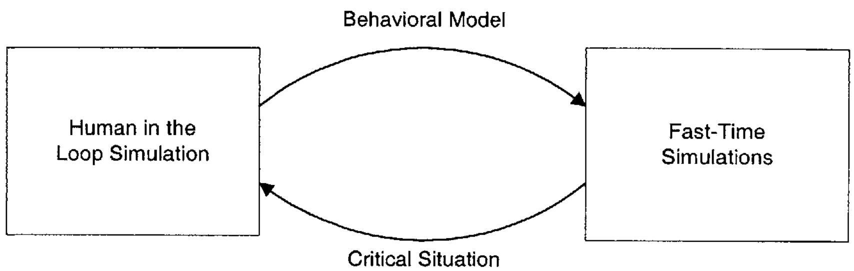


Figure 1 Relation of Human in the Loop Simulations and Fast-Time Simulations

1.1 Large Simulation with Autonomous Agents

One approach to simulating the system is to treat each aircraft and controller as an independent autonomous agent. Each autonomous agent is made up of two primary pieces: a Situational Awareness model and a Decision model as shown in Figure 2 (Harper, K., et al., 1998). The agent also interacts with the environment, which includes other aircraft and hazards. The situational awareness model is defined by capturing the human pilot's or controller's behavior and converting it into a set of rules or behaviors. Accurate quantification of the qualitative and subjective information from the human subjects presents the most challenge in this process. The primary purpose of the situational awareness model is to break down the current situation into quantifiable elements that can be used to make decisions. The decision model then defines the appropriate course of action to take in a particular situation. However, in the same situation two humans could disagree on the correct course of action to be taken. In many ways any large-scale simulation would have to simulate the varied or inconsistent behavior across many different people if it is to present an accurate representation of the operational system. To fully simulate the interactions in the real system the independent agents communicate with each other through passive methods such as their actions and also through active methods like sharing information or intent.

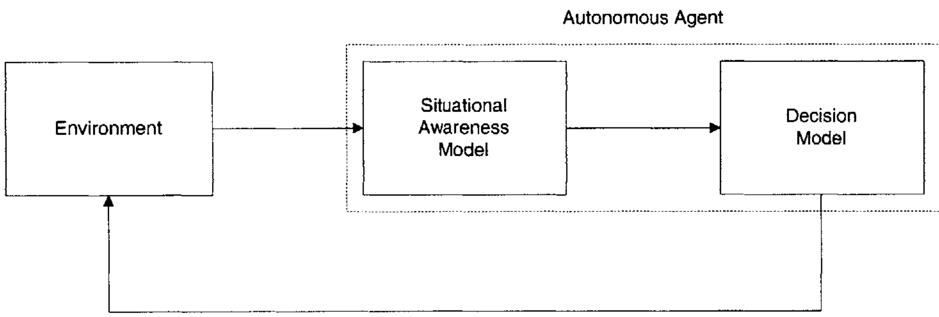


Figure 2 Autonomous Agent Model

1.2 Weather Issues

In general, the capacity of the air traffic control system is most taxed on days where adverse weather limits the number of flight operations, departures and arrivals, that can be conducted over a time period. This reduction in operational efficiency leads to delays and cancellations. The FAA maintains an Air Traffic Control (ATC) System Command Center that monitors the effect of weather on operations, but focuses on strategic and system-wide solutions like the Ground Delay Program which reduces the number of aircraft in flight under these conditions.

Though tools have been developed that help to optimize various issues such as aircraft routing and sequencing, departure planning, and maintaining aircraft separation, these tools do not directly address the effect of weather on airspace operations. Weather tools are generally limited to the prediction of motion and severity of adverse weather, but do not attempt to optimize individual aircraft operations using the constraints posed by the weather. Understanding how pilots perceive and operate around weather would be extremely useful in designing decision-aids that might help in reducing delays and increase efficiency.

1.3 Effects of Traffic on Weather Avoidance

Weather and traffic are highly interconnected since avoiding weather may result in a solution that conflicts with an aircraft that is also attempting to avoid weather. Figure 3 shows an example of traffic conflicts that occurred during one study of pilot/ATC information sharing (Farley & Hansman 1999). The figure shows six aircraft in close proximity to a break in the weather, where two of the aircraft DAL768 and DAL189 are at the same altitude and within 5 nmi of each other thus violating separation standards. Such traffic situations may occur because adverse weather constrains the number of possible routes. Particular routes such as routing through breaks in the weather may quickly become congested, resulting in a sharp increase in the workload of the Air Traffic Controller. Though the route through the hole in the weather is highly desirable, congestion might make it unacceptable and another less desirable route must be chosen instead. A similar interaction occurs when two aircraft have a conflict with each other. The conflict requires another route to be chosen, but the new route might be unacceptable if it does not meet the pilot's weather criteria.

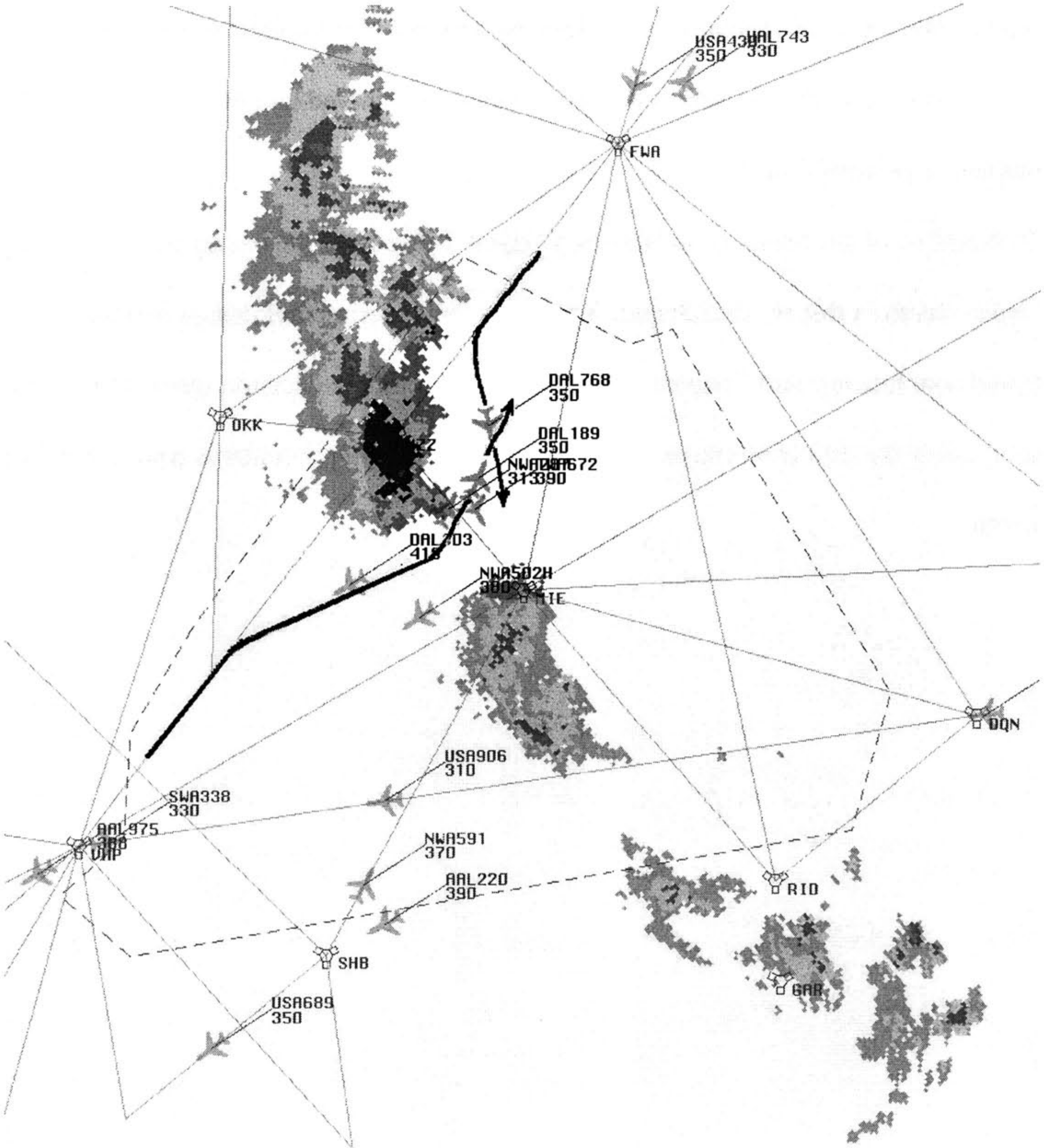


Figure 3 Conflict of Traffic & Weather Avoidance Example
(Farley & Hansman, 1999)

1.4 Thesis Outline

The primary goal of this thesis is to develop a model of pilot behavior in adverse weather conditions. Some preliminary pilot data was gathered and used to design and implement a prototype agent.

The outline of the thesis is as follows: Chapter 2 discusses the background information for the research in this thesis, Chapter 3 presents the experimental design and the raw data and conclusions, and Chapter 4 describes two prototype decision models that were created using the data from the experiment. Finally, Chapter 5 contains a summary of the research.

Chapter 2 Background

2.0 Background

Hazards constantly impose constraints on decisions, making the understanding of decision-making in the presence of hazards an important goal. Adverse weather is one of the common hazards for commercial pilots, and developing a model of pilot behavior in the presence of weather could have important benefits for the safety and efficiency of air transportation. To begin to understand pilot behavior, it is necessary to develop models that can represent observed behavior and ultimately predict future behavior in a variety of conditions.

Figure 4 shows a model of a pilot's multi-staged decision-making process (Endsley, 1995). A pilot's situational awareness is developed through a three staged process: Detection and analysis, assessment, and prediction. With each stage a clearer understanding of the weather hazard and the current and potential future effect on the aircraft become better understood. In the first stage, various information sources are used to detect and then analyze a weather cell, which results in data about the position and severity of the weather hazard. In the assessment stage, a pilot would then determine the hazard's risk and overall threat to the aircraft. During the final stage of situational awareness the pilot creates an internal model of future positions and severity of the weather cell. With this information the pilot can determine the appropriate resolution maneuver, either to continue as originally planned or reroute on a different path that avoids the hazard.

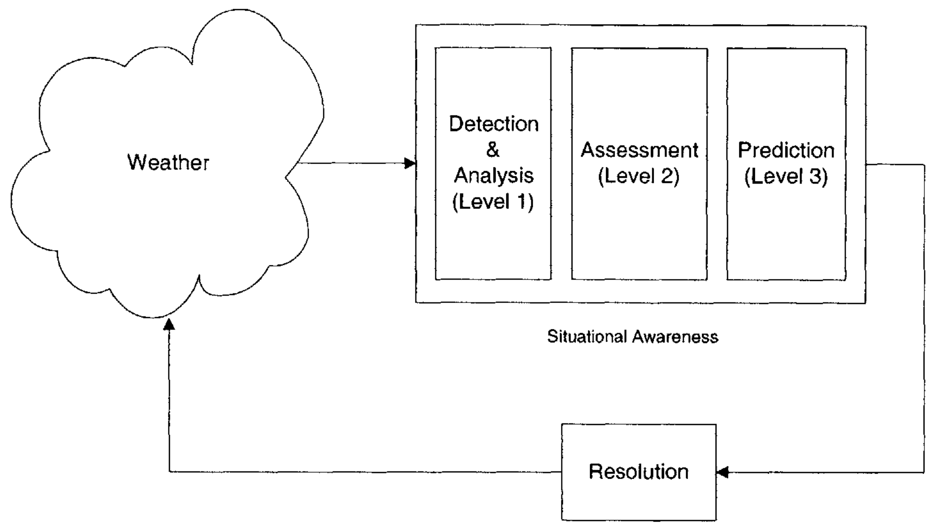


Figure 4 Basic Situational Awareness Model (Endsley, 1995)

Situational awareness is rarely 100% complete under normal conditions which is due to various uncertainties in the information sources or incorrect models of a hazard's risk or movement. Generally information sources have at least some uncertainty about a hazard's position, size, severity, and future path. This uncertainty propagates through the process and can reduce overall pilot awareness of everything around the aircraft. Pilots counteract this uncertainty in their information sources by fusing the data gathered from several independent sources and by following time-based changes in the data.

2.1 Weather Information Sources and Prior Research

The cockpit contains several different information systems for weather hazards. On commercial aircraft, the primary source is the weather radar, which gives information on precipitation intensity, size, and position relative to the aircraft. All three of these allow the pilot to assess the overall risk of a particular weather cell. Precipitation intensity is considered to be an indicator of severity and is normally shown using a four-color scale; Green represents light intensity, yellow moderate intensity, red severe intensity, and magenta for turbulence. Some displays use intermediate shades to provide more exact information on severity, while others reassign red to high intensity and use magenta for severe.

The view from the cockpit window provides visual indications of weather position, cell shape and structure, cell height, and lightning intensity, which are all indicators of weather severity. However, the windows become significantly less useful at night, when already in a cloud, or for long-range planning.

Weather information from controllers and other pilots is also a valuable source of information. Ground based radar gives a different view on the storm activity, though in many instances the radar information is not available to controllers since current enroute ATC displays do not display weather information. However, controllers will often draw out on their screens where they believe weather is, based on pilot diversion requests and pilot reports (PIREPS), which helps them to predict future diversions and route requests. PIREPS provide information about intensity, location, and effects on the aircraft. Information is also shared over the radio channel with ATC. The information is often referred to as "Party-line" information, since information is being shared over a common channel. Even though it is directed at ATC, other pilots in the area use it to form a model of particularly adverse weather or future requests by ATC.

2.1.1 Effects of Weather in the Approach Sector

In one previous study, pilot behavior was measured by using radar data from the Dallas-Fort Worth Airport (Rhoda & Pawlak, 1998). The study focused on pilot reactions within the approach region and found several interesting results. One result was that as the distance to the runway goes down the pilot becomes less averse to flying through severe weather. The study suggested that pilots more or less will fly through even the most severe weather cells when they are within 25 km of the runway. The study also asserted that aircraft that were arriving more than 15 minutes late also tended to penetrate severe weather more often than planes that were early or on-time. It can be surmised that airline on-time statistics might be a driving factor because the current definition of on-time is if the aircraft arrives within 15 minutes of the scheduled flight time. A strong correlation was also found that suggested pilots would follow the path of a preceding plane through weather. This fact might be related to "party-line" information passed between pilots either on the ATC channel or through pilot reports (PIREPS).

2.1.2 Effects of Lead Aircraft on Pilot Decision-Making

A further study of "Party Line" information transfer suggested that lead aircraft act as distributed sensors for following aircraft (Hyams & Kuchar, 1999). The information provided through this channel is used primarily as a supplement to the weather radar and was most useful when the impact of weather along the original route was ambiguous.

2.1.3 Prior Research on Modeling Tactical Rerouting around Weather

Other research has focused on developing models that can create new aircraft routes in the terminal area to balance weather avoidance against the resulting delay. Krozel, et al. (1997) have proposed a computational method that optimizes aircraft routings based on assigning penalty weights to varying levels of weather severity. Their work has explored several methods (e.g., Dijkstra's algorithm or Snell's Law of refraction) for representing weather and efficient ways of processing and developing new routes. The result is a potential controller tool to reroute aircraft tactically and rapidly based on current weather information.

The research presented in this thesis, in contrast, focuses on specifically modeling pilot behavior. The intent, therefore, is not to necessarily optimize routings, but rather to capture pilot preferences and actions in the presence of weather.

2.2 Hazard Modeling

A hazard can be generally described as an object or state in a situation that affects decision-making due to a potential negative outcome if it is ignored. In the aviation environment, examples include weather, terrain, other aircraft, and turbulence. In military applications missiles and radar sites are hazards, and hazards can also be more intangible, like aircraft performance limits.

2.2.1 Hazard Types

Hazards can generally be clumped into either "soft" or "hard" hazards (Hyams, et al., 1999). A "hard" hazard is defined as a hazard that cannot be entered without a catastrophic effect and should be avoided. Examples of this type of hazard in the aviation domain would be a collision with terrain or other aircraft. Some "hard" hazards may also have established buffer zones around them that simulate a desire to maintain a certain range from the "hard" hazard. Although not desirable, these zones can be penetrated and in many ways are similar to a "soft" hazard.

A "soft" hazard is defined as a hazard whose boundary may be penetrated, but there is risk associated with entry. The effects range from catastrophic to relatively benign depending on the type of hazard. Examples include weather, stall, and missile sites. The decision to penetrate or avoid a "soft" hazard is much more complex and depends on several factors such as the perceived risk, the cost associated with avoidance, and the decision-maker's current goals.

2.2.2 Hazard Risk Models

The effects of a hazard vary depending on the type of hazard and how the consequences of entering the hazard are manifested. For example an aircraft entering a region of adverse weather has a different associated risk and consequences than an aircraft entering an area controlled by a missile site. As a result several basic models were developed to describe how a hazard's risk is quantified. The models all assume that the hazard's position, size, and severity are perfectly known, though uncertainties in these parameters can be added (Hyams et al., 1999).

The most basic model has been labeled "One-Shot" since the effect of the hazard can only occur once, when the hazard is entered. This model assumes that the event occurs with a probability of P. The risk of the hazard is a combination of the penalty associated with the incident and the probability of it occurring. An example of this type of risk could be a missile radar site. An aircraft entering the radar site's coverage zone is not necessarily detected since the radar might not be functioning at that time. P is the probability that the radar site is operating. Equation 1 displays a simple linear relation where risk, R, is equal to the probability of an incident, P, times the cost associated with the incident occurring, C.

$$R = P \cdot C \tag{1}$$

Risk grows with increasing cost or probability of an incident. A "hard" hazard is simply the limit of this equation where the probability of incident is 1. The equation thus simplifies to the risk being equal to the incident cost.

A second model has been referred to as "exposure-dependent" since the risk level accumulates with increasing exposure to the hazard. A good example of this model would be a weather cell since the potential for a turbulence encounter is cumulative as the length of exposure is increased. The risk would be a function of time as shown in Equation 2 where risk, *R*, is equal to the incident cost, *C*, times the average incident rate, *p*, times the hazard exposure time, *t*. Risk would increase as the exposure time, incident rate, or the incident cost grows.

$$R = C \cdot p \cdot t \tag{2}$$

A third model is one where the probability and cost of the event vary as the amount of exposure increases. The probability of incident, *P(t)*, and its cost, C(t), are a function of the amount of hazard exposure time, *t*. An example of this might be flying through a region of varying weather severity. Equation 3 shows that risk, *R*, is an integrated function over a duration T. Risk would increase as the exposure time or incident cost grows.

$$R = \int_0^T C(t) \cdot P(t)\, dt \tag{3}$$

2.2.3 General Decision Models

When presented with a hazard the decision-maker assesses the situation focusing on the risk posed by the hazard, the risks and costs associated with maneuvering around the hazard, and the goals of the decision-maker (Dershowitz, 1997). This assessment allows the comparison between the current path and possible alternate routes. Figure 5 shows how these various concerns are combined into a final decision about the correct resolution. The decision-maker would weigh the risk of the original route versus the risks and costs associated with the alternate routes with the goal of determining if the reduced risk justified the cost of taking an alternate route. The decision-maker's goals and constraints take into account other factors like the destination and available fuel. These allow the decision-maker to determine the best of relatively equal options or disregard options that break the current constraints. For example, flying around a weather cell may not be beneficial if the aircraft becomes fuel critical as a result.

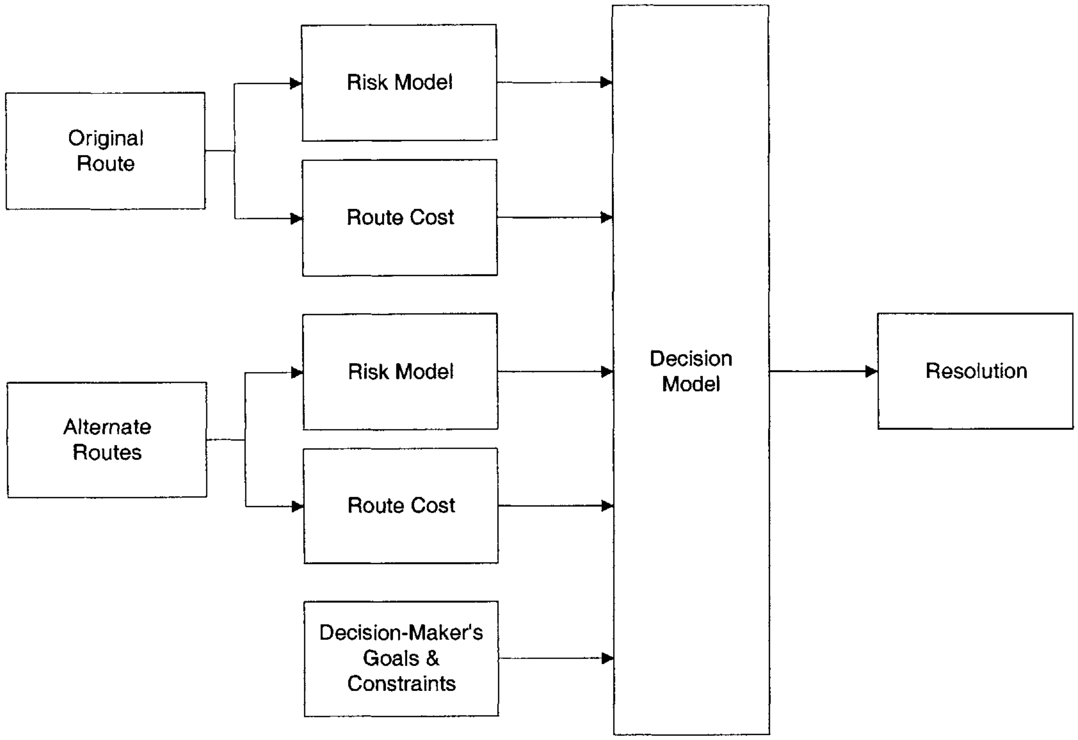


Figure 5 General Decision Model Diagram

2.2.4 Weather Model

Representing adverse weather is a complex affair. However, since the focus of this study is on the decision-maker's process and modeling various aspects of it, exact modeling of the weather is not required. Certain simplifications can be made without affecting the accuracy of the pilot model.

The weather radar display on an aircraft shows the data in four primary colors which represent three severity levels and one turbulence level as shown in Figure 6. However, the data tends to be amorphous in shape and pixellated, which makes it difficult to determine specifically what the pilot is observing and reacting to. Simplifying the weather through a set of ellipses allows for more accurate generation of metrics to measure the pilot's intent, though at a loss of some realism.

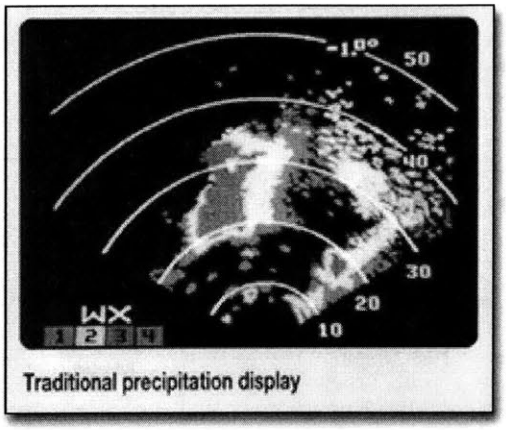


Figure 6 Example of Traditional Precipitation Display (Honeywell, 2000)

The simplification to use of ellipses to represent weather removes some of the gradient information that pilots use in severity assessment. There are two primary types of severity gradient effects, which are the severity transition distance and the close proximity of multiple transitions shown in Figure 7. The severity transition distance is the space over which the severity changes from one level to another. If this distance is small there will be a single dividing line between two severity levels, signaling to the pilot that the cell is well developed and more severe than a case where the edge is highly pixellated and transitions over a larger distance. A similar type of signaling also occurs when multiple transitions are in close proximity to each other. This type of situation tells the pilot that this region of the storm is well developed and should be avoided.

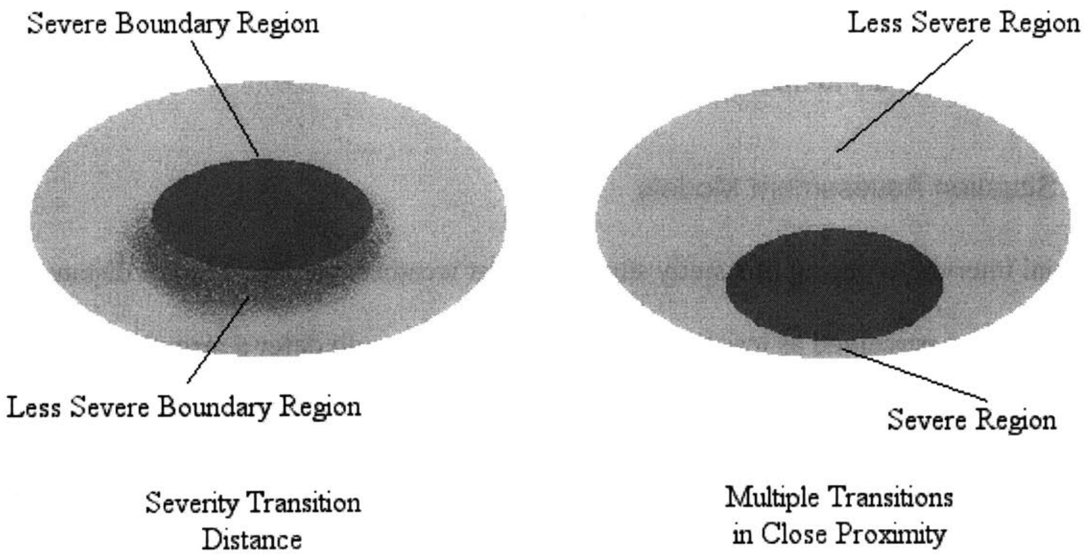


Figure 7 Weather Transition Schematic

2.3 Effects of Weather on Decision-Making

Adverse weather strongly effects the decision-making of pilots, Airline Operations Center personnel, and air-traffic controllers. A decision-maker in adverse weather conditions would have to consider several different sources of information, such as weather radar, other aircraft, or visual assessments, but the accuracy and validity of the data must be considered. This analysis is the first step in forming a picture of the situation around the aircraft. This picture is then used to assess the effect of weather on the aircraft given its current route. If the default route is acceptable given the current situation then the decision-maker would proceed as previously planned. If the original route is not acceptable, the decision-maker would have to decide whether to penetrate or divert around the dangerous region. This decision would require the decision-maker to account for system-wide goals like the destination, characteristics of the aircraft, determination of the actual weather threat, and assessment of the uncertainty. All of these issues contribute to making an informed decision.

2.3.1 Situation Assessment Models

Initial interviews during this study suggested that weather that was a larger distance away would be perceived as less threatening so the pilot would defer a rerouting decision until a future point. Under normal conditions the pilot would also defer decisions in this case due to the increased uncertainty in weather position and severity as the distance to the cell rises. Even over the relatively short period of time it takes to approach the hazard the overall situation might change dramatically with it either becoming significantly better or worse.

Since the focus was on tactical decision-making versus strategic, a large number of possible geometries could be reduced to a couple of basic scenario types. Figure 8 shows a scenario with a single weather cell that conflicts with the original route of the aircraft. In making the decision about an alternate route, the pilot weighs economic and ATC pressure versus the safety of the aircraft and passenger comfort. Economic issues such as fuel cost drive the alternate route towards the original route since the original route would have a shorter path distance than the alternate route. ATC generally wants to minimize the amount of diversion since large diversions may interfere with the flow and predictability of the aircraft in the sector. To maximize safety the pilot would prefer to make a larger diversion maneuver to maximize the distance to the weather. A large diversion is also preferred for passenger comfort since going around a weather cell would offer a smoother ride.

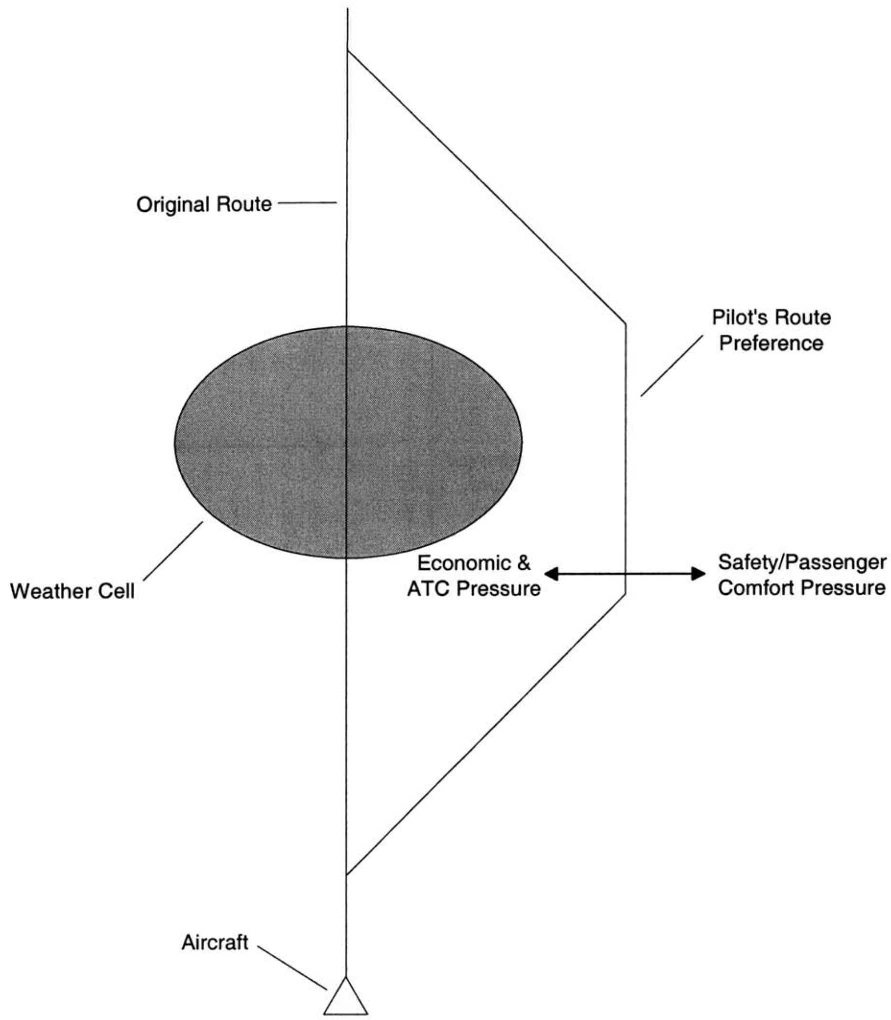


Figure 8 Single Cell Schematic

Figure 9 shows a route that is constrained by two weather cells. In this case the original route would be optimal for safety, passenger comfort, and economics since any deviation would result in a less preferable situation. Hypothetically, ATC might request the subject pilot to deviate since this would create space for other aircraft to move through the gap. It should be noted though that if the weather cells encroach further on the route, a point will be reached where the original route's closest point of approach to the weather cells would be unacceptable to the pilot due to safety and passenger comfort concerns.

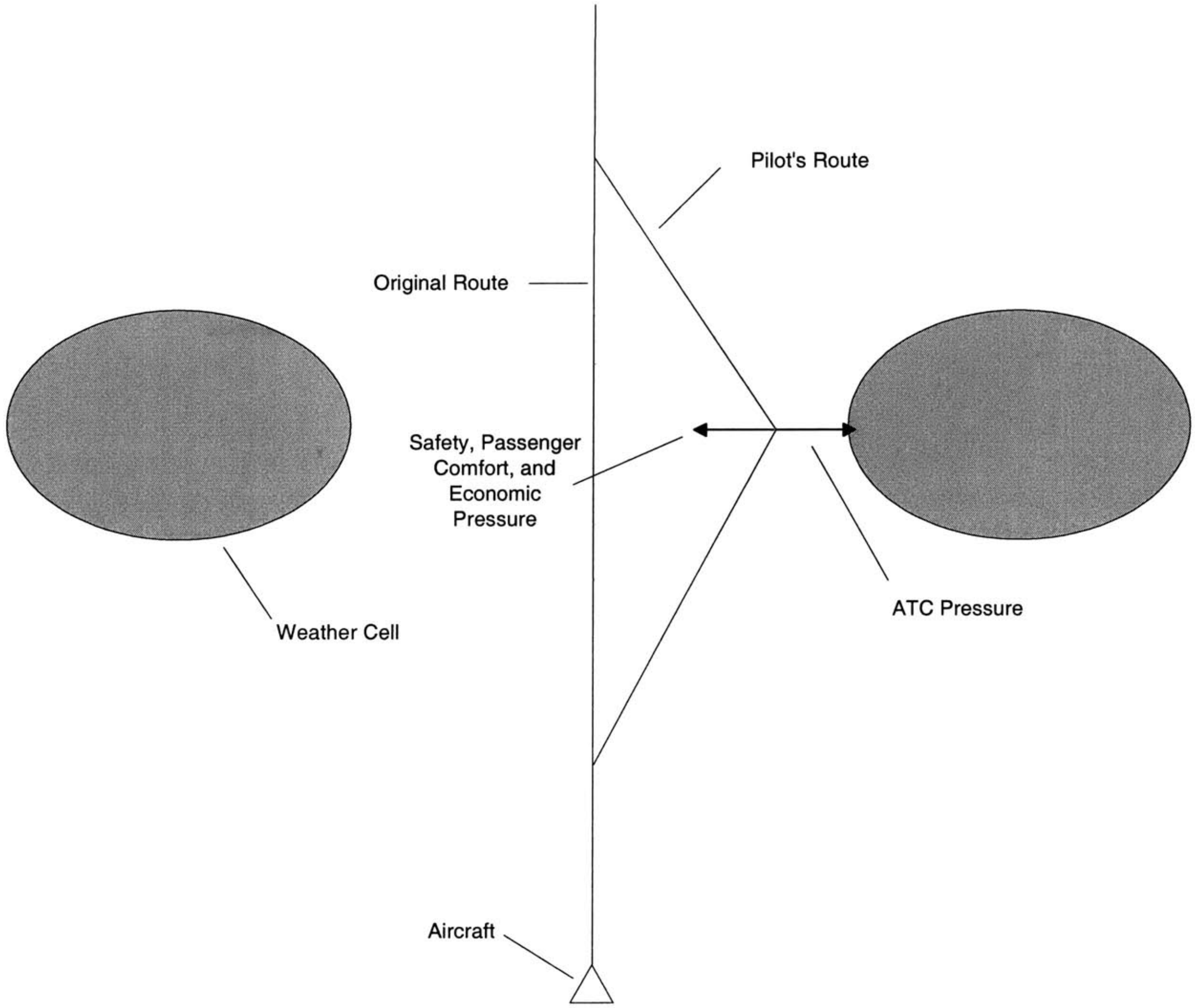


Figure 9 Weather Constrained Route Schematic

2.4 Resolution Models

The pilot decides on the correct resolution maneuver by developing an awareness of the current situation. Situational awareness is established when the pilot analyzes the current route and the hazards and converts certain measured metrics such as weather severity and range into a measure of the actual threat to the aircraft. If there are no serious conflicts or it is too early to make the decision to reroute a pilot would most likely continue along the current route. The pilot would continue to monitor the situation for future conflicts or to wait for information to become more certain in the case of deferring due to uncertainty. However, if a diversion is required the pilot would then decide to choose a route that minimized the diversion while still satisfying the requirements imposed by safety constraints.

2.5 Agent-based Pilot Models

Autonomous agents operate using a set of rules that describe the goals or intent of the agent. The most basic agent model works by assimilating information from the simulated environment and processing it into an understanding of that environment, which is often referred to as situational awareness. One popular technique for this assimilation and processing has been belief networks since it allows the agent to infer data that might be true though the agent has no direct means to measure it. Another popular technique is an expert system, which acts on a set of rules with predefined resolutions that are generated by experts in the domain.

Both the situational awareness and decision model are calibrated from empirical data gathered through experiments using scenarios or by using domain experts to define the rules directly. However, in many cases a single experiment using one individual or domain expert isn't sufficient to define the agent behavior since there is relatively large variability in the actual decision making of particular individuals even given the same goals. This variability has to be addressed in the development of the agent models.

Many times the actual goals of human operators are not well defined or are not directly quantifiable. Typically there is not an exact rule that defines the relationship between one variable and another and more often than not there are many variables that when combined define the proper behavior. Even if the behavior is well understood, there is no guarantee that the implementation of the behavior will be on target. When it comes to human subjects much of this can be explained by the "fuzzy" nature of human thought.

2.5.2 Expert Systems

Expert systems are systems that use a series of rules to govern their behavior (Buchanan & Shortliffe, 1984). Experts in the field most often generate these rules, but in some cases the rules can also be generated from empirical data of a system. Most expert systems use rules in an "if-then" format where a series of conditions are tested for validity in the "if" part of the statement to decide if the behavior in the "then" part of the rule should be used. An example of the rule base is shown below:

If:

Weather severity is unacceptable

AND

Range to weather cell is less than 15 nmi

Then:

Divert around weather cell by choosing a route that maintains a minimum distance of 5 nmi

An expert system's primary weakness is that the rule-base must cover all possible situations that require action or the system will simply decide to do nothing since none of the rules would apply.

2.5.3 Belief Networks

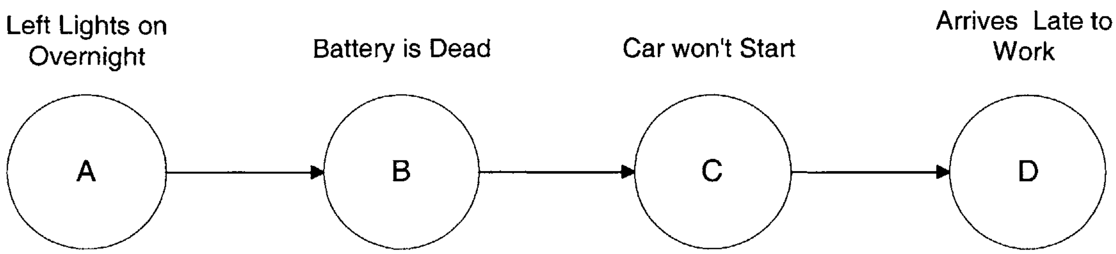
Belief networks are another technique that allows some of the aspects of human behavior to be captured (Pearl, 1988). Instead of using predefined rules the belief network uses a series of nodes to represent various measurements or states within the system. A simple example of a belief network is shown in Figure 10, which describes a simple diagnostic of a car that assesses one reason why the car might not start. Nodes A, B, C, and D represent basic conditions of the car such as the lights were left on overnight, the battery is dead, the car won't start, and the driver arrives late to work. Each node has a series of values that describe the probability of that nodc being in any particular state. The values are normally stated in a vector as shown in Equation 4. For example, the "car won't start" and "late to work" nodes contain two states, true and false, and as a result would be described as a vector with two elements. The arrows between the nodes represent the direction of conditional dependence between the nodes. For example, whether the car starts depends directly on only whether the battery holds a charge, not on whether the lights were left on. The relation between the various states is described by a conditional probability matrix represented, for example, by M_{CD} in Equation 5. This matrix is the formal relation using Baye's Rule between the state vectors of node C and D. The *i*th row and *j*th column of a conditional probability matrix between any two states (say X and Y) represents the probability that the *i*th state of node Y is true given the *j*th state of node X is true. The complete matrix then defines all possible conditional probability relationships between the two nodes.

$$\begin{aligned} \textit{Node C State Vector} &= \begin{bmatrix} P_{C1} \\ P_{C2} \\ \vdots \end{bmatrix} \\ \textit{Node D State Vector} &= \begin{bmatrix} P_{D1} \\ P_{D2} \\ \vdots \end{bmatrix} \end{aligned} \tag{4}$$

$$\begin{bmatrix} P_{D1} \\ P_{D2} \\ \vdots \end{bmatrix} = M_{CD} \begin{bmatrix} P_{C1} \\ P_{C2} \\ \vdots \end{bmatrix} \tag{5}$$

Example conditional probability matrices are shown in Figure 10. For example as shown by M_{CD}, if the engine won't start there is a 0.9 chance that the driver arrives late to work and a 0.1 chance that the driver arrives on time anyway. If the engine does start the probability that the driver is late to work drops to 0.3 and the probability they are on time rises to 0.7.

The power of the belief network lies in the fact that assertions can be made about measureable states, while probabilistic data about the unmeasurable or unmeasured states can be inferred. For example, given an a priori assumption that the lights are left on 10% of the time, the first column in Table 1 shows the resulting probabilities for each node. With no prior information, the driver would be late to work 25.2% of the time. However, if the person knows the car did not start this morning, recomputing the network changes the probabilities to what is shown in column two. The probability of the lights having been left on overnight has changed to 0.33, and of being late to work has been updated to 0.7. Thus, the network can be used both to *diagnose* the cause of a condition (e.g., diagnosing the likelihood that the lights were left on is the cause for the engine to not start) and also to examine the *causal* effect of information (e.g., whether the failure of the car to start will cause the driver to be late).



$$M_{AB} = \begin{bmatrix} 0.9 & 0.2 \\ 0.1 & 0.8 \end{bmatrix}$$

$$M_{BC} = \begin{bmatrix} 0.9 & 0.0 \\ 0.1 & 1.0 \end{bmatrix}$$

$$M_{CD} = \begin{bmatrix} 0.9 & 0.3 \\ 0.1 & 0.7 \end{bmatrix}$$

Figure 10 Belief Network Example

Table 1 Belief Network Probabilities

Node States: (after computation)	A Priori	Given Car Won't Start
Lights Left on	0.1	0.33
Dead Battery	0.17	0.67
Car won't start	0.253	1.0
Late to work	0.252	0.7

Chapter 3 Experimental Study

The development of a preliminary pilot model required actual pilot input and data for modeling and calibration. The data were collected using several methods including interviews, a scenario snapshot survey, and through the use of an interactive weather display experiment.

3.1 Pilot Interviews and Survey

The interviews were intended to gather preliminary pilot preferences and determine major factors affecting decision-making. Initial interviews were conducted in a series of one-on-one interviews with a current captain of a major airline. The interview questions were free response in order to probe the pilot's major concerns when in the presence of severe weather. Follow on interviews fine tuned the model and led to the conclusion that there were three primary goals that this pilot used to decide if a particular route was acceptable. These in relative importance were safety, passenger comfort, and economic efficiency, which agrees with similar information gathered by a previous survey (Hyams & Kuchar, 1999).

Decision-making regarding safety is primarily concerned with the possibility of catastrophic failure, such as a crash, damage to the aircraft, and injuries to the passengers or the crew. The pilot uses a satisificing type of logic where the minimum safety conditions are satisfied first, without regard for optimizing with other concerns. Passenger comfort covers more of the area of prolonged exposure to lower severity levels of weather, which cause discomfort for the passengers, while still remaining safe. Economic issues such as fuel cost and the costs associated with aircraft delays also drive route choice since unnecessary deviations affect airline profitability. Passenger comfort and economic issues are often optimized relative to each other to improve overall route desirability. Air Traffic Control (ATC) acceptance is also of importance since ATC is responsible for maintaining separation and flow within a sector. Though the pilot has final authority over the final acceptance of the route, the pilot will often negotiate taking a less desirable route to satisfy ATC's preferences.

Using the information developed from the interviews a preliminary model of the pilot's logic was developed as shown in Figure 11. The model's primary purpose is to show the interactions between the various information elements with the overall route acceptability. Safety, passenger comfort, and economic concerns for a particular flight are the pilot's responsibility, while ATC acts independently and is concerned primarily about system efficiency, aircraft flow, and traffic separation.

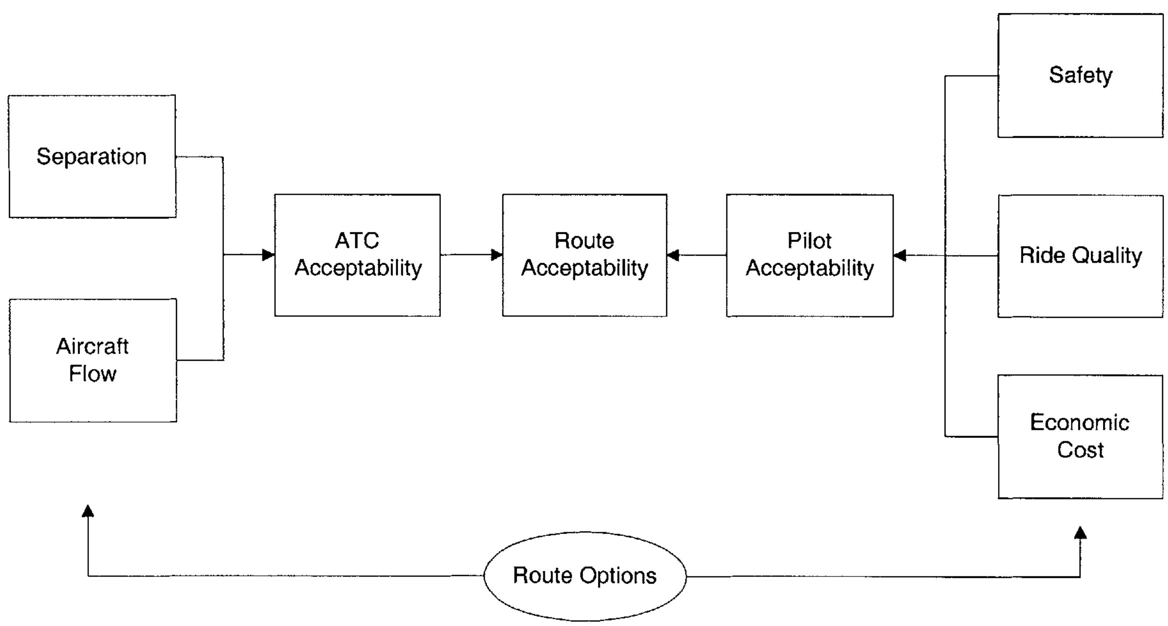


Figure 11 Preliminary Logic Model

A survey was also conducted to begin to qualitatively assess the parameters and metrics that a pilot uses when assessing adverse weather. An example of one of the scenarios is shown in Figure 12 and a complete survey questionnaire is contained in Appendix A. The first question asked if the pilot would continue along the specified route, request a change, or if the pilot would have requested a change earlier than the situation displayed. The second question requested the overall perceived safety estimate for the scenario. The third question asked about the predicted passenger comfort level for the given route. Thirty-eight scenarios were conducted with examples of each shown in Figure 13. The main variables between the scenarios were the position of the weather cells relative to the route, the range to the weather, and the extent of the weather. Analyzing the data led to several conclusions. Green weather did not seem to be of major importance to the pilot. The weather's along-track distance also seemed to have relatively low effect when compared to simply being exposed to the yellow or red severity levels.

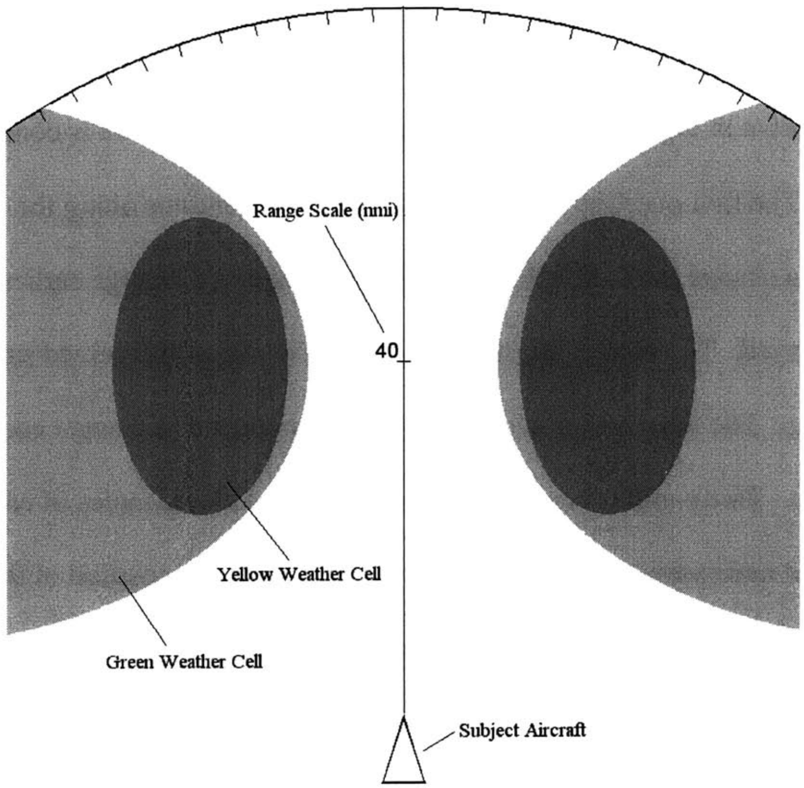


Figure 12 Survey Scenario Example

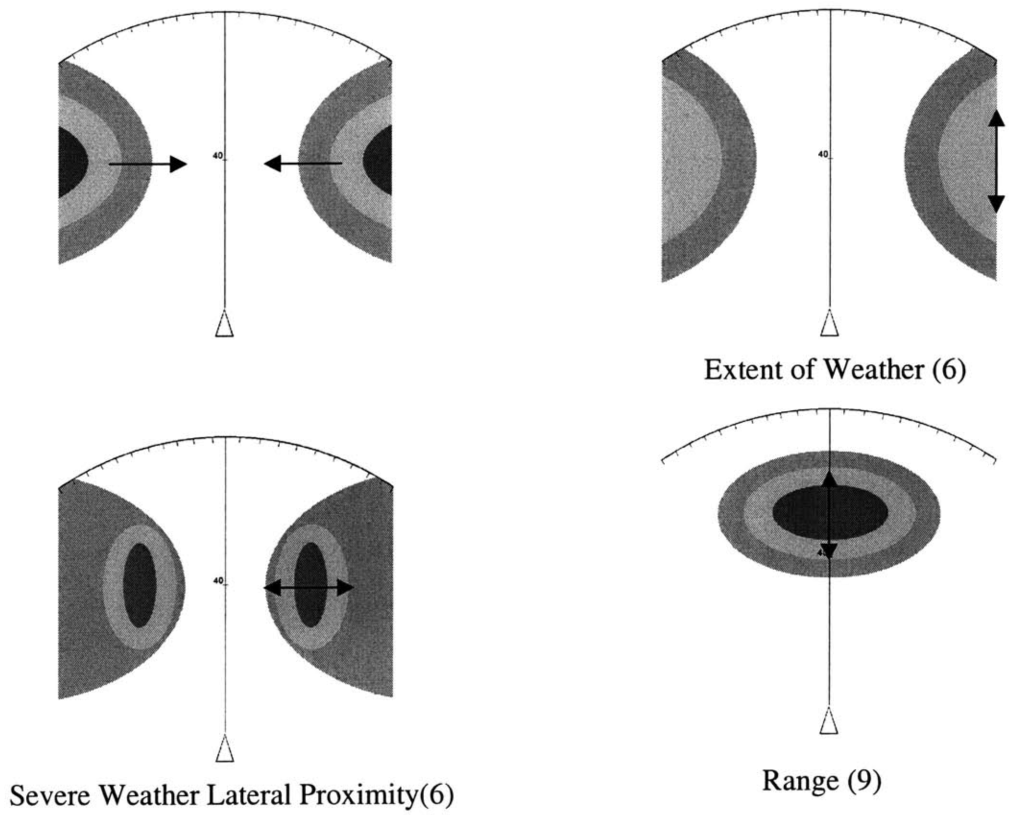


Figure 13 Weather Survey Scenario Types

3.2 Weather Rerouting Experiment

An interactive weather display was built to allow the direct measurement of a pilot's route selection with respect to known weather cells. The interactive weather display simulated a standard cockpit weather radar display, but also allowed the pilot to draw up to four different routes around the weather. Figure 14 shows an example scenario from the experiment. The figure shows an example weather cell to the right of the aircraft's original route, and also the pilot's revised reroute to the left to avoid the weather.

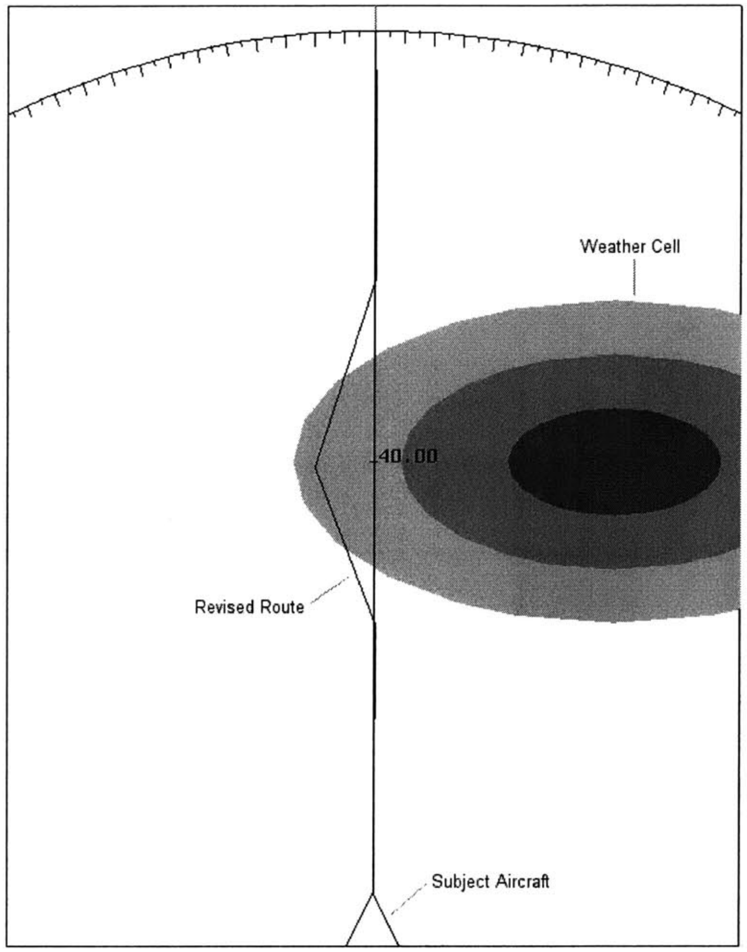


Figure 14 Interactive Weather Display

3.3 Experimental Procedure

The experiment was run as a series of different scenarios in which a pilot was asked to plot his preferred routes. The pilot was briefed that the aircraft was a commercial jet transport currently in cruise, and was given a simulated view of the navigation display including weather radar information. All scenarios were static snapshots, allowing the pilot as much time as needed to think about whether a reroute was needed. The instructions given also varied depending on the type of scenario, which fell into two categories: a single cell along or near the original route, and cases with two cells straddling the route. When the scenario only consisted of a single weather cell, the pilot was asked to plot the ideal route for the aircraft. When the scenario contained two weather cells, the pilot was informed that ATC requested that the aircraft deviate as much as acceptable to make room for other aircraft. This type of situation may occur when aircraft are deviating through "holes" in adverse weather, which allows them to safely navigate around severe weather cells. An initial route was also plotted for each of the scenarios, which was simply proceeding straight. The pilot could then plot a new route, if desired, using the computer mouse. If the pilot gave no additional routes, it was assumed that the default route was considered acceptable. After completing a scenario the pilot continued on to the next scenario. There was a total of fifty-one unique scenarios.

3.3.1 Scenario Design

The scenarios were created with the intention of quantifying a pilot's behavior when deviating around weather. Several properties of weather cells, as shown in Figure 15, were manipulated to gather data on the effects of weather cell size and relative position. The parameters included: cross-track (semi-major, a) and along-track (semi-minor, b) axes, lateral position of the route to the weather's center (c), edge position (e), and the distance from the aircraft to the weather's centerline (r).

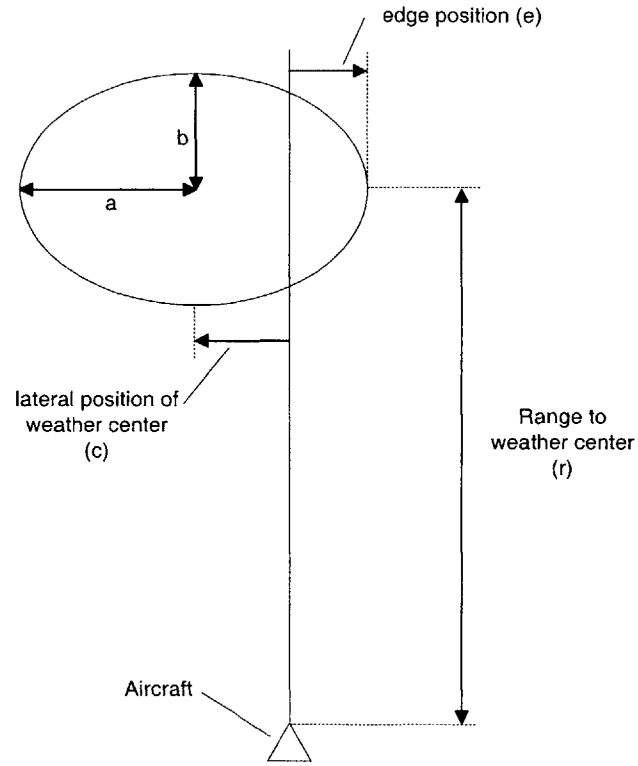


Figure 15 Weather Independent Variables

These sub-types were focused on testing particular aspects of the decision process and any differences in perceptions to given different situations. There were three single cell scenario sub-types: Lateral Coverage, Distance, and Lateral Position. There were two sub-types of dual cell scenarios: Collocated centers and Non-Collocated centers. First, an overview of each type is given, followed by the specific test conditions.

The Lateral Coverage scenarios were focused on eliciting behavior associated with varying the size of the cross-track axis (a) while holding the along-track axis (b) constant. The effect was to vary the amount of the screen covered by weather while holding the along-track distance constant.

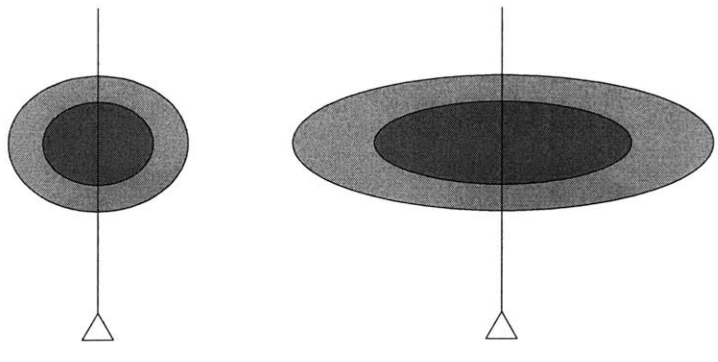


Figure 16 Schematic of Lateral Coverage Scenarios

The Distance scenario varied the range (r) of the weather from the subject aircraft and in some cases the display scale. The primary purpose was to determine the range from the hazard when the pilot left the default route and proceeded in diversion around the weather. A secondary goal was to determine if there were any perception differences if the weather was viewed at different display scales since the weather would be appear larger or smaller depending on the scale.

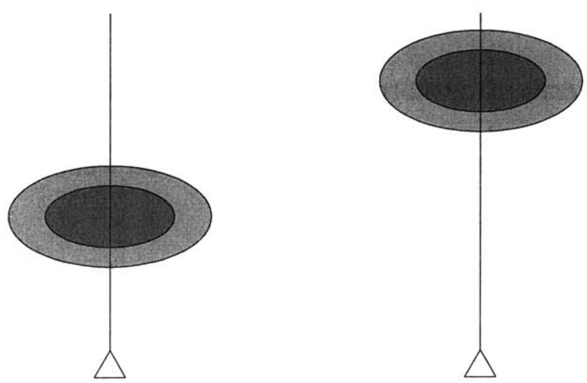
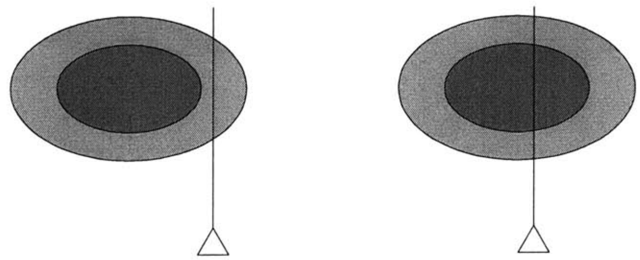


Figure 17 Schematic of Distance Scenarios

The Lateral Position scenarios allowed the determination of rerouting behavior around weather cells that were not centered on the aircraft's current route. These scenarios were also intended to determine if the rerouting behavior differed significantly from the scenarios where the weather was centered. Lateral Position (c) and Edge Position (e) were varied (though these parameters were not independent since the size of the hazard was held constant).



(a) (b)

Figure 18 Schematic of Lateral Position Scenarios

The Weather Corridor scenarios were a series of two-cell scenarios to elicit the minimum acceptable distances from weather when the pilot's decision-making is constrained. Symmetric weather constrained the available options since little or no space was free of weather. Figure 19 shows the two different types of scenarios that were tested. The collocated scenarios concentrated on testing the effect of two independent hazards in close proximity. The non-collocated scenarios simulated a hole between two severe weather cells in a convective line storm. A large green weather cell was centered on the current route and the lateral position of the yellow and red weather cells were varied.

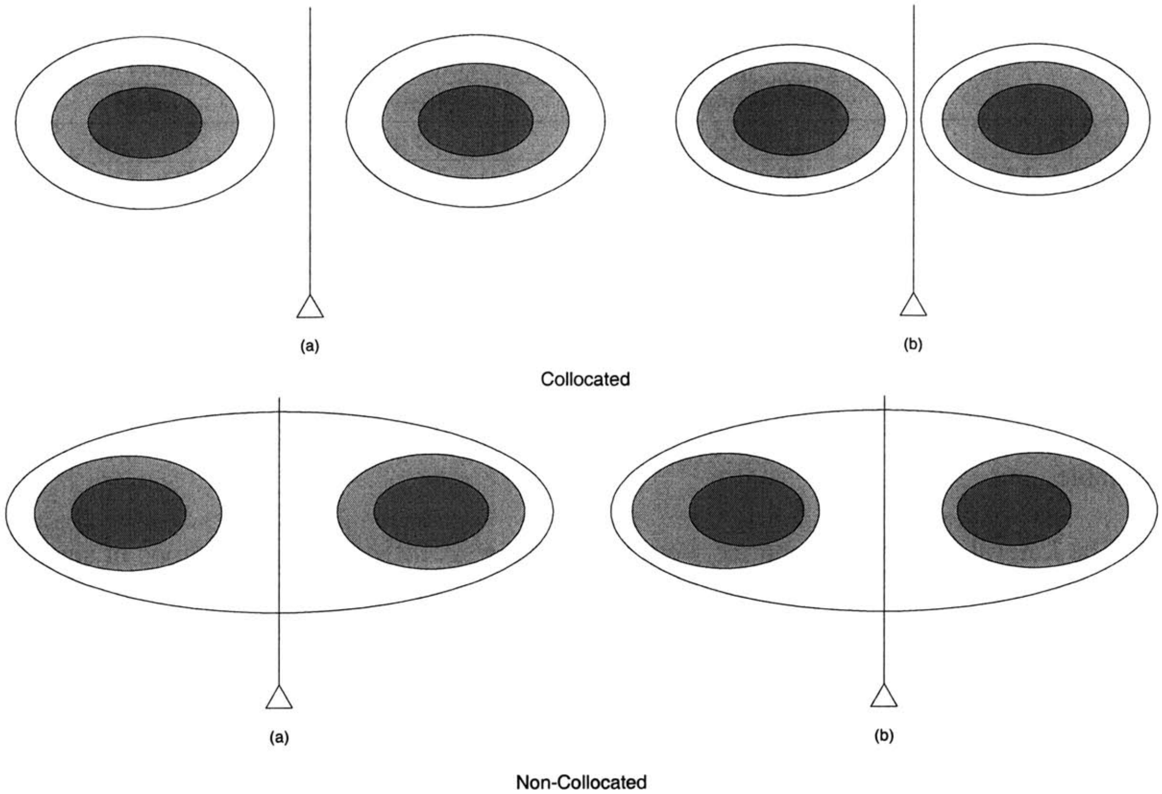


Figure 19 Weather Corridor Scenario Examples

3.3.2 Test Matrices

Three categories of cell sizes were defined with different cross-track (a) and along-track (b) axes. The cell dimensions used in the experiment are shown in Table 2. The weather cells are related by constant ratios where a green cell of a given size is three times larger then the red cell of the same size category. The yellow cell is two times larger than a red cell of the same size category. The along-track axis was also kept constant for each weather type to remove the effect of along-track distance on pilot behavior.

Table 2 Weather Dimensions

Type:	Dimensions (Cross-Track x Along-Track Axes)		
	Green	Yellow	Red
Small (S)	15 x 15 nmi	10 x 10 nmi	5 x 5 nmi
Medium (M)	30 x 15 nmi	20 x 10 nmi	10 x 5 nmi
Large (L)	60 x 15 nmi	40 x 10 nmi	20 x 5 nmi

A constant display scale of 80 nmi was maintained in every type of scenario, with the exception of the Distance scenarios where the scale was varied as an independent variable.

The Lateral Coverage scenarios were tested using six different combinations of sizes and three severities for a total of sixteen scenarios, which are shown in Table 3. Weather included either a single green cell, G, a green and a yellow cell, GY, or a green, yellow, and red cell, GYR. The small, medium, and large cases used fixed ratios of hazard sizes that changed in their lateral dimension, as seen in Table 2. For example, L/M/M indicates a large green cell with dimensions 60x15 nmi, a medium yellow cell of 20x10 nmi, and a medium red cell of 10x5 nmi. The weather cells were centered on the route at a distance (r) of 50 nmi. The L/S GY and L/M/S GYR scenarios were repeated once each and are noted with a (x2).

Table 3 Lateral Coverage Scenario Specifications

Severity Level:	**Size Combinations:**					
G	S	M	L			
GY	S/S	M/M	L/S (x2)	L/M	L/L	
GYR	S/S/S	M/M/M	L/S/S	L/M/S (x2)	L/M/M	L/L/L

The Distance scenarios used five different combinations of range and display scales along with three different severity levels as shown in Table 3. Cells with • represent the scenario conditions that were used. Overall there were a total of fourteen scenarios. The weather cells were the Medium size and were held constant across all the scenarios. The cases of 80 nmi distance at the 80 nmi scale and 160 nmi distance at the 160 nmi scale were chosen to test if there was any difference in perception if the hazard was along the top edge of the display. During the experiment the pilot was not allowed to change the range setting of the display.

Table 4 Distance Scenarios Specifications

Range (r) : (nmi)	40	80		160	
Display Scale: (nmi)	80	80	160	160	320
G (M)	•		•		•
GY (M/M)	•	•	•	•	• (x2)
GYR (M/M/M)	•	•	•	•	•

The Lateral Position scenarios varied the cross-track distance of a single weather cell from the default route and used two different severities as shown in Table 5. There were a total of seven lateral position scenarios. The cells were all made up of the medium size and their centers were collocated at a distance of 40 nmi ahead of the subject aircraft. Three different lateral positions, c, were used: 15, 22.5, and 32.5 nmi which correspond to the distance of the weather cell's center from the default route. Cases were conducted with weather cells on both the right and left sides of the default route to test for any pilot bias. The edge position is the minimum distance from the weather cell to the default route. A negative value means that the weather cell does not intersect the default route while a positive value means the route overlaps by that distance. As Table 5 shows the 15 nmi case had a yellow weather cell intersecting the route. The 22.5 and the 32.5 nmi cases did not have yellow or red weather extending across the default route. Green weather overlapped the default route in both the 15 and 22.5 nmi scenarios.

Table 5 Lateral Position Scenario Specifications

Lateral Position (c):	15 nmi	22.5 nmi	32.5 nmi
Edge Position (e) (Y/R):	5/-5 nmi	-2.5/-12.5 nmi	-11.5/-22.5 nmi
GY (M/M)	•		
GYR (M/M/M)	• (x2)	• (x2)	• (x2)

The Weather Corridor scenarios are broken into two groups; collocated and non-collocated weather cells. In the collocated case, as shown in Figure 19, each severity level was centered on the same point and moved as a single group. The three cases varied by the distance that the center was from the default route. There were a total of eleven collocated scenarios, which are shown in Table 6.

Table 6 Weather Corridor Specifications for Collocated Weather Cells

Lateral Position (c):	21 nmi	28 nmi	35 nmi
G (M)	•	•	•
GY (M/M)	• (x2)	•	•
GYR (M/M/M)	•	• (x2)	•

The non-collocated scenarios, as shown in Figure 19, all had a centered green weather cell that extended the entire width of the display. The parameters are shown in Table 7 with all measurements in nautical miles from the default route. Three of the cases had the yellow and red weather cells collocated while in the fourth case the red weather cell was moved closer to the default route.

Table 7 Weather Corridor Specifications for Non-collocated Weather Cells

Lateral Position (c):	G	Centered (0 nmi)			
	Y	21 nmi	21 nmi	25 nmi	30 nmi
	R	15 nmi	21 nmi	25 nmi	30 nmi
GY (M/M)			•	• (x2)	•
GYR (M/M/M)		• (x2)	•	•	•

The scenarios were assigned in a random sequence to avoid order bias and redundant scenarios were included to check consistency.

3.3.3 Dependent Variables

During the course of the experiment the pilot specified a series of waypoints using a mouse. These waypoints were displayed and connected with a line to give the pilot visual feedback on his route choice. The waypoints were saved when the pilot completed the scenario. This data was used to produce three different measurements, which were the closest point of approach, the decision range, and the deviation of the pilot's route as shown in Figure 20.

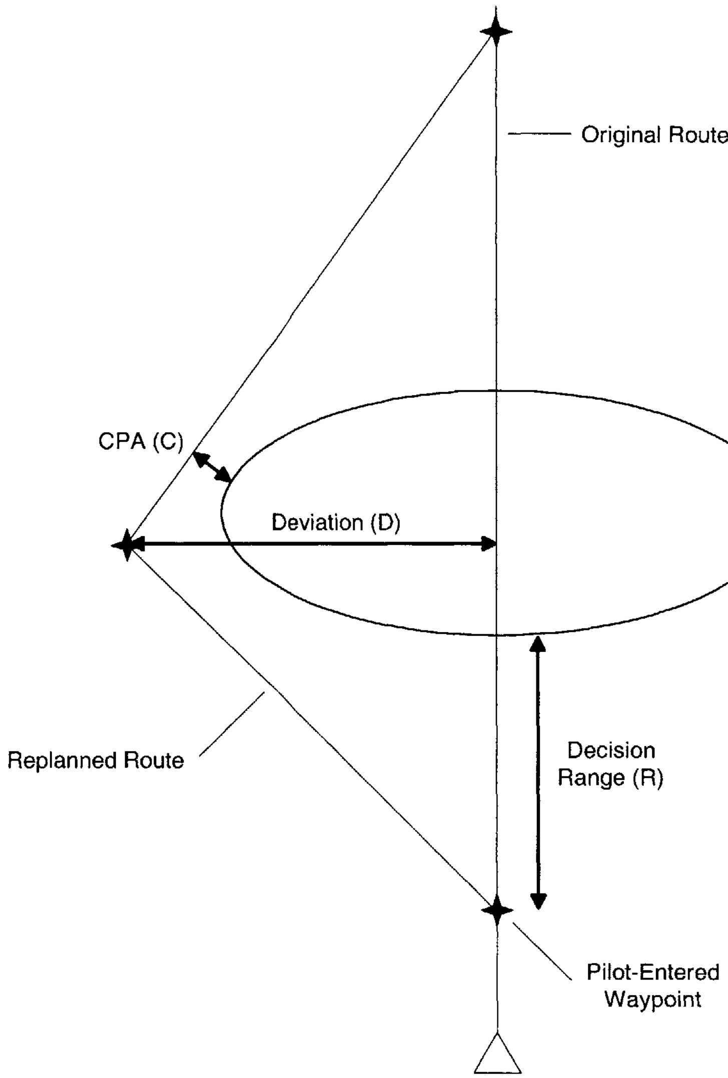


Figure 20 Metric Diagram

The closest point of approach (CPA), C, was defined as the shortest distance between the pilot's chosen route and the weather within the scenario. This calculation was repeated for each severity level (green, yellow, or red) contained in the scenario.

Decision range, R, was defined as the distance from the weather where the pilot began to reroute around the hazard. This reroute point is defined as the point when the pilot leaves the scenario's default route. The decision range was calculated for each level of severity.

Deviation is the maximum lateral distance between the pilot's chosen route and the default route. The default route is the shortest and any deviation off of this route increases both fuel cost and delay. It was believed that the pilot would want to limit deviation as a way of limiting economic cost.

3.4 Results

Several general conclusions can be made about the pilot's behavior. Green weather seemed to have little to no effect on route acceptability and in several cases the pilot simply chose to fly directly through a green weather cell even if deviating less than 15 nmi laterally would have avoided it. Yellow and Red weather were never penetrated, suggesting that any contact with these weather types is considered hazardous.

3.4.1 Histograms

Figure 21 shows a histogram of the red weather decision range data for all Lateral Coverage, Distance, and Lateral Position scenarios. The data shows that 83% of the time the pilot made a re-route decision at some point between 13 – 24 nmi from the red cell hazard. The yellow decision range histogram, Figure 22, states that the pilot's decision range for yellow weather cells was in the region between 8 nmi – 19 nmi 81% of the time. The yellow range histogram contains a mix of scenarios with only green and yellow cells along with scenarios that have green, yellow, and red cells.

The decision range data tends to have a relatively dense distribution considering the large number of differences between the scenarios, including the weather's size, lateral position, and the range to the weather.

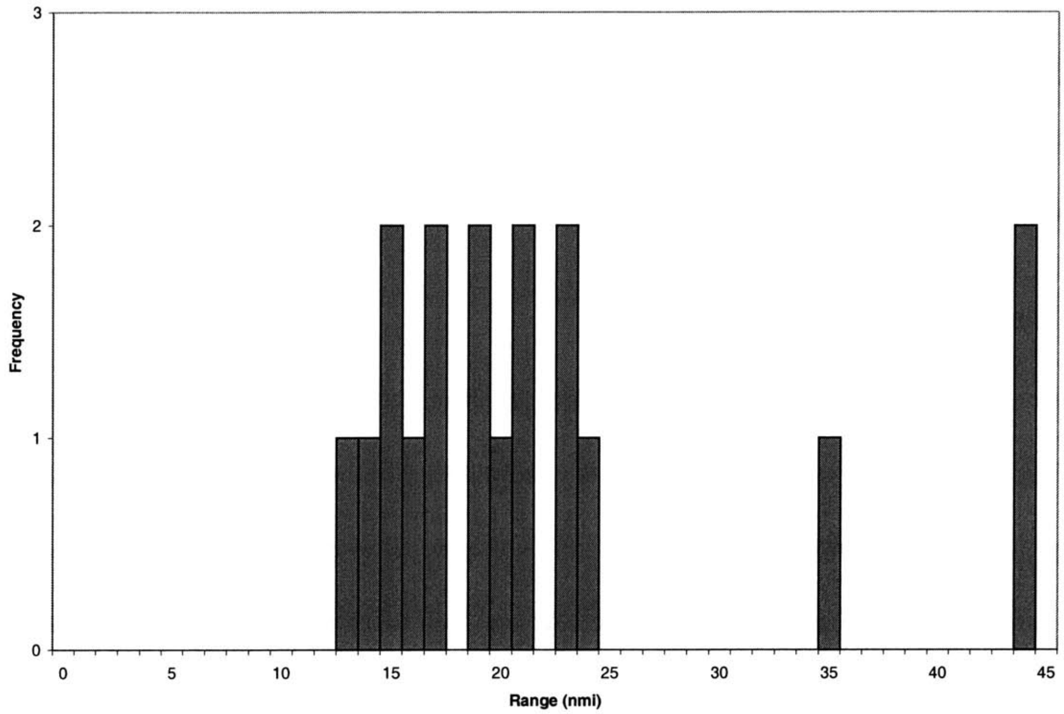


Figure 21 Red Decision Range Histogram
(Lateral Coverage, Distance, and Lateral Position Scenarios, n=18)

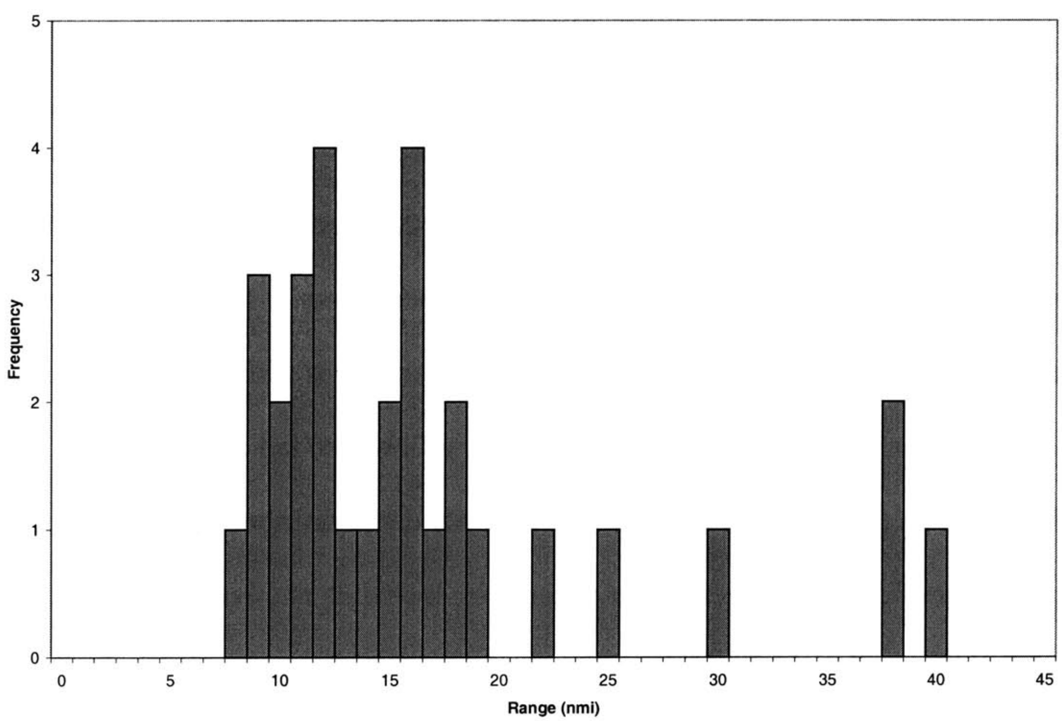


Figure 22 Yellow Decision Range Histogram
(Lateral Coverage, Distance, and Lateral Position Scenarios, n=31)

A histogram for the CPAs to red weather for all the single weather cell scenarios is shown in Figure 23. 88% of the cases had a CPA between 10 and 17 nmi suggesting this region is an acceptable CPA to maintain around red hazards. The yellow hazard CPA histogram contained in Figure 24 states that 97% of the cases have a CPA between 2 – 8 nmi and implying this is considered an acceptable buffer region. The yellow CPA histogram also combines data from scenarios that had red cells.

It is also important to note that the overall distribution is relatively dense considering the variability in the conditions contained within the scenarios. The scenarios included in this histogram vary over a large number of sizes, ranges (r), and lateral positions (c) while still remaining relatively consistent with respect to CPA.

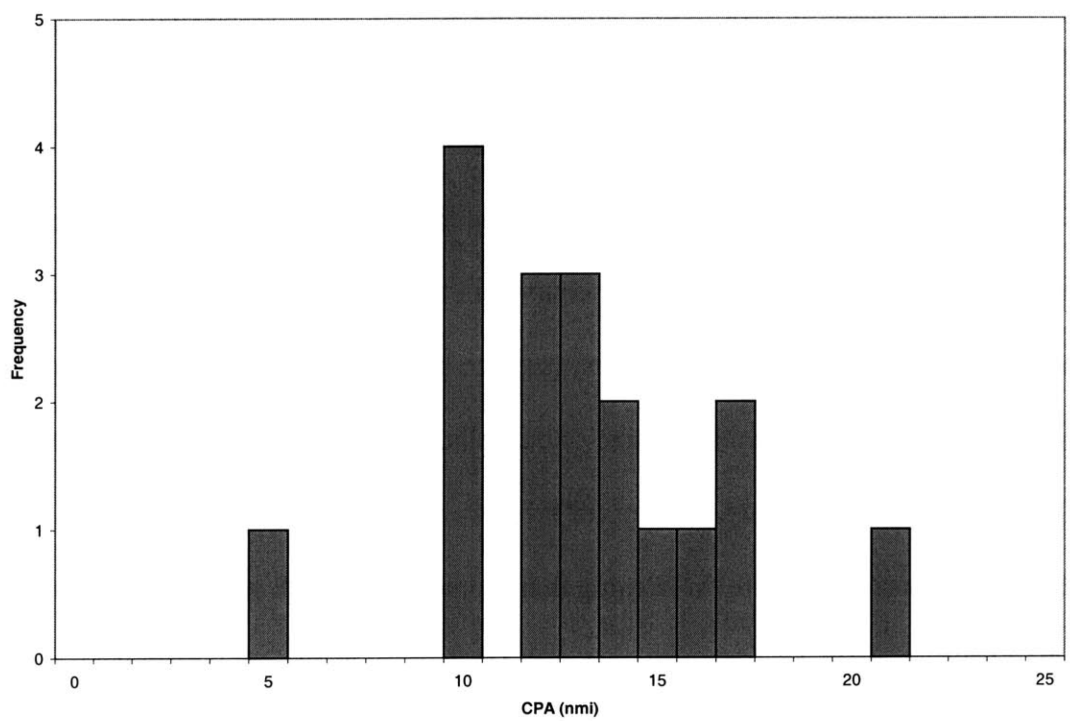


Figure 23 Red CPA Histogram
(Lateral Coverage, Range, and Lateral Position Scenarios, n=18)

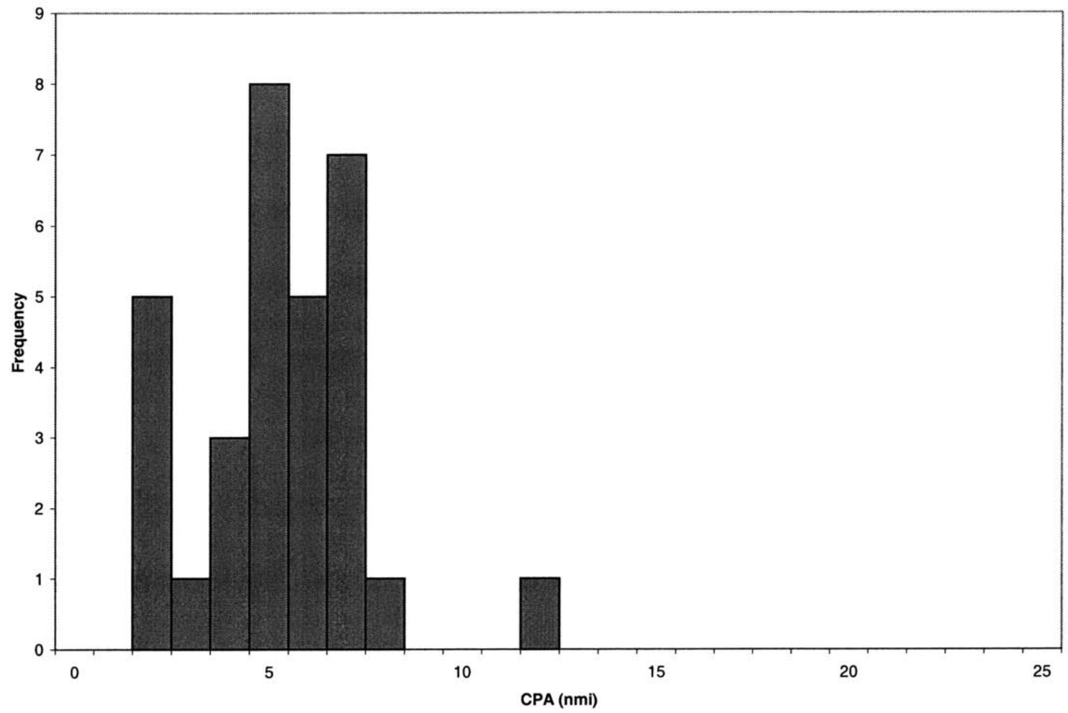


Figure 24 Yellow CPA Histogram
(Lateral Coverage, Distance, and Lateral Position Scenarios, n=31)

3.4.2 CPA vs. Scenario Type for Lateral Coverage Scenarios

Figure 25 and Figure 26 show the CPA data for red and yellow weather cells plotted against the Lateral Coverage scenario type. These figures show that there seems to be a trend between perceived threat (roughly equivalent to weather size) and CPA. The scenarios are ordered in what was approximated to be the increasing weather threat. The order was defined by the increasing size of the cells, moving from small to medium and finally to large. The scenarios with mixed sizes were ordered internally, with medium sized yellow considered more threatening that a small yellow cell when the other cells are equal.

Generally, the graph suggests that as the weather size increases the CPA also increases. This trend is not statistically significant due to the small sample size.

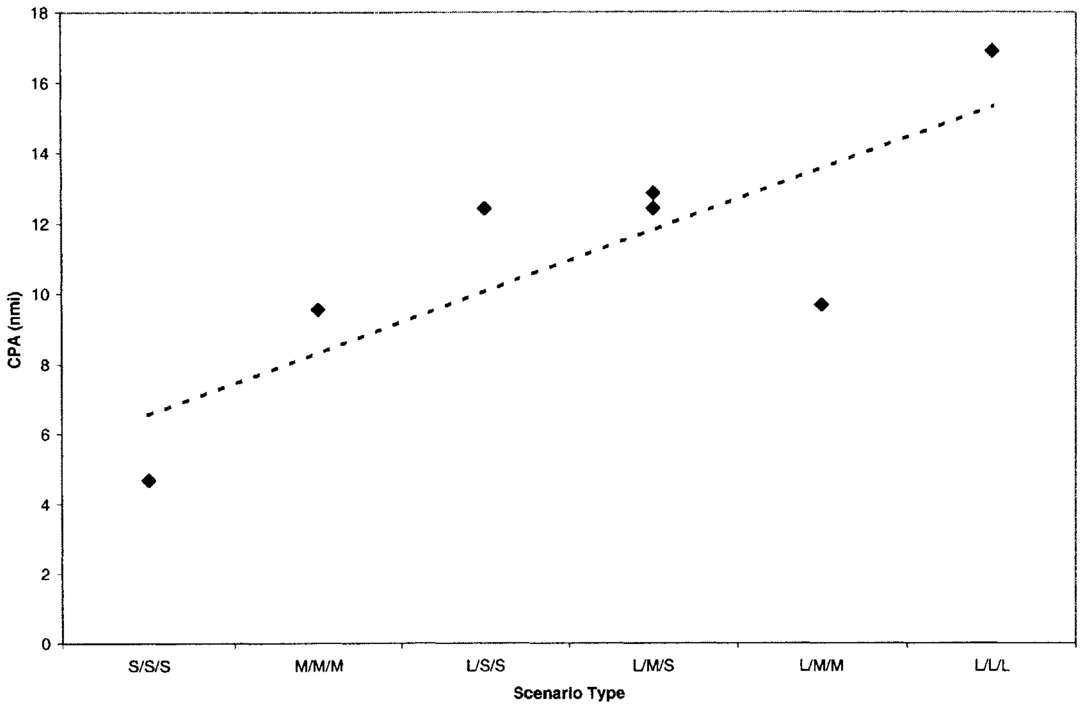


Figure 25 Red CPA vs. Scenario Type for Lateral Coverage Scenarios

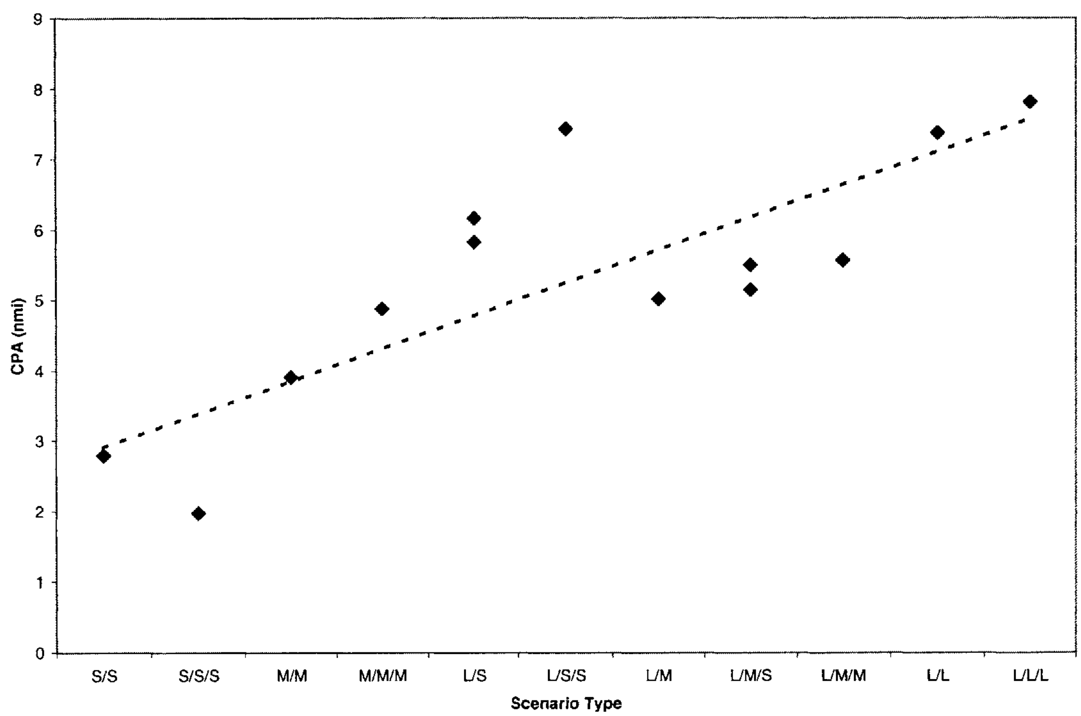


Figure 26 Yellow CPA vs. Scenario Type for Lateral Coverage Scenarios

The scenarios that contained only large weather cells (L/L/L) were treated differently by the pilot than the other scenarios. These scenarios were different since the entire width of the display was blocked with weather. In the other scenarios the pilot plotted a route that either penetrated or deviated around the weather. However, in the cases with only large weather cells the pilot chose a route that pushed towards the edge as shown in Figure 27. As a result the pilot deferred the final route decision until more data about the surrounding region could be obtained. The pilot would most likely reassess the situation as the aircraft approached the weather and ultimately make a decision to either penetrate, locate a "hole" of less severe weather, or turn back. The overall effect is that the pilot will defer a decision until the uncertainty in the decision has been resolved or a decision must be made based on the available information. If there is no "hole" in the foreseeable future the decision might be made to fly a route that penetrates severe even though it would normally be considered unacceptable. If absolutely no safe route exists the decision would be made to reverse course.

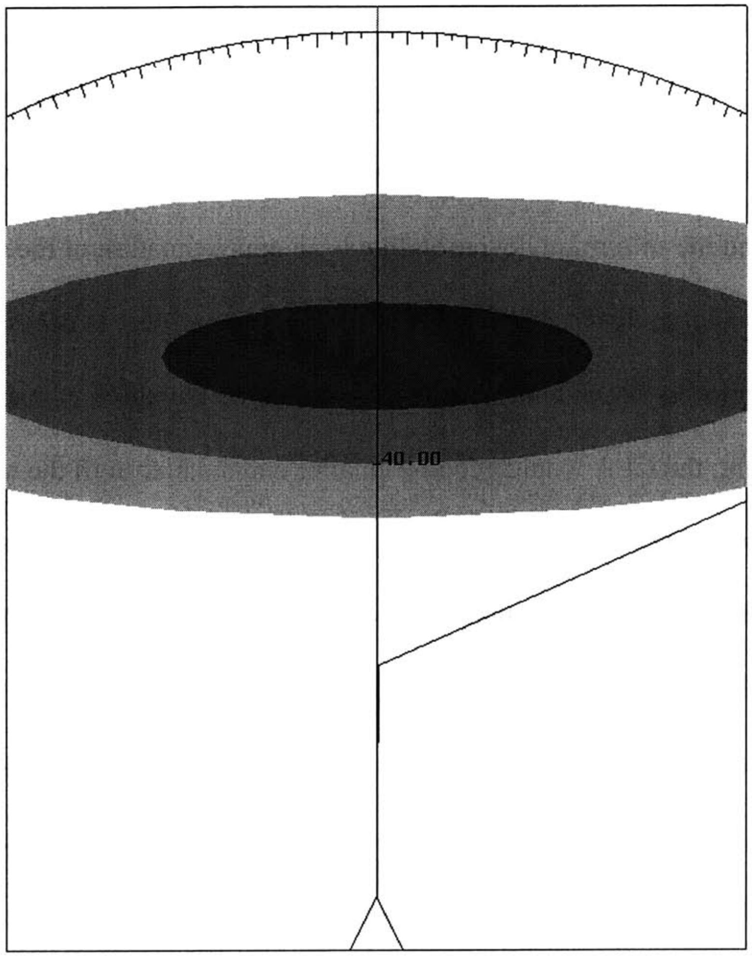


Figure 27 Deferred Decision Example

3.4.3 Shifting Weather Position of Single Cells

Using the data from the Distance and Lateral Position scenarios it was possible to correlate the movement of a single weather cell across the path of an aircraft with the pilot's measured deviations. Figure 28 shows the pilot's deviation (vertical axis) plotted against the location of the rightmost edge of the red cell, e (horizontal axis). For example, an edge position value of –5 indicates that the weather's edge is 5 nmi away from the default route while +5 indicates that the route penetrates 5 nmi into the weather. The solid minimum deviation line marks the cutoff between penetrating and remaining clear of the weather cell. Deviation data from the tested scenarios are shown as squares in the figure. As long as the actual deviation remains above the required minimum deviation the pilot successfully avoided the weather cell. The difference between the deviation line and the minimum deviation line is an approximation of the CPA. When the right edge is a large distance to the left of the route no reroute is necessary and the data shows the pilot in fact did not deviate. Assuming no deviation is made as the cell moves to the right, the CPA would become smaller and smaller until the aircraft penetrates. However the data shows that the pilot does make a deviation maneuver to avoid entering the cell. It is clear that the pilot is matching the motion of the weather with deviation though at a slightly slower rate, thus leading to a decreasing CPA. This illustrates the interplay between safety and economic cost. However at some point the deviation cost to go to the right of the single-cell hazard will be greater than going to the left and the pilot will then begin to reroute on the left side.

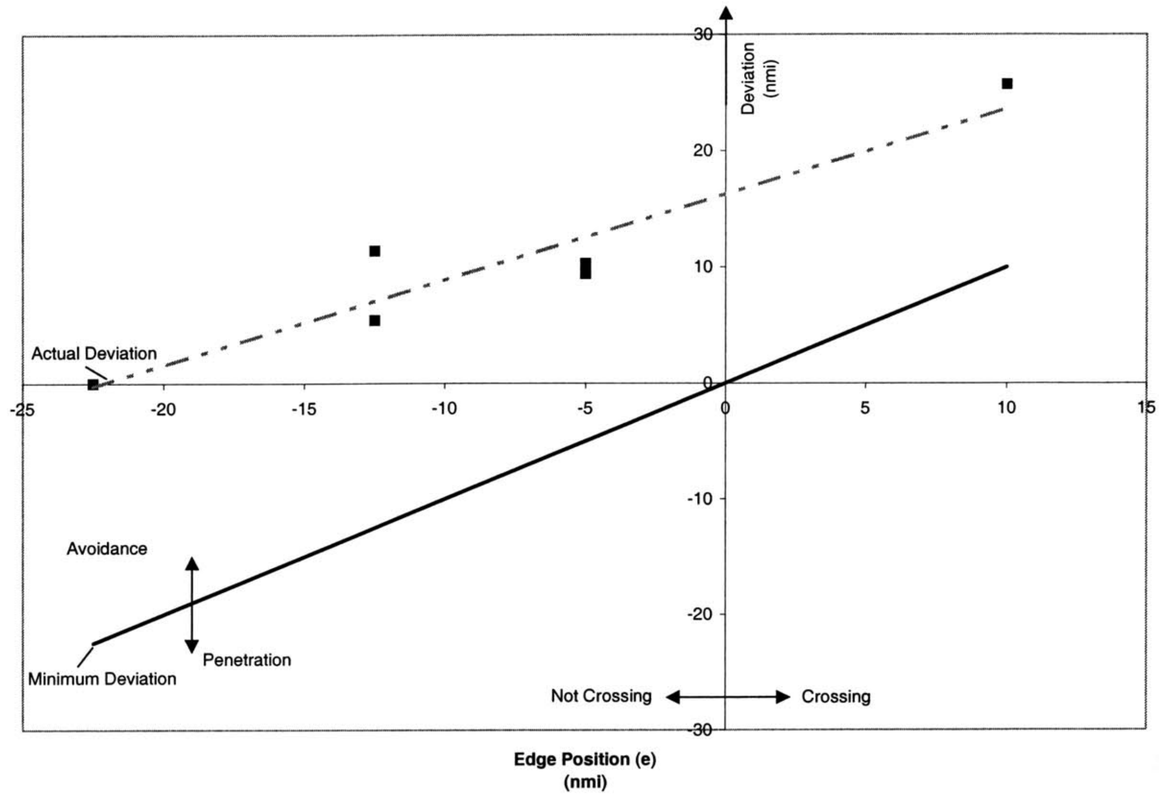


Figure 28 Red Weather Deviation vs. Shifting Weather Position

A similar graph can be drawn in the case with a yellow weather cell and is shown in Figure 29. However there are a few differences in the overall behavior. It should be noted that the pilot seems less inclined to deviate from the yellow hazard and thus the distance between the deviation line and the right edge of the cell is decreasing more rapidly when compared to red weather case. This change in behavior also causes a decline in the maintained CPA to the weather cell.

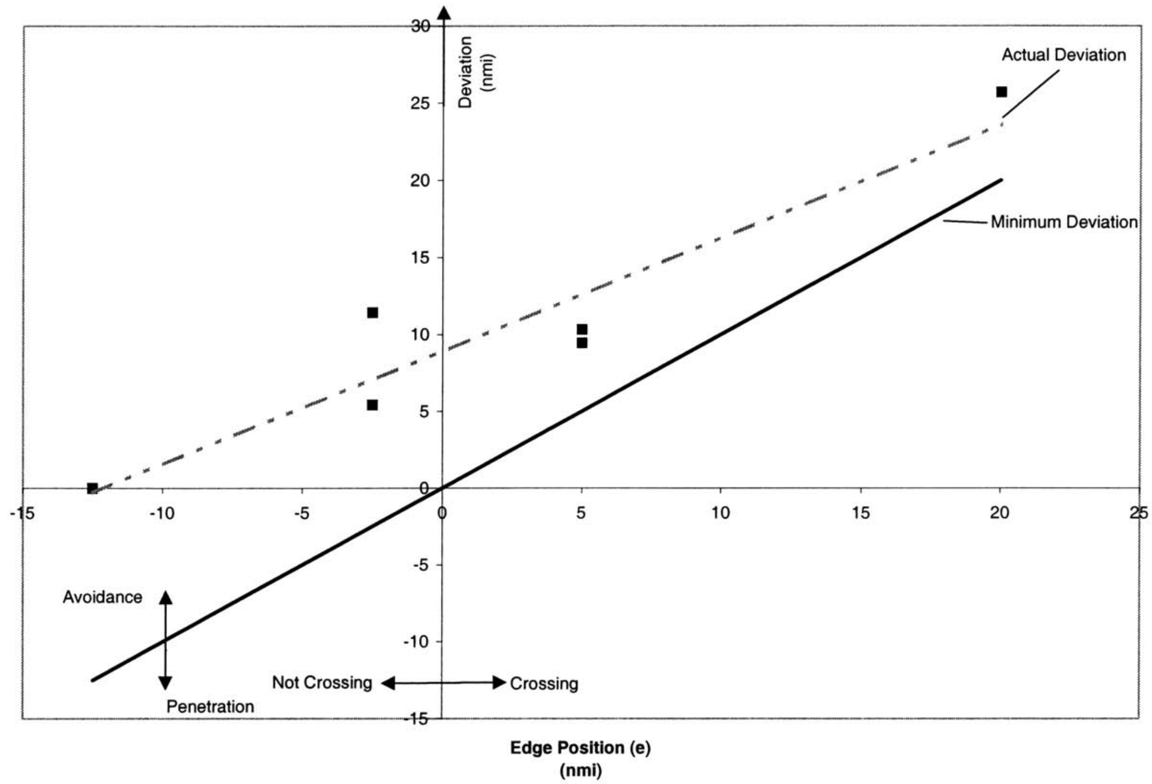


Figure 29 Yellow Weather Deviation vs. Shifting Weather Position

3.4.4 CPA vs. Range from Weather

The data also suggested the existence of a relation between CPA and the range the pilot was from hazard as shown in Figure 30. However, the relation is not statistically significant to a significance level of 0.10 for either the red or yellow CPA lines. The most likely reason is that the overall number of samples are too small to get a good significance measurement using the t-test for a regression coefficient.

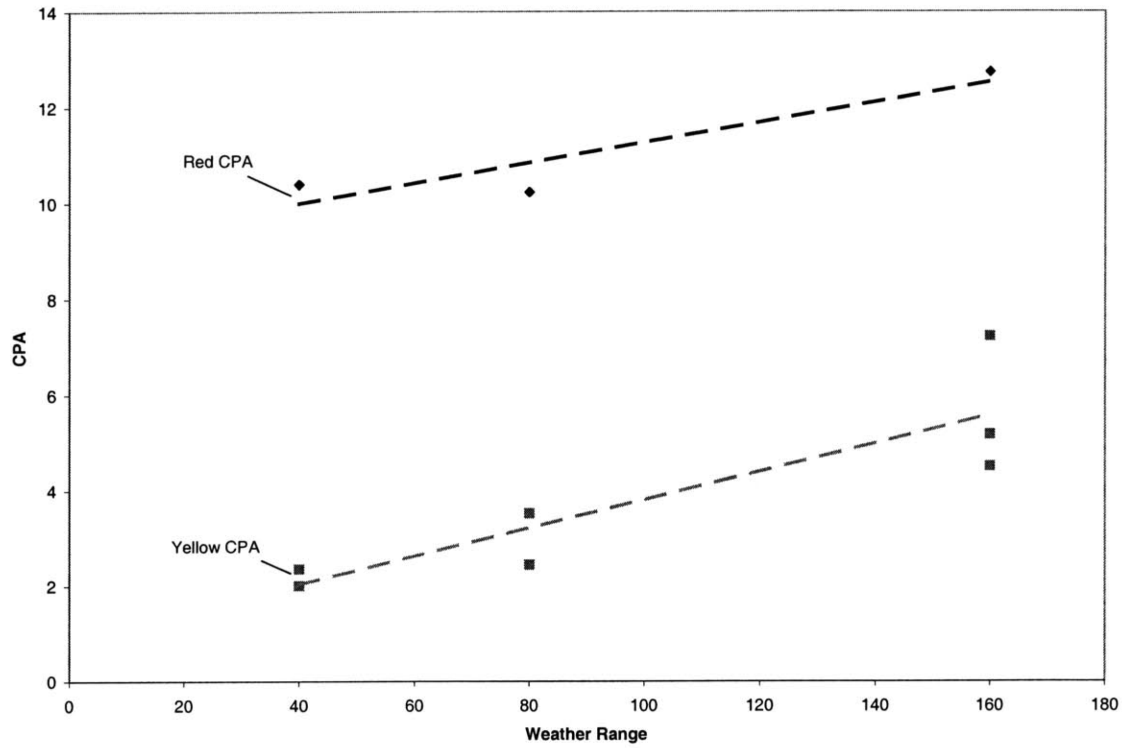


Figure 30 CPA vs. Weather Range for Distance Scenarios

3.5.5 Deviation vs. Weather Position for Weather Corridor Scenarios

The dual-cell weather corridor scenario data can be combined to illustrate the connection between deviation and the weather's edge position as shown in Figure 31 and Figure 32. Due to the constrained nature of the space and the pilot's instruction to deviate as much as deemed safe, the measured deviation actually reduces the CPA maintained between the weather and the aircraft. The deviation decreases to zero as the edge position shifts to the right. This behavior is expected since the weather corridor scenario's weather is symmetric and the maximum CPA is reached when the aircraft travels straight and deviation is zero. Again, the data shows that the pilot is willing to come close to yellow weather if constrained.

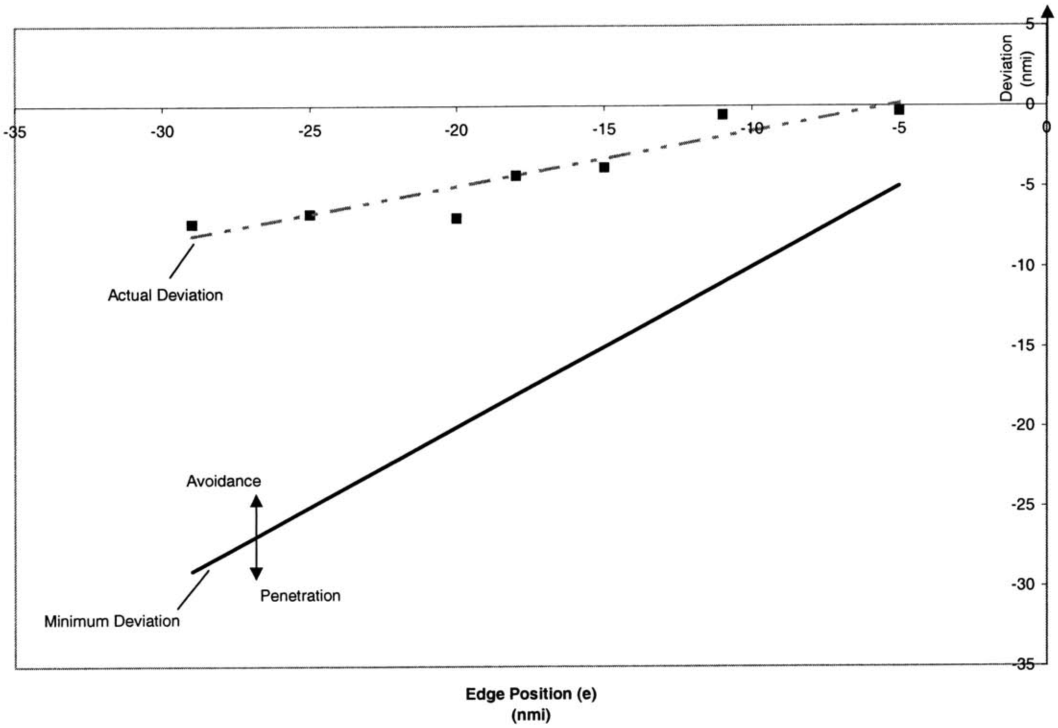


Figure 31 Red Weather Deviation for the Weather Corridor Scenarios

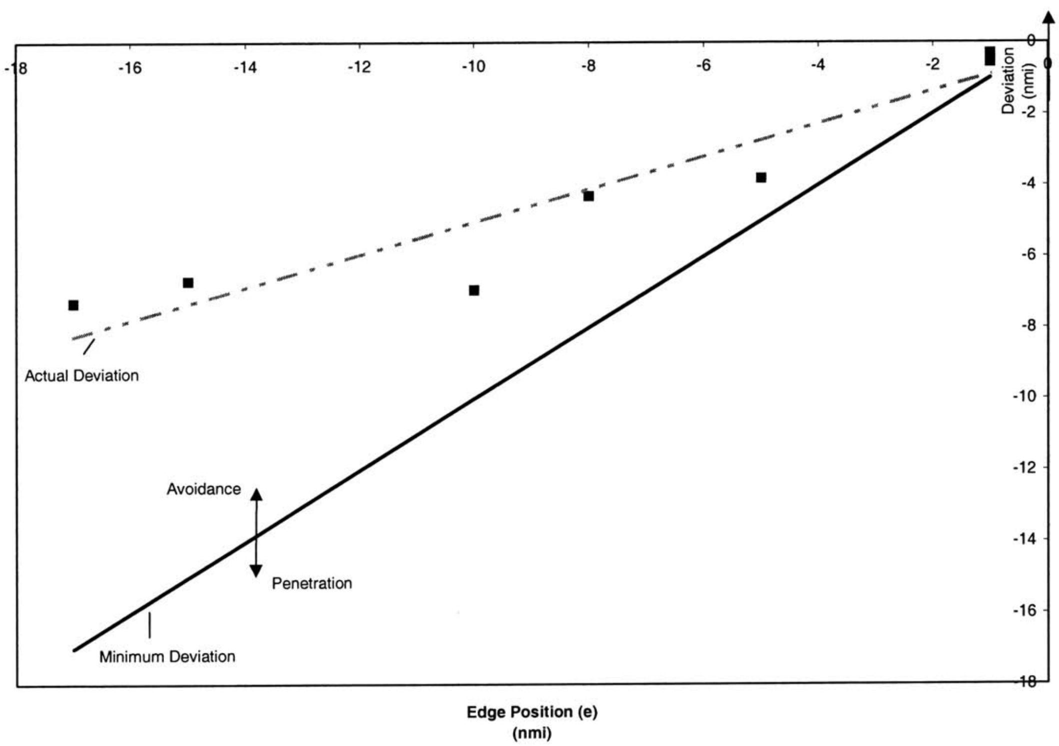


Figure 32 Yellow Weather Deviation for the Weather Corridor Scenarios

Chapter 4 Decision Models

4.0 Decision Models

The data gathered in the experiment can be used to create a decision model that would simulate pilot behavior in the presence of severe weather. The pilot decisions were generally consistent, but contained some scatter or variability between similar scenarios. Two different decision models were considered, with the goal of modeling the pilot's decision-making demonstrated in the experiment. One model is randomized, based on the collected histogram data. The second model is a belief network, which attempts to capture the pilot's situational awareness and generate a weather threat metric.

4.1 Basic Decision-Aid

A basic decision-aid that can use either decision model as input was developed and is shown in Figure 33. Given a particular weather situation, the actual route's CPAs and ranges are calculated for both the yellow and red severity levels. As a comparison, CPA thresholds and decision range threshold values are then generated using one of the two decision models. If the measured CPA values are greater than the threshold values the system goes back into supervisory mode and is periodically rechecked to determine if the route is acceptable. If the measured CPA values are less than the threshold CPA values, the current route is considered unacceptable to the pilot. The measured range is then compared to the threshold decision ranges. If measured range is greater than the threshold decision range, the system defers and waits until the next route check. If the measured range is equal to or less than the decision range, then the pilot would decide to reroute immediately. A new route is chosen by increasing the deviation off the initial route and repeating the CPA test until an acceptable route is found. One potential method to develop a new route that achieves the target CPA and decision-range is the Gears Algorithm (Irvine, 1998). The route chosen would be locally optimal because it would be the route with the minimum economic cost that still satisfies the CPA requirements.

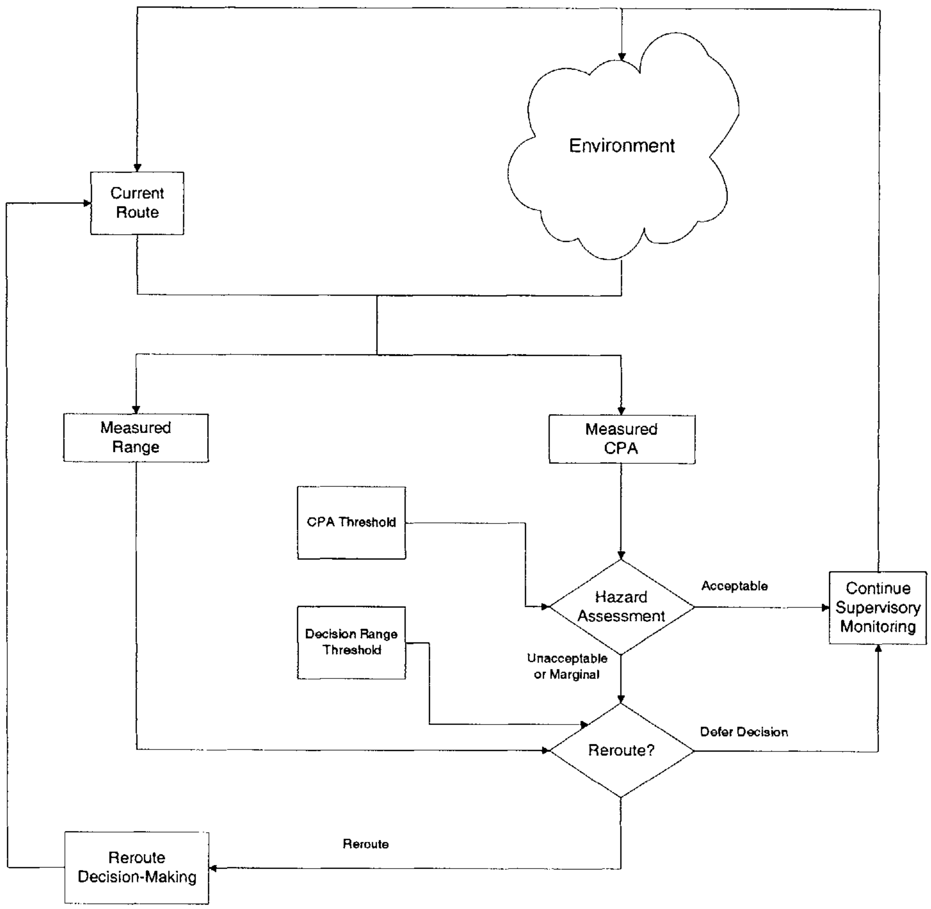


Figure 33 Basic Weather Rerouting Model

It is important to notice that at least based on the observed pilot behavior, risk is a function of CPA and weather severity and is not directly dependent on the range to the hazard. Thus, CPA and severity level are used first to determine whether a reroute is needed. If so, then the decision range data is used to determine when the reroute should begin.

4.2 Randomized Model

The randomized model attempts to capture the pilot's behavior and has an advantage in that it accounts for some of the variability that occurs with human decision-making. The primary drawback of the model is that the generated behavior is not directly dependent on the perceived metrics in a particular situation.

Pilot behavior is captured by the specification of a cumulative mass function (CMF) for CPA and decision range for each severity. The cumulative mass function is the probability that the actual value is less than or equal to a given threshold and is generated from the CPA and decision range histograms. Examples of a histogram and its complementary cumulative mass function are shown in Figure 34.

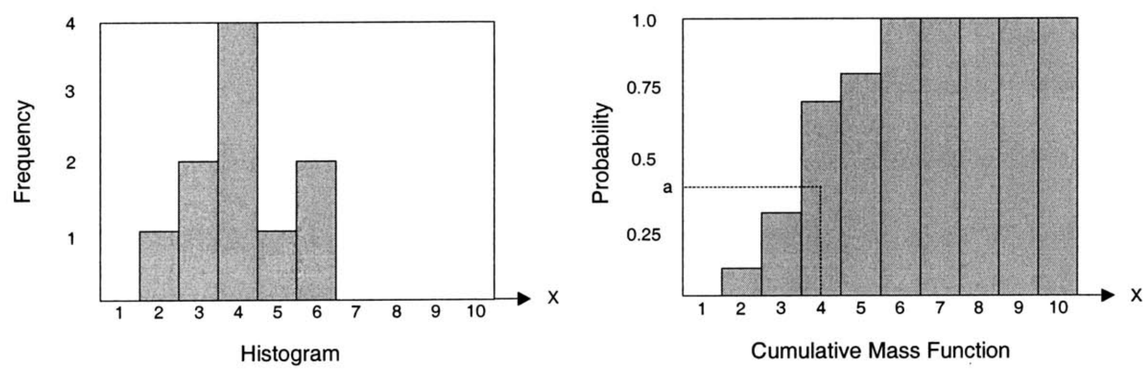


Figure 34 Example Histogram and Cumulative Mass Function

The randomized model uses a CMF to generate a predicted acceptable CPA and decision range value for each weather encounter. For each encounter, a random number would be chosen between 0 and 1 using a uniform distribution. The random number is used to pick a threshold value by picking the value in the CMF that has the probability equal to the random number. As shown in Figure 34, the random variable of "*a*" would result in choosing x = 4 as the output. This action converts the uniform distribution of the random variable into the weighted distribution of the histogram. This occurs because the more likely a particular value is, the more height it occupies in the region between 0 and 1, thus increasing the probability that it will be chosen.

Due to the probabilistic nature of the choice of the route metrics, variability will exist between the decision-aid's generated routes even when given the same scenario. The variability occurs in both the decision range and the required CPA. An example of the route distribution based on the subject pilot's decision histograms is shown in Figure 35. The effect is that the routes will be located in the space between the minimum and maximum value of CPA and Decision Range. The distribution of the routes will depend on distribution of the CPA and Decision Range CMFs.

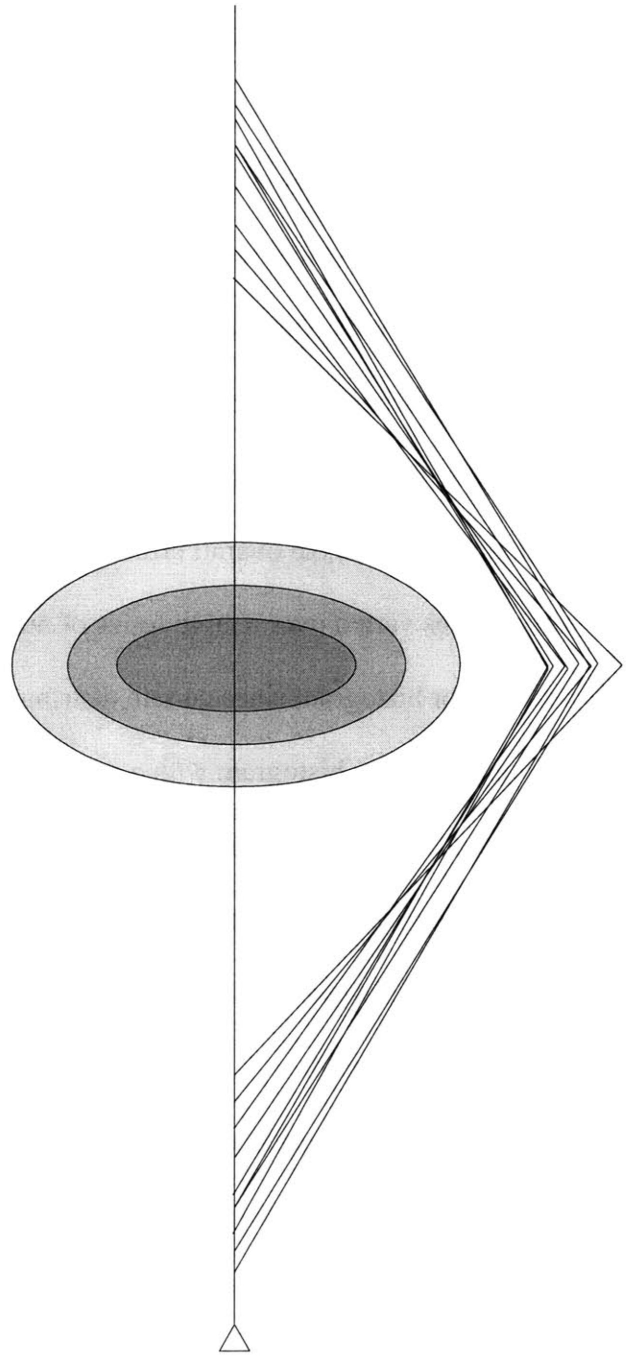


Figure 35 Route Variability Schematic

4.2.1 Performance

The actual performance of the randomized model is hard to assess because the measured error would actually be an error distribution for each situation instead of a single constant. This behavior results from the model generating a value based on a random number and the cumulative mass function, versus the measured values from the actual situation. If the situation were repeatedly run through the decision-aid for a large number of iterations, the error distribution would reflect the original histogram. The implication is that the performance of the system would be described by the variance of the original histogram and also by the shape of the distribution. The histogram's variance is important since it describes the width of the distribution. If a distribution was concentrated over a small number of values the overall error would be substantially less than if the number of possible values varied over a large series of numbers. The shape of the distribution also effects the error histogram since certain distributions would reduce the net error of the system. For example a histogram with a normal distribution would have the pilot's measured values closer to the center of the distribution thus resulting in a net lower error when compared to a distribution with two regions of concentrated probability. The selected value would always be in one region or the other, thus resulting in more error over a large number of iterations.

Performance would be assessed on how similar the system is to the human pilot. The primary metric in this case would be if the system is generally more conservative or more aggressive than the pilot. It should also be noted that an overly conservative system would not be beneficial since unnecessary rerouting would occur.

4.3 Belief Network

A belief network was designed to capture the behavior of the pilot in this project and is shown in Figure 36. The belief network is made up of two independent sub-trees that account for CPA (or duration, should the route penetrate weather) and weather cell severity, as measured by its general size. The Weather Threat node then combines these sub-trees into a single recommendation that can be used by the pilot agent to assess a weather route's threat level.

The measured values are fed in at the lowest level of the tree represented by the oval nodes. In actual practice the oval nodes fuzzify the numerical data into a series of states. The current design uses three main states for the CPA nodes, which are Unacceptable, Marginal, and Acceptable. The unacceptable state is one that describes a value that is considered to be dangerous independent of any other factors. The Acceptable state describes a value that would be acceptable independent of other factors. One example would be a CPA value of 100 nautical miles since the weather is no threat to the aircraft. The Marginal state is more ambiguous in that the value is in the gray area between the two and depends on the other variables to determine if the route is actually acceptable. The CPA nodes were set to Unacceptable if the default route crossed yellow or red weather. The Marginal and Acceptable states depended on the pilot histogram defined as the region that contained most of the data points in the experiment. The Marginal state was set when the CPA to a weather cell was within the histogram's bounds and considered Acceptable if the CPA was greater than the maximum value in the histogram.

The Duration nodes have four states, which are Unacceptable, Marginal, Acceptable, and None. If the route does not enter weather the duration nodes are set to None. In this experiment, any exposure to yellow and red weather was considered Unacceptable since the pilot never decided to enter either type, though additional experiments might suggest situations where entering yellow or even red weather might be considered Marginal or Acceptable. The CPA and Duration node, which depends directly on the underlying CPA nodes and Duration nodes has four states: Acceptable, Low risk, Medium risk, and High risk.

The Size nodes (one each for green, yellow, and red cells) are broken up as they were in the experiment's scenarios with each having three states, which are Small, Medium, and Large. These lead to the Severity node, with states of Minimal, Low, Medium, and Severe.

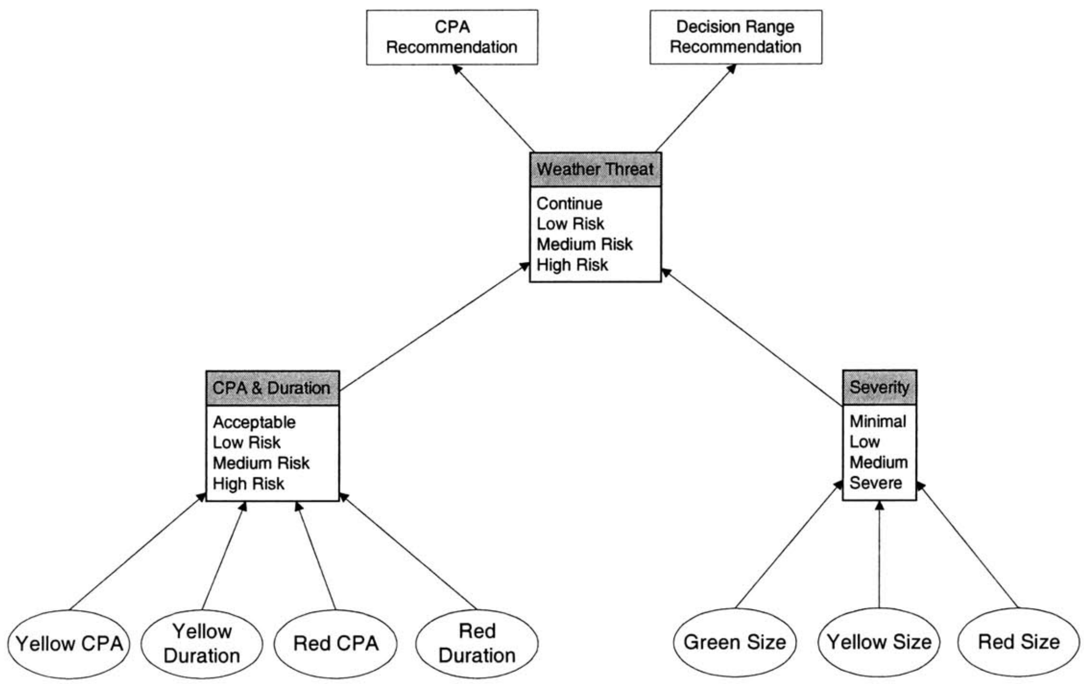


Figure 36 Prototype Weather Threat Belief Network

The relations between the nodes of the belief networks are specified in matrices referred to as conditional probability tables (CPTs), as discussed in Chapter 2. An example of the CPT between CPA & Duration, Severity, and Weather Threat nodes is shown below in Table 8. All of the CPTs for the entire belief network are listed in Appendix B. The CPT is multi-dimensional and is a function of the number of nodes feeding into it. In this case the complete CPT is three-dimensional to account for the different states in each of the two parent nodes (CPA & Duration, and Severity) and the states within the Weather Threat node. The CPT determines the value that each of the states of Weather Threat will contain when the belief network is updated with the data from the situation. For example, if the combined severity of the weather was Medium and the CPA & Duration measurements are Low risk the Continue state value in the Weather Threat node would be 0.7. The other states of Weather Threat will depend on the CPT relations as shown in Table 8.

Table 8 CPT between Severity and CPA & Duration Nodes for Weather Threat State "Continue"

		Severity			
		Minimal	Low	Medium	Severe
CPA & Duration	Acceptable	1.0	1.0	1.0	1
	Low Risk	0.8	0.75	0.7	0.6
	Medium Risk	0.6	0.3	0.1	0
	High Risk	0.5	0.2	0	0

The scenarios from the experiment were used to calibrate and test the belief network model. The scenario parameters (CPA, duration, and weather cell size) were input into the base nodes of the network and the weather threat state probabilities were generated for each scenario. The sum of the four weather threat state probabilities (Continue, Low Risk, Medium Risk, and High Risk) equals one. To tune the relationship between weather threat state values and the thresholds for CPA and range, a linear optimization program was used to select optimal costs that minimized the error between the predicted CPA and decision range values from Equation 6 and the measured CPA and decision range values from the pilot. Separate constants were determined for each of the decision-aid's outputs of Red CPA, Yellow CPA, and for Red decision range and Yellow decision range. The optimized constants are shown in Table 9. The threshold values for acceptable CPA and decision range for yellow and red weather cells can be calculated using equation 6 and the optimized constants. Equation 7 shows an example of the red CPA threshold calculation using Equation 6 and an assumed weather threat state vector.

$$\begin{aligned}
&\textit{Threshold Value for CPA or range} = AL + BM + CH \\
&\textit{where } A, B, \textit{and } C \textit{ are constants} \\
&L = [\textit{Low Risk State Value}] \\
&M = [\textit{Medium Risk State Value}] \\
&H = [\textit{High Risk State Value}]
\end{aligned} \tag{6}$$

Table 9 Optimized Constants

	Red CPA	Yellow CPA	Red Range	Yellow Range
A	13.9	6.2	21.7	17.85
B	13.95	6.25	21.75	17.9
C	14.0	6.25	21.8	17.95

$$\textit{Weather Threat} = \begin{bmatrix} \textit{Continue} \\ \textit{Low Risk} \\ \textit{Medium Risk} \\ \textit{High Risk} \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.4 \\ 0.25 \\ 0.05 \end{bmatrix} \tag{7}$$

$$\textit{Red CPA Threshold} = 13.9 \cdot 0.4 + 13.95 \cdot 0.25 + 14.0 \cdot 0.05 = 9.75 \textit{ nmi}$$

4.3.1 Performance

As an initial check of performance, the belief network was exposed to the same weather situations as the pilot was in the initial study. Figure 37 and Figure 38 show the error histograms for Yellow and Red CPA predictions calculated from comparing the measured experimental results versus the predicted results from the model. Negative error means that the predicted value was greater than the experimental value and thus the belief network suggested a more conservative option than the pilot. A positive error suggests that the model is more aggressive than the pilot. About 50% of the Red CPA predictions have 0 error or are more conservative than the pilot and 83% are within 1 nmi of the actual CPA or are more conservative. 65% of the yellow CPA predictions have 0 error or are more conservative than the data measured from the pilot.

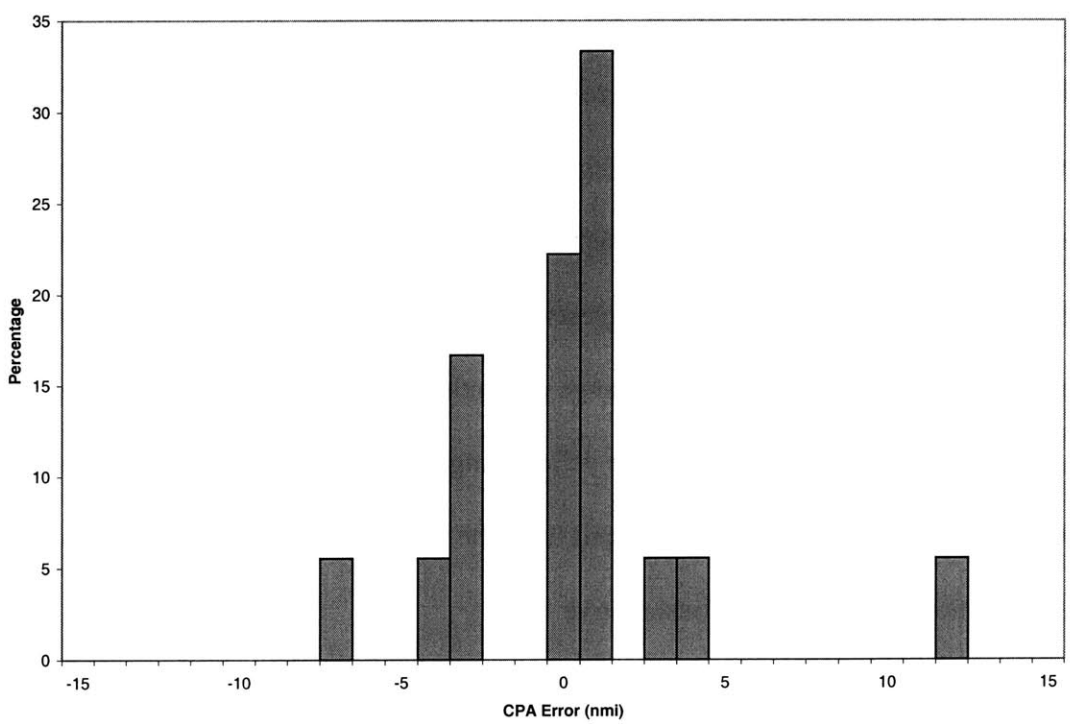


Figure 37 Red CPA Error Histogram (n=18)

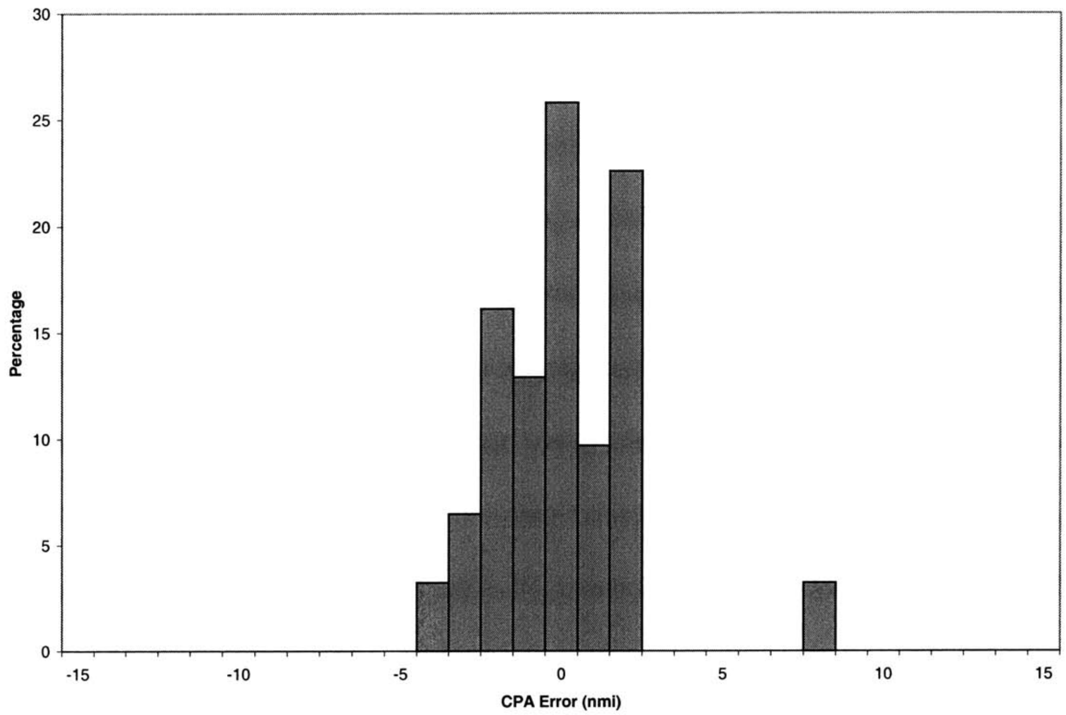


Figure 38 Yellow CPA Error Histogram (n=31)

Figure 39 and Figure 40 show the error histograms for the Yellow and Red Decision Range predictions. Negative error means that the predicted value was greater than the experimental value and thus the belief network suggested a more conservative option than the pilot while a positive error suggests that the model is more aggressive than the pilot. About 56% of the red decision range predictions have zero error or are more conservative than the pilot. 59% of the yellow range predictions have zero error or are more conservative than the data measured from the pilot and 72% are within 1 nmi of the actual decision range or more conservative.

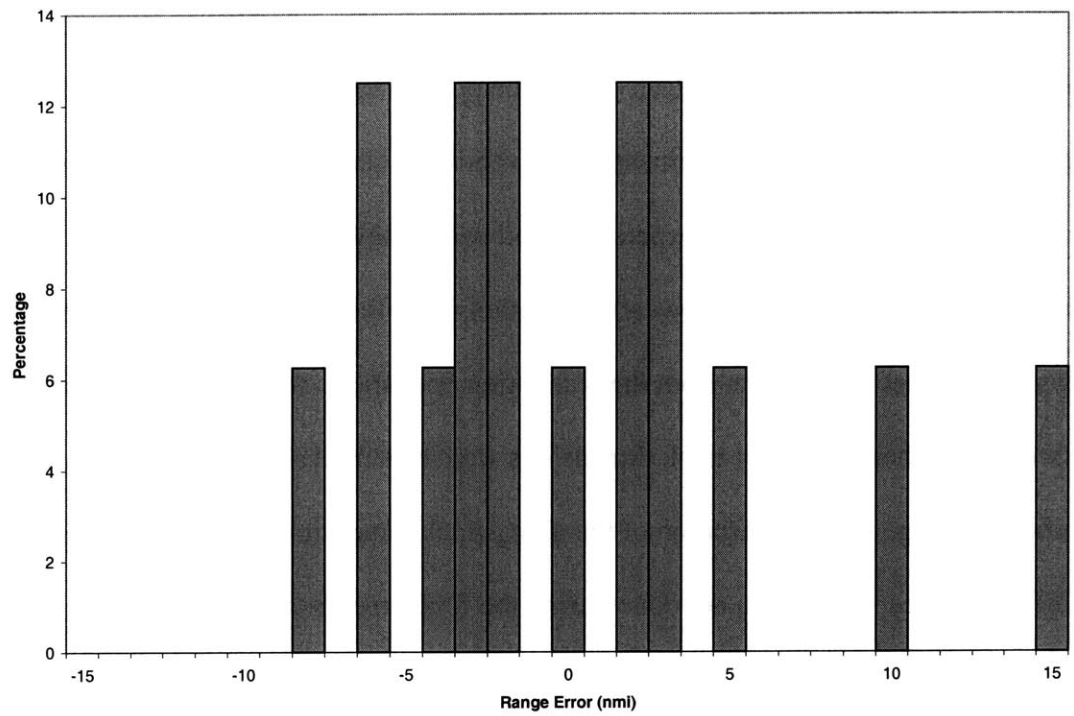


Figure 39 Red Decision Range Error Histogram (n=16)

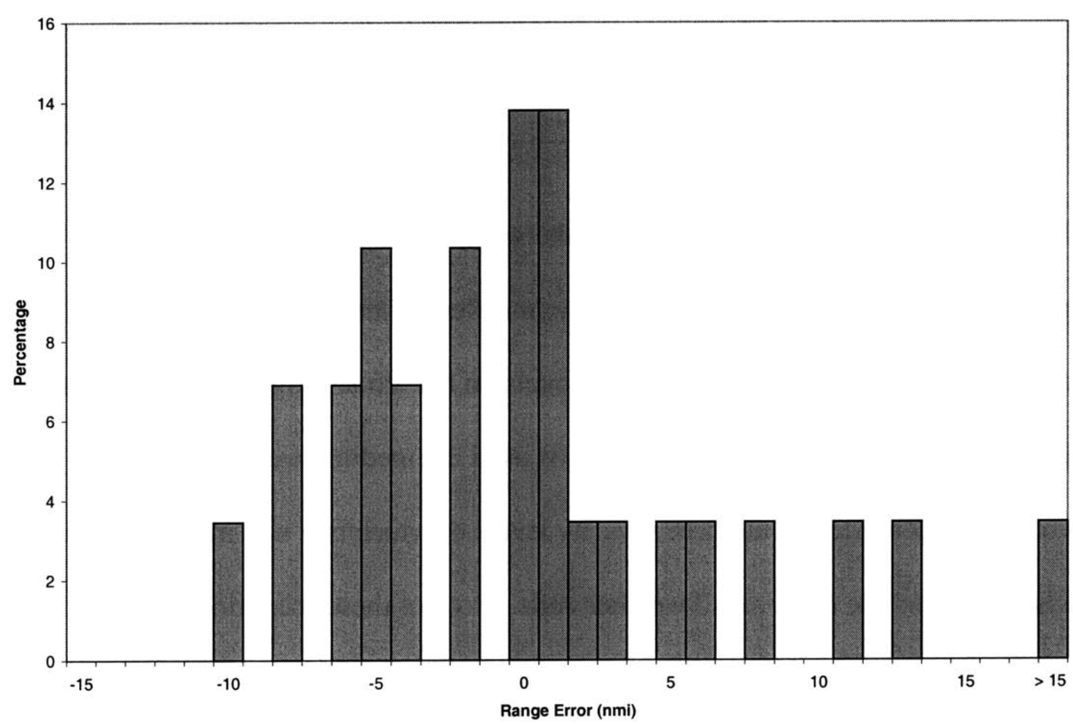


Figure 40 Yellow Decision Range Error Histogram (n=29)

4.4 Validation Scenarios

A second data set was then collected from the pilot to validate the model (which was based on data from the first experiment). The validation scenarios consisted of seven scenarios repeated from the first experiment and twelve new scenarios, which use different weather dimensions and weather locations than the first experiment. Table 10 shows the weather dimensions from the Validation Scenarios. All cases involved single-cell scenarios where the cross-track dimensions were modified slightly. The most significant change was the variation of the along-track dimension of the weather across the different sizes, which was not done during the first experiment.

Table 10 Validation Scenarios Weather Dimensions

Type:	Dimensions (Cross-Track x Along-Track Axes)		
	Green	Yellow	Red
Small (S)	17.5 x 10 nmi	10 x 5 nmi	3.5 x 2.5 nmi
Medium (M)	22.5 x 15 nmi	15 x 10 nmi	7.5 x 5 nmi
Large (L)	27.5 x 20 nmi	20 x 15 nmi	12.5 x 10 nmi

Table 11 shows the lateral positions of the weather in the validation scenarios, (specified in nautical miles). There were eight different scenario types that varied the relative locations of the different severity levels on the left and right sides of the default route. Ten of the twelve validation scenarios used the medium weather size. The last two scenarios consisted of all three severity levels of which one was made up of large weather cells and the other small weather cells. Both of these scenarios were centered on the route and all three cells had a lateral position of zero. All the weather cells were located 60 nmi ahead of the subject aircraft.

Table 11 Validation Scenarios Lateral Positions (nmi)

Lateral Position (c):	G	0	1		10		12	15
	Y	0	1	7.5	5	10	12	
	R	0	7.5		5	10	12	
G								•
GY						•		
GYR		• (x2)	•	• (x2)	• (x2)	•	• (x2)	

Figure 41 and Figure 42 show the pilot's red and yellow decision range histograms for the validation scenarios. 85% of the scenarios had a red decision range between 18 and 25 nmi from the hazard (compared to between 13 and 24 in the first experiment). The yellow decision range histogram states that the pilot's decision range is between 13 and 20 nmi 83% of the time (compared to between 8 and 19 in the first experiment).

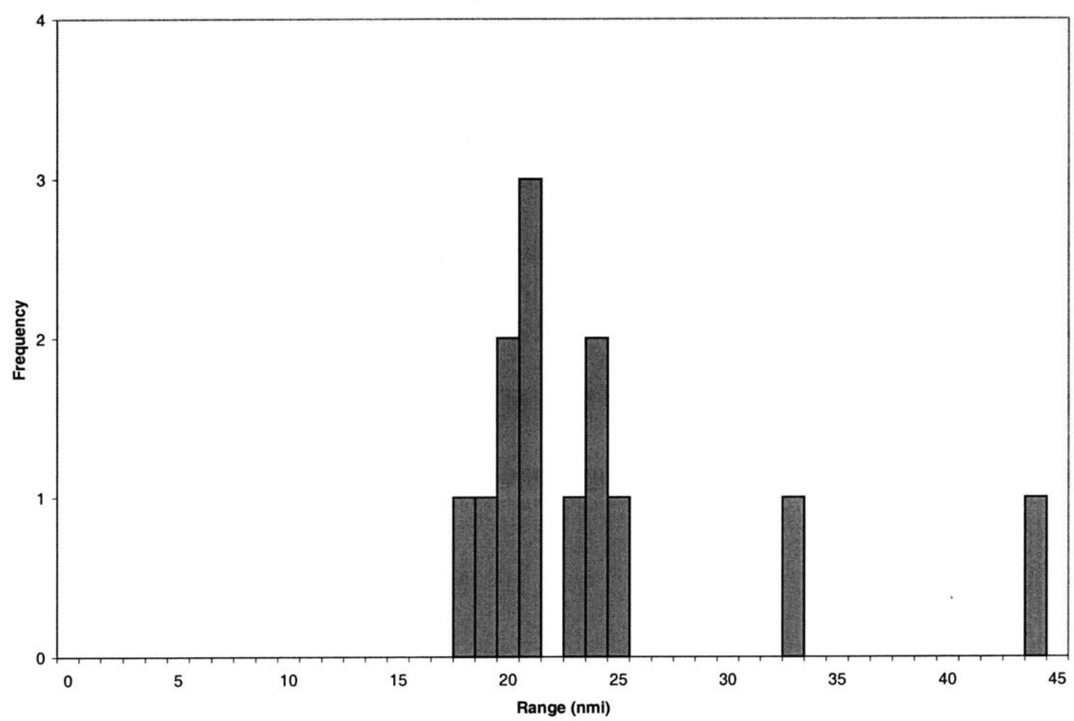


Figure 41 Validation Scenario Red Decision Range Histogram

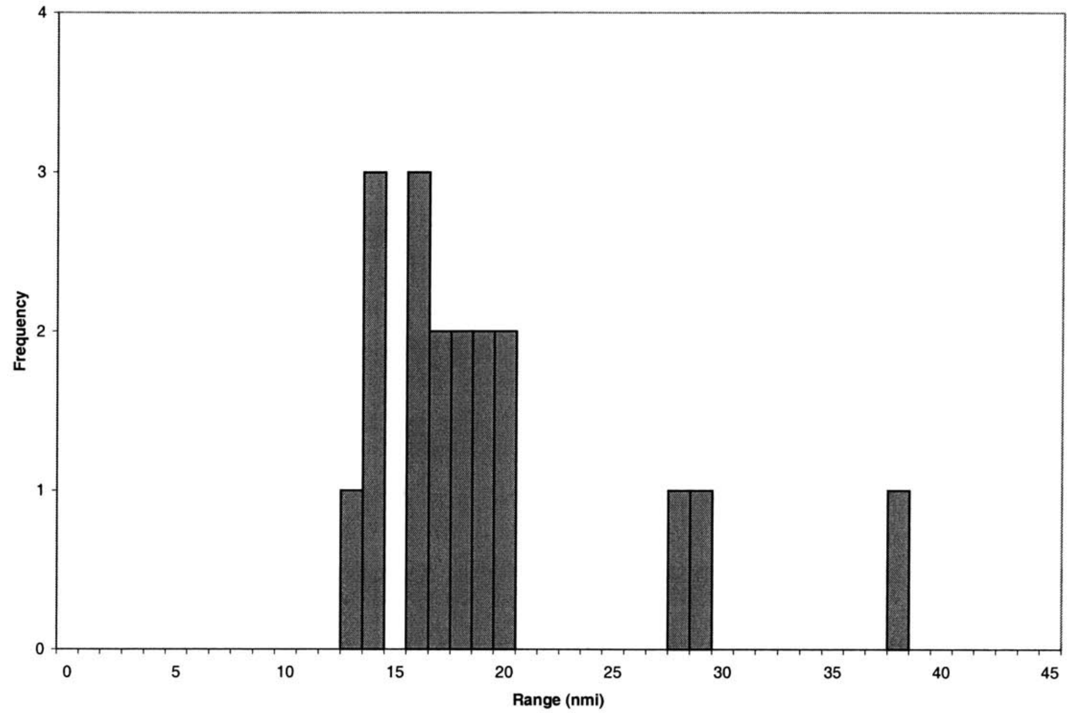


Figure 42 Validation Scenario Yellow Decision Range Histogram

A histogram for the red CPAs for the validation scenarios are shown in Figure 43. 77% of the scenarios had a CPA between 10 and 16 nmi which is very similar to the results from the first experiment (between 10 and 17 nmi). The yellow hazard CPA histogram shown in Figure 44 states the 89% of the scenarios have yellow CPAs between 2 and 7 nmi (similar to the 2 to 8 nmi suggested in the first experiment).

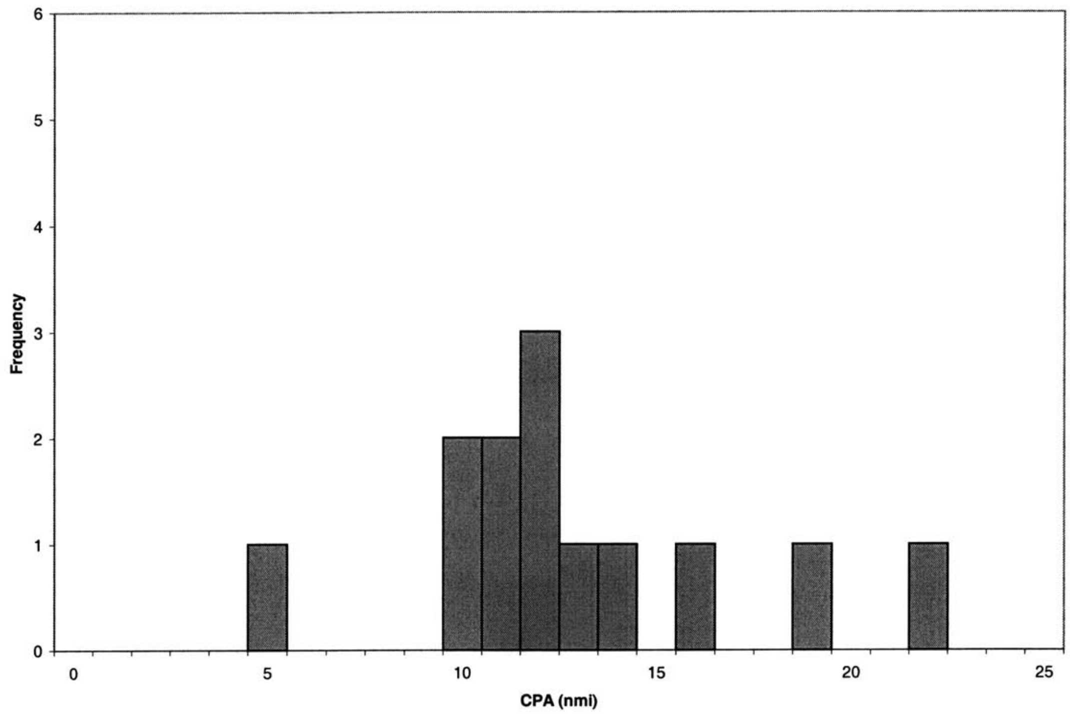


Figure 43 Validation Scenario Red CPA Histogram (n = 13)

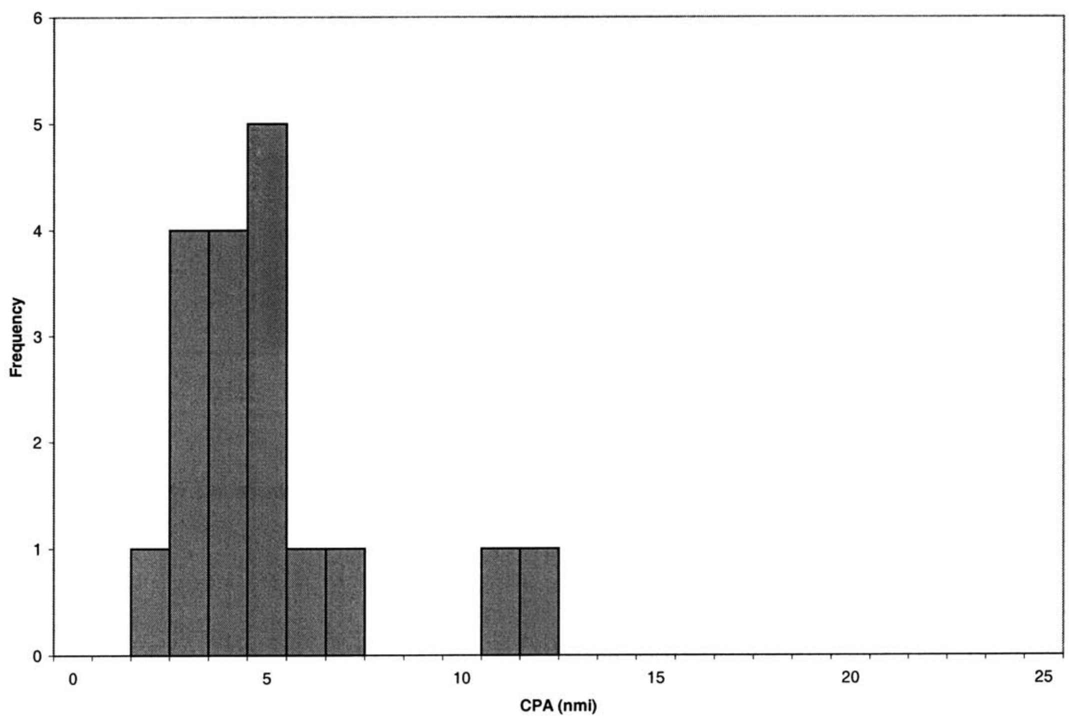


Figure 44 Validation Scenario Yellow CPA Histogram (n = 18)

The belief network was then exposed to the same validation scenarios, but using the parameters that had been tuned from the first set of data. Figure 45 and Figure 46 show the red and yellow CPA error histograms for the validation scenarios. 77% of the red CPA predictions had 0 error or were more conservative than the pilot though no data point had more than 7 nmi error. The yellow CPA predictions had 0 error or were more conservative 78% of the time. 94% of the scenarios were within 1 nmi of the pilot's choice or are more conservative.

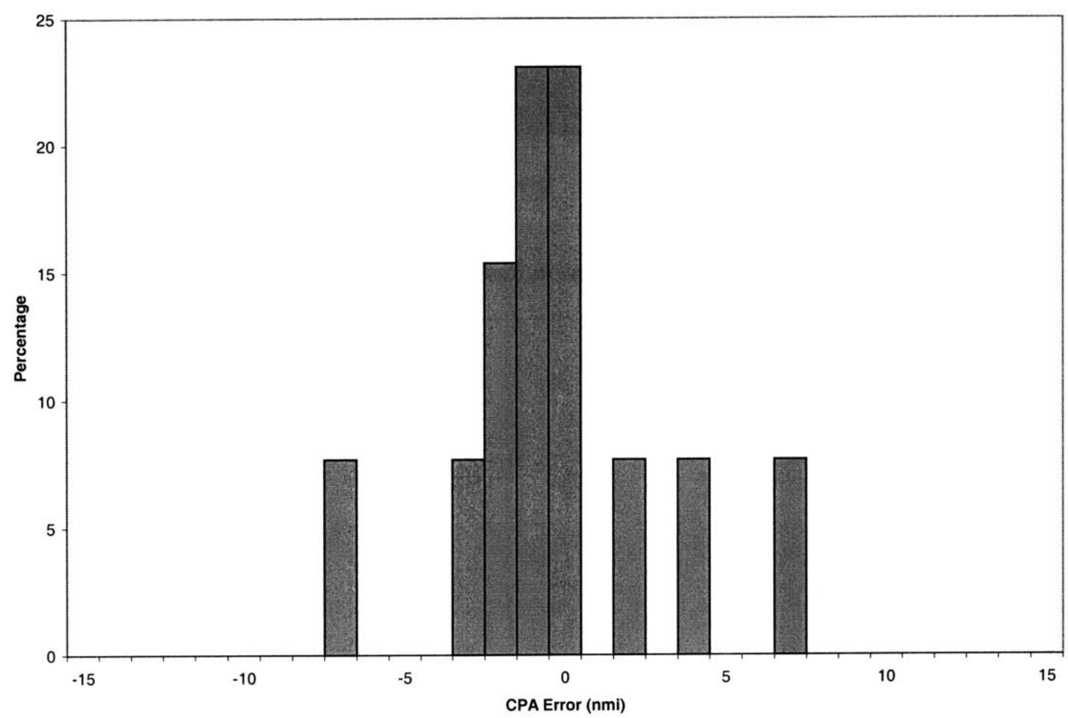


Figure 45 Validation Scenario Red CPA Error Histogram (n = 13)

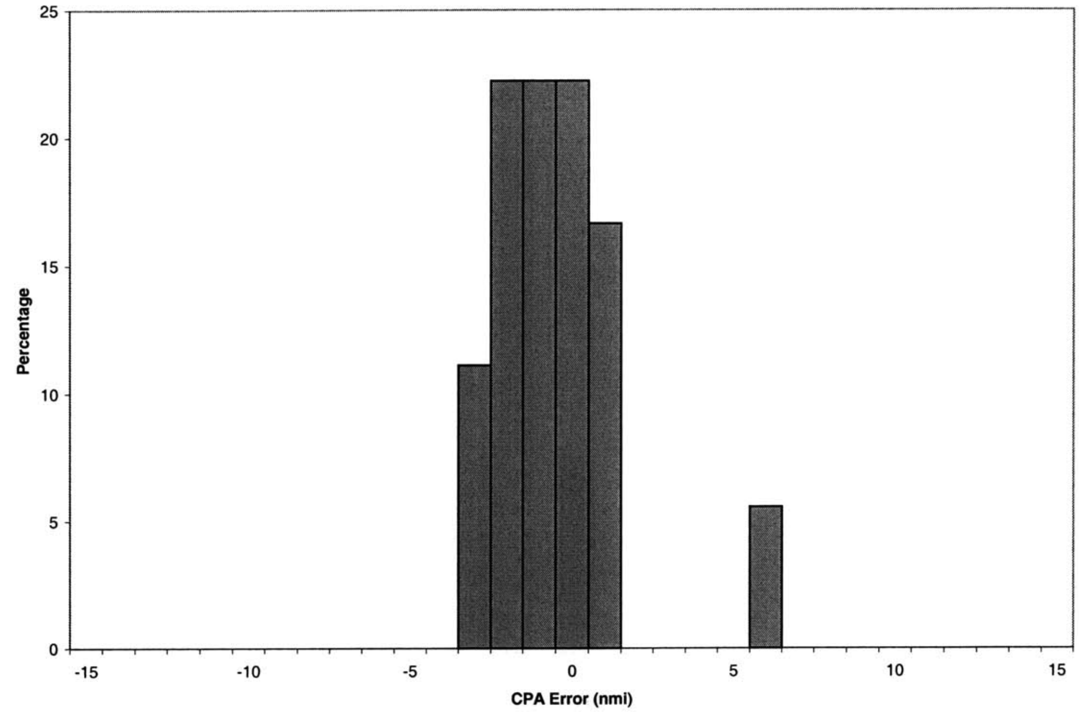


Figure 46 Validation Scenario Yellow CPA Error Histogram (n = 18)

Figure 47 and Figure 48 show the red and yellow range error histograms. The red range predictions had 0 error or were more conservative than the pilot 31% of the time. 44% of the yellow range predictions had zero error or were more conservative than the pilot's preference.

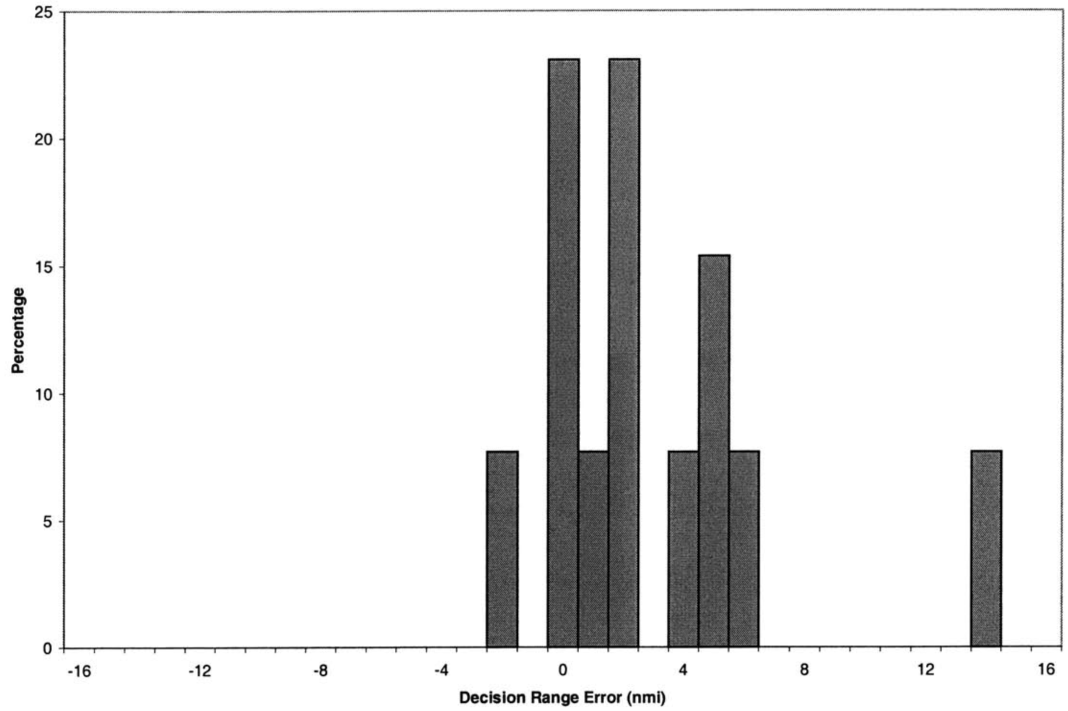


Figure 47 Validation Scenarios Red Range Error Histogram (n = 13)

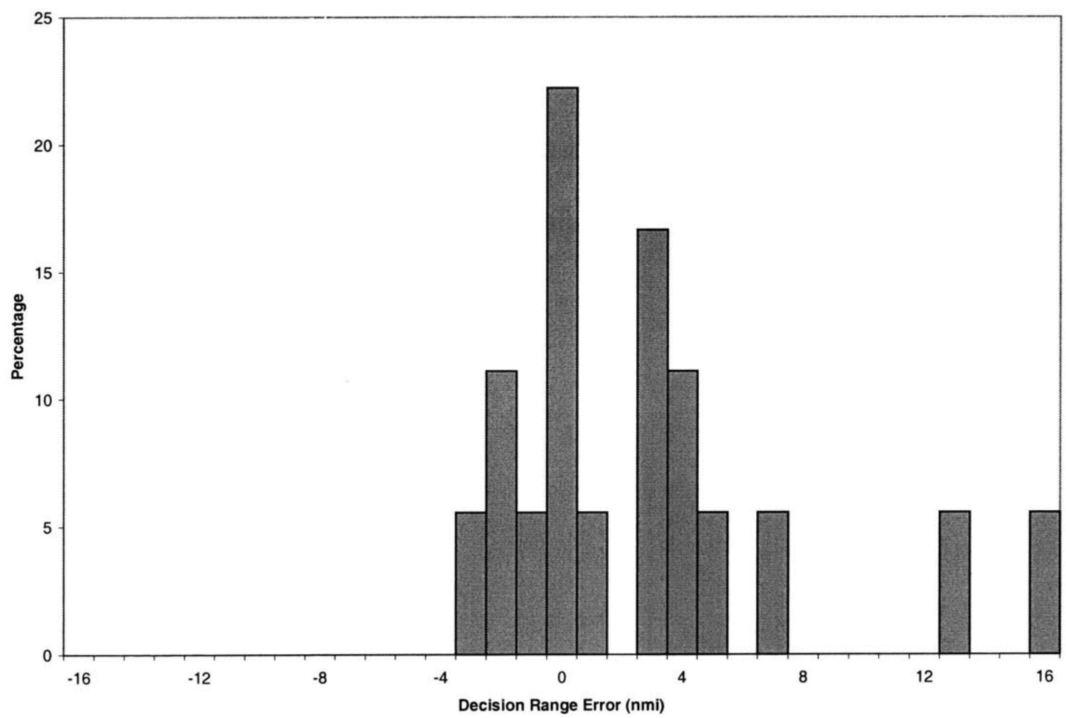


Figure 48 Validation Scenarios Yellow Range Error Histogram (n = 18)

4.4.1 Results

The pilot behavior measured in the validation scenarios is generally consistent with the data gathered during the first experiment. Though the most of the validation scenarios were different from the first experiment in the size of the hazards, the position of the hazards, and the variability between scenarios, the histograms from each set of scenarios were fairly similar in both shape and bounds. It also appears that CPA, the size of the hazards, and the range from a hazard capture the pilot's behavior when faced with simplified weather situations.

The error histograms implied that the belief network model was fairly effective in capturing the pilot's general behavior in both the scenarios that were used to train it and in the validation scenarios. However, the CPA error histograms had a lower variance than the decision range error histograms suggesting that the belief network was more effective at generating CPA values that were closer to the pilot's preferred CPA.

Chapter 5 Conclusions

As a result of increasing traffic congestion and the desire to have more accurate predictions of traffic flow in complex situations, it is becoming necessary to develop large-scale simulations that would involve hundreds of aircraft to allow the validation and testing of system enhancements. Currently this type of simulation is difficult and expensive to run since the number of humans that would have to be involved is somewhat intractable. The use of autonomous agents would be one solution to the problem though an accurate model of pilot behavior would be required to allow the agents to react in a similar manner to a real pilot. Though developing a complete model of all pilot behavior in every situation would be impossible in the short term, it is possible to model a subset of the pilot's behavior, which in this case was limited to the pilot's reactions in the presence of adverse weather.

Through the use of a preliminary survey, a series of initial scenarios, and a set of validation scenarios a pilot's basic assessment model was probed, quantified, and validated. Two models were explored: a randomized model that captures the variability in the pilot's decision-making, even when posed with the same situation twice, and a belief network model that attempts to capture the basic situational awareness parameters affecting the rerouting decision.

Based on the subject's performance data, it appears that the closest point of approach (CPA) of the current route relative to a hazard is the driving factor in determining if a new routing is required. Once the decision to reroute is made the determination of whether to begin the resolution maneuver at the current time depends on the range of the aircraft to the hazard. Other factors such as the size and the severity of the hazard serve primarily to define the acceptable values for CPA and decision range. Though the models are relatively simple, the data gathered in both experiments suggest that the pilot's behavior is captured reasonably well by both the belief network and randomized models.

5.2 Behavior Model Extension

Since pilots may not agree on the correct maneuver to make in every situation, it is important to address the issues associated with gathering data from multiple pilots. Several methodologies could be used to develop a model that works for more than one pilot, but each has its benefits and problems.

One of the simplest techniques would be to gather pilot data by presenting pilots with the same scenarios and measuring the CPAs and decision ranges that the pilot considered acceptable in a particular situation. The data from individual pilots would then be averaged to produce a combined histogram representing all the pilots' behavior. However, this method could also produce a histogram that does not model any single pilot well since the averaging operation loses information from any particular histogram and thus reduces the accuracy of the model for any particular pilot.

Another technique would take the generated histograms from multiple pilots and sort them from conservative to aggressive, or along some other axis of behavior. The sorting action creates a third dimension to the histograms that would allow for the selection of the level of the pilot's aggressiveness as another variable. Individually the histograms directly model an individual pilot so the accuracy of the model should be unaffected. This technique also has some drawbacks since there might be some difficulty in sorting by aggressiveness since a pilot might be aggressive in a particular part of their behavior, but conservative in other situations. A second problem is that this technique would generate a large number of models, which might not be necessary for a system-wide simulation. It is of interest to note, however, that similar methods have been applied in other large-scale autonomous agent simulations, notably for modeling automobile driver behavior and the resulting traffic congestion in roadway systems.

5.3 Future Work

This experiment limited the assessment of pilot behavior to a single, current jet transport pilot. The behavior of additional pilots needs to be assessed and quantified to determine if the tested pilot is indeed representative of the larger pilot pool. Once the data is collected it would also be possible to determine how similar the behavior of one pilot is when compared to another and may allow individual pilots to be grouped into behavior categories and the relative frequency of each of the behaviors forming a distribution of pilot behavior. This distribution could then be used by large-scale simulations to populate the aircraft with autonomous agents with the right assortment of pilot behaviors to model the interactions in the real system.

Since adverse weather is not the only type of hazard that confronts a pilot, the behavior model would need to be extended to support the other important hazards in the pilot's decision space. One example would be the introduction of other aircraft because a weather avoidance maneuver is not independent of the other aircraft in the region. Other aircraft might also be making resolution maneuvers around weather, which might be in conflict with the pilot's current rerouting option thus requiring additional rerouting or negotiation between the aircraft.

Finally, the weather situations considered here were relatively simplistic, using ellipsoidal representations of only one or two isolated storm cells. Certainly the weather modeling must be improved in order to handle more realistic situations including large-scale line storms or other convective weather. This will require a significant effort since the true basis for decision-making is believed to be extremely complex and will likely not be adequately captured by the few metrics used in the model presented here.

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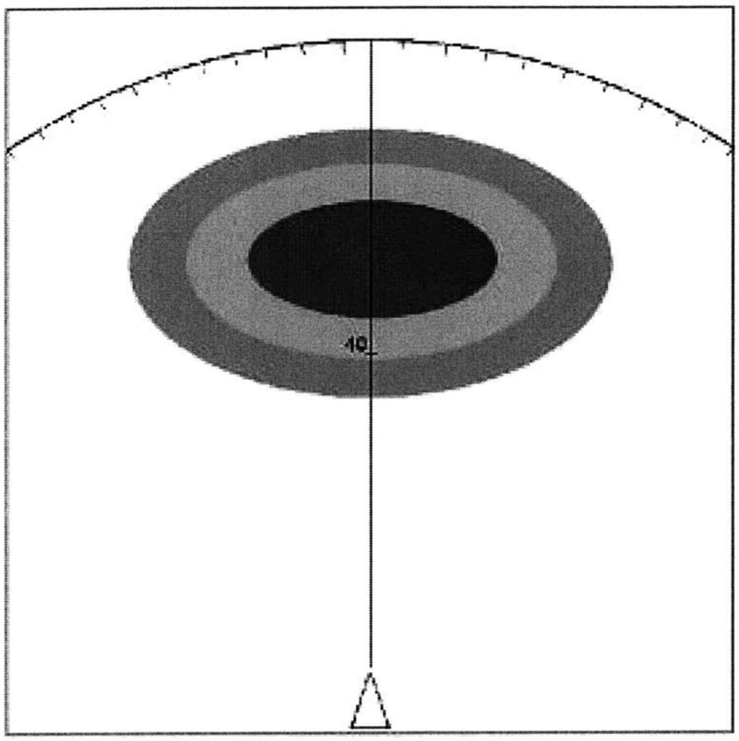
Appendix A

Survey Form



1. Would you continue along the route as is, request a change, or would have never ended up in this situation?

○ Continue ○ Request Change ○ Unacceptable

2. What would you rate the safety level of this scenario?

Completely Unacceptable	Unacceptable	Marginally Acceptable	Acceptable	Completely Acceptable
○	○	○	○	○
1	2	3	4	5

3. What would you predict the passenger comfort level to be along the current route?

Severe Turbulence	Moderate Turbulence	Light Turbulence	Light Chop	Smooth
○	○	○	○	○
1	2	3	4	5

4. Please include additional comments or insights about the scenario such as particular reasons why the current route is or isn't acceptable and if applicable what would you request from ATC. Any other pertinent information would also be appreciated.

Enter

Appendix B

Belief Net CPT Values

CPA & Duration Node CPT Values

Red Duration Node	Red CPA Node	Yellow Duration Node	Yellow CPA Node	CPA & Duration State			
				Acceptable	Low	Medium	High
U n	Unacceptable	Unacceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Marginal	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Acceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		None	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
	Marginal	Unacceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Marginal	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Acceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		None	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
	A c	Unacceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Marginal	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1

		Acceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		None	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
Marginal	Unacceptable	Unacceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Marginal	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Acceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		None	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
	Marginal	Unacceptable	Unacceptable	0	0	0.4	0.6
			Marginal	0	0.5	0.4	0.1
			Acceptable	0.1	0.4	0.5	0
		Marginal	Unacceptable	0.1	0.3	0.5	0.1
			Marginal	0.2	0.5	0.3	0
			Acceptable	0.35	0.55	0.1	0
		Acceptable	Unacceptable	0.1	0.3	0.4	0.2
			Marginal	0.3	0.7	0	0
			Acceptable	0.6	0.4	0	0
		None	Unacceptable	0.2	0.3	0.4	0.1
			Marginal	0.5	0.3	0.2	0
			Acceptable	0.7	0.3	0	0
	Acceptable	Unacceptable	Unacceptable	0	0.2	0.5	0.3
			Marginal	0	0.3	0.5	0.2
			Acceptable	0.1	0.2	0.7	0
		Marginal	Unacceptable	0.1	0.3	0.4	0.2
			Marginal	0.3	0.4	0.3	0
			Acceptable	0.7	0.3	0	0
		Acceptable	Unacceptable	0.6	0.3	0.1	0
			Marginal	0.8	0.2	0	0
			Acceptable	0.9	0.1	0	0
		None	Unacceptable	0.1	0.5	0.4	0
			Marginal	0.4	0.6	0	0
			Acceptable	1	0	0	0
Ac	Un	Unacceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1

		Marginal	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Acceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		None	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
	Marginal	Unacceptable	Unacceptable	0	0.1	0.2	0.7
			Marginal	0.2	0.5	0.3	0
			Acceptable	0.3	0.5	0.2	0
		Marginal	Unacceptable	0.1	0.5	0.3	0.1
			Marginal	0.3	0.4	0.3	0
			Acceptable	0.8	0.2	0	0
		Acceptable	Unacceptable	0.1	0.3	0.6	0
			Marginal	0.6	0.4	0	0
			Acceptable	0.9	0.1	0	0
		None	Unacceptable	0.1	0.3	0.6	0
			Marginal	0.4	0.4	0.2	0
			Acceptable	0.9	0.1	0	0
	Acceptable	Unacceptable	Unacceptable	0	0.2	0.6	0.2
			Marginal	0.1	0.2	0.7	0
			Acceptable	0.1	0.3	0.6	0
		Marginal	Unacceptable	0.2	0.6	0.2	0
			Marginal	0.6	0.4	0	0
			Acceptable	1	0	0	0
		Acceptable	Unacceptable	0.1	0.3	0.6	0
			Marginal	0.7	0.3	0	0
			Acceptable	1	0	0	0
		None	Unacceptable	0.2	0.5	0.3	0
			Marginal	0.4	0.5	0.1	0
			Acceptable	1	0	0	0
No	Unacceptable	Unacceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Marginal	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		Acceptable	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1
		None	Unacceptable	0	0	0	1
			Marginal	0	0	0	1
			Acceptable	0	0	0	1

	Marginal	Unacceptable	Unacceptable	0	0.3	0.4	0.3
			Marginal	0.1	0.4	0.4	0.1
			Acceptable	0.2	0.5	0.3	0
		Marginal	Unacceptable	0	0.3	0.4	0.3
			Marginal	0.15	0.45	0.3	0.1
			Acceptable	0.3	0.5	0.2	0
		Acceptable	Unacceptable	0	0.5	0.3	0.2
			Marginal	0.1	0.6	0.2	0.1
			Acceptable	0.2	0.7	0.1	0
		None	Unacceptable	0	0.3	0.5	0.2
			Marginal	0.1	0.3	0.5	0.1
			Acceptable	0.2	0.7	0.1	0
	Acceptable	Unacceptable	Unacceptable	0	0	0.4	0.6
			Marginal	0	0	0.6	0.4
			Acceptable	0	0.4	0.6	0
		Marginal	Unacceptable	0	0.4	0.5	0.1
			Marginal	0.4	0.4	0.2	0
			Acceptable	0	0.4	0.6	0
		Acceptable	Unacceptable	0.1	0.3	0.6	0
			Marginal	0.7	0.3	0	0
			Acceptable	1	0	0	0
		None	Unacceptable	0.1	0.3	0.6	0
			Marginal	0.7	0.3	0	0
			Acceptable	1	0	0	0

Severity Node CPT Values

Green Size Node	Yellow Size Node	Red Size Node	Severity Node States			
			Minimal	Low	Medium	Severe
Ex	Large	Large	0	0	0.2	0.8
		Medium	0	0.2	0.55	0.25
		Small	0	0.6	0.4	0
		None	0.1	0.6	0.3	0
	Medium	Large	0	0.1	0.2	0.7
		Medium	0	0.3	0.4	0.3
		Small	0.1	0.45	0.45	0
		None	0.2	0.5	0.3	0
	Small	Large	0	0.2	0.3	0.5
		Medium	0.05	0.45	0.5	0

		Small	0.1	0.7	0.2	0
		None	0.3	0.6	0.1	0
	None	Large	0	0	0.3	0.7
		Medium	0.1	0.6	0.3	0
		Small	0.3	0.7	0	0
		None	1	0	0	0
Large	Large	Large	0	0	0.2	0.8
		Medium	0	0.2	0.55	0.25
		Small	0	0.6	0.4	0
		None	0.1	0.6	0.3	0
	Medium	Large	0	0.1	0.2	0.7
		Medium	0	0.3	0.4	0.3
		Small	0.1	0.65	0.25	0
		None	0.2	0.5	0.3	0
	Small	Large	0	0.2	0.3	0.5
		Medium	0.05	0.45	0.5	0
		Small	0.1	0.7	0.2	0
		None	0.3	0.6	0.1	0
	None	Large	0	0	0.3	0.7
		Medium	0.1	0.6	0.3	0
		Small	0.3	0.7	0	0
		None	1	0	0	0
Medium	Large	Large	0	0	0.2	0.8
		Medium	0	0.2	0.55	0.25
		Small	0	0.6	0.4	0
		None	0.1	0.6	0.3	0
	Medium	Large	0	0.1	0.2	0.7
		Medium	0	0.3	0.4	0.3
		Small	0.1	0.65	0.25	0
		None	0.2	0.5	0.3	0
	Small	Large	0	0.2	0.3	0.5
		Medium	0.05	0.45	0.5	0
		Small	0.1	0.7	0.2	0
		None	0.3	0.6	0.1	0
	None	Large	0	0	0.3	0.7
		Medium	0.1	0.6	0.3	0
		Small	0.3	0.7	0	0
		None	1	0	0	0
Sm	Large	Large	0	0	0.2	0.8
		Medium	0	0.2	0.55	0.25
		Small	0	0.4	0.4	0.2
		None	0.1	0.6	0.3	0
	Medium	Large	0	0.1	0.2	0.7
		Medium	0	0.3	0.5	0.2
		Small	0.1	0.4	0.4	0.1

		None	0.2	0.5	0.3	0
	Small	Large	0	0.2	0.3	0.5
		Medium	0.05	0.35	0.4	0.2
		Small	0.1	0.5	0.3	0.1
		None	0.3	0.6	0.1	0
	None	Large	0	0	0.3	0.7
		Medium	0.1	0.6	0.3	0
		Small	0.2	0.6	0.2	0
		None	1	0	0	0
None	Large	Large	0	0.1	0.5	0.4
		Medium	0	0.2	0.7	0.1
		Small	0.4	0.3	0.3	0
		None	0.6	0.4	0	0
	Medium	Large	0	0.2	0.6	0.2
		Medium	0.1	0.3	0.6	0
		Small	0.8	0.2	0	0
		None	0.8	0.2	0	0
	Small	Large	0	0.3	0.5	0.2
		Medium	0.2	0.3	0.5	0
		Small	0.95	0.05	0	0
		None	0.95	0.05	0	0
	None	Large	0	0	0.2	0.8
		Medium	0	0.6	0.4	0
		Small	0.8	0.2	0	0
		None	1	0	0	0

Weather Threat Node CPT Values

CPA & Duration	Severity	Weather Threat Node States			
		Continue	Low	Medium	High
High Risk	Severe	0	0	0	1
	Medium	0	0.2	0.3	0.5
	Low	0.2	0.3	0.4	0.1
	Minimal	0.5	0.3	0.3	0
Medium Risk	Severe	0	0.2	0.5	0.3
	Medium	0.1	0.3	0.5	0.1
	Low	0.3	0.4	0.3	0
	Minimal	0.6	0.3	0.1	0

Low Risk	Severe	0.6	0.3	0.1	0
	Medium	0.7	0.3	0	0
	Low	0.75	0.25	0	0
	Minimal	0.8	0.2	0	0
Acceptable	Severe	1	0	0	0
	Medium	1	0	0	0
	Low	1	0	0	0
	Minimal	1	0	0	0

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