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Development of a Multicriteria Spatial Decision Support System with Application to the Economic Optimization of Aircraft Based Weather Data Collection

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DEVELOPMENT OF A MULTICRITERIA SPATIAL DECISION SUPPORT SYSTEM WITH APPLICATION TO THE ECONOMIC OPTIMIZATION OF AIRCRAFT BASED WEATHER DATA COLLECTION

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ABSTRACT

DEVELOPMENT OF A MULTICRITERIA SPATIAL DECISION SUPPORT SYSTEM WITH AN APPLICATION TO THE ECONOMIC OPTIMIZATION OF AIRCRAFT BASED WEATHER DATA COLLECTION

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Old Dominion University, 2003
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This research is motivated by the economic optimization of the Troposherical Airborne Meteorological Data Reporting (TAMDAR), an aircraft-based meteorological data collection system. In the envisioned TAMDAR system, meteorological data collected by the onboard sensors of selected aircraft are transmitted to the ground as aircraft fly their missions. The data is processed by a national center, which disseminates the data to diverse users such as weather forecasters and aviation control centers. Substantial government funding is required for the implementation and operation of this new data acquisition system and data transmission expenditures constitute the largest portion of the costs. To achieve economic optimization of the data gathering activities, the TAMDAR system requires a multicriteria spatial decision support system (MC-SDSS) that facilitates the efficient selection of the most desirable data points to collect based on a limited budget. To optimize the data collection each data point must be assigned a value by the TAMDAR DSS and a specialized data valuation technique is developed for this purpose.

This work presents a design methodology for practical integrated application of multi-attribute utility, simulation and spatial decision analysis techniques in the optimization of aircraft-based weather data collection systems. The TAMDAR DSS demonstrates tools to address a number of challenging decision support design problems such as inherent uncertainty, required subject-matter knowledge, geo-spatial data dimension,

resolution of conflicting goals, reduction of complexity and, qualitative judgment. The developed model has wide application to other weather information and data gathering problems.

This dissertation is dedicated to my father
who has been an endless source of inspiration for me.

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1 INTRODUCTION

The main focus of this research is to develop a multicriteria spatial decision support system for the economic optimization of Tropospheric Airborne Meteorological Data Reporting (TAMDAR), a new aircraft-based meteorological data collection system. In this system, meteorological data collected by the onboard sensors of selected aircraft are transmitted to the ground as aircraft fly their missions. This data is processed by a national center, which disseminates the data to diverse users such as weather forecasters and aviation control centers. The difficulties of analyzing and optimizing meteorological data gathering systems are caused by many factors such as inherent uncertainty of the system, integration of required subject-matter knowledge, combining interrelationships of geo-spatial and temporal dimensions, handling concurrent conflicting goals, complexity and inclusion of qualitative judgment. As a result, developing such systems constitutes a very complex problem, which is unstructured and has a high degree of uncertainty, characteristics often addressed by multicriteria spatial decision support systems.

This work develops a practical model, which integrates multi-attribute utility, simulation and spatial decision analysis techniques in the optimization of the TAMDAR data collection process. Although the proposed methodology is designed for a specific meteorological data acquisition system, it can be adapted to a wide range of weather information and data gathering problems.

1.1 Background of the Problem

Tropospheric Airborne Meteorological Data Reports (TAMDAR) is a new airborne weather data acquisition system, which is currently being studied by National Aeronautics and Space Agency (NASA) and other government agencies. The TAMDAR hardware consists of sensor packages, information processors, and communications equipment carried aloft by participating aircraft. As these aircraft complete their missions, the airborne TAMDAR system reports weather conditions to ground-based

The journal model for this work is the *Engineering Management Journal.*

receiving stations that process and distribute this data into a national system for dissemination of weather information. The main architecture of TAMDAR system is summarized in Figure 1.

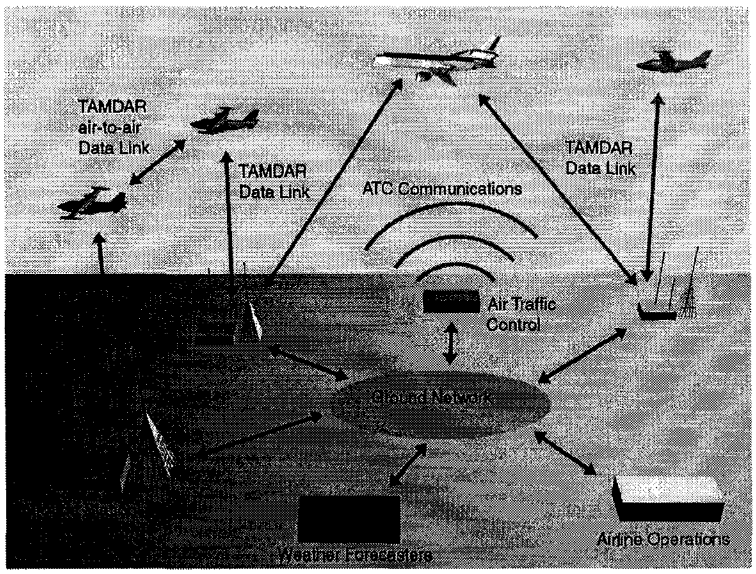

Figure 1 Architecture of the TAMDAR System.

The TAMDAR sensor probe is mounted on either the wing or fuselage and is connected to a signal processing module and a communication unit. TAMDAR data covers a variety of meteorological measurements such as temperature, wind velocity, turbulence, level of icing, and humidity along with time and location information. A complete list of measured parameters and data characteristics are given in Table 1. TAMDAR targets aircraft that fly in the mid layers of the troposphere (typically below 25,000 feet) because these altitudes provide high value for short-term forecasts. Therefore, turboprops and piston aircraft, which typically fly at these altitudes are the primary candidate platforms for this system.

The Federal Aviation Administration (FAA), National Weather Service (NWS), and NASA have concluded that TAMDAR systems have potential to enhance the accuracy and completeness of weather data and the resulting weather forecasts. Improved aviation safety, along with other benefits for various groups (general society benefits) is anticipated as a result of these improved forecasts.

This research is sponsored by NASA and builds upon recent studies of the TAMDAR business case (Kauffmann and Ozan, 2001). It develops a spatial decision support system for TAMDAR. Specifically, it addresses a core problem involving selecting the best combination of meteorological data points to assure the data coverage mixture (spatial and temporal) that leads to the highest level of forecast improvement and data utility at the lowest program cost.

Table 1 Measured Parameters (ODS, 2002).

Parameter	**Range**	**Accuracy**	**Resolution**
Pressure	10 -101 Kp	3 hPa	0.05 hPa
Temperature	-70 to +65°C	±0.5°C	0.1°C
Humidity	0 to 100%RH	Typical ±5% Typical ±10%	1%
Heading	0-360°	±5°	
Ice Detection		0.020 inch	
Pressure Altitude	0 – 25,000 ft.	±150 feet	10 feet
Pressure Altitude	25K – 50K ft.	±250 feet	10 feet
Indicated Airspeed	70-270 knots	±3 knots	1 knot
True Airspeed	70-450 knots	±4 knots	1 knot
Turbulence	0-20 $cm^{2/3} sec^{-1}$	N/A	
Winds Aloft		± 4-6 knots ±5 deg.	1 knot

This decision support system manages the major cost factor of the TAMDAR system, which is the communication cost, incurred by the transmission of the weather data to the ground. One can decrease data transmission costs by reducing the volume of data being sent to the ground. This can be achieved by switching off the sensors when data acquisition is unnecessary and hence collecting only the desirable data. To implement this selection process, one has to decide which data points are more desirable for collection and which ones are less valuable. In other words, there should be a mechanism to value data points in order to acquire the best data set with a minimum cost.

1.2 Objectives and Scope of this Research

The fundamental objective of this research is to develop the TAMDAR Decision Support System (TAMDAR DSS), a simulation-optimization based spatial decision support system, which helps decision makers to optimize the data collection activities within the TAMDAR system. The developed model supports trade off analysis involving simulated patterns of weather data points provided by a given combination of flights and carrier types, the cost of gathering weather data from those points, and the utility they provide to weather forecasters. The spatial decision support model identifies the most desirable combination of flight segments in which weather data would be acquired. To achieve the required performance goals, this research uses the multi-attribute utility functions for valuing the meteorological data points.

At a higher level, the specific, technical objective is to identify and test a feasible approach for a spatial-temporal decision tool that provides capability for four-dimensional analysis using a Geographical Information System (GIS) database. The research outcome is development and a demonstration of this tool and its capability to evaluate the utilities of weather data points for a given region of the country. In addition to providing a tool to select the best data gathering scheme, a principal benefit of the developed system is that it is designed to provide the capability to conduct various what-if analyses to help decision makers.

At the highest level, the goal of this research is to develop a novel decision support system model, which achieves the synergistic fusion of different technologies to solve a complex multicriteria spatial decision problem. The proposed design develops a tractable model that deals with the complexity of the system without overwhelming the decision makers with excessive information. The approaches developed in this research can be applicable to other decision problems in a range of areas.

1.3 Contributions

Building on the objectives discussed above, the contributions of this research are stated as follows:

-Expansion of Multicriteria Spatial Decision Support System Frontiers: This research is the first multicriteria spatial decision support system, designed for a weather data collection decision problem. As a result, this research expands the application areas of multicriteria spatial decision support systems (MC-SDSS) and reaffirms the flexibility and effectiveness they offer to decision makers. In addition, this research provides first hand guidance about the practical aspects of MC-SDSS design.

-A novel approach to analyze economic decisions in meteorological data acquisition: This research serves to develop practical tools for tactical and strategic decision making that can be adopted as a standard approach in the decision-making processes, which involve weather data acquisition systems investments. Although this research is based on airborne sensors, the same approach can be adapted to other weather sensors (surface and/or satellite). No model presently exists that addresses all the important relevant issues that have been identified.

-Unique use of different technologies for solving a complex problem: The proposed model has the capability to address effectively a massive discrete optimization/simulation problem that poses a significant solution challenge. The TAMDAR DSS employs a unique combination of different technological elements such as simulation, optimization, multicriteria analysis, geographical information systems, and computer-based data visualization. One of the primary contributions of the TAMDAR DSS is demonstrating its tractability in addressing complex and arduous spatial decision problems with a combination of decision science and technology tools.

1.4 Organization of the Dissertation

Building on the basic overview of Chapter 1, Chapter 2 and Chapter 3 examine and research literature related to Weather Data Valuation methods and Spatial Multicriteria Decision Techniques respectively. Chapter 2 builds a background for valuing weather data by comparing different approaches. Chapter 3 describes the principles of multicriteria spatial decision support systems and illustrates the utilization of the techniques in a number of applications. Chapter 4 presents the TAMDAR DSS model and explains its elements. Chapter 5 focuses on the test and validation of the TAMDAR DSS and evaluates the results. Finally, Chapter 6 presents conclusions and reviews the results of the research from a wider perspective. This chapter also discusses advantages of the model and identifies new research areas, based on the results of this work.

2 VALUATION OF THE TAMDAR DATA

The TAMDAR DSS operation requires a valuation scheme to rank different data collection choices. As a starting point, one should understand what factors determine the value of meteorological data to assure design of a realistic decision support system. This chapter provides a compilation of the previous studies, which present different perspectives in valuing weather data. There are two main measures which can be used to value meteorological data and weather forecasts: monetary measures and utility scores. This chapter studies both alternatives. Monetary techniques, which employ expected value analysis and Bayesian approaches, provide the most direct measure but they are not always feasible as in the case of the TAMDAR problem. The multi-attribute utility techniques provide an alternative way to value TAMDAR data.

As a point of clarification, the words criterion and attribute are often used synonymously in the literature on multicriteria analysis, which is sometimes referred to as multi-attribute analysis. Attribute is commonly used to refer to a measurable criterion. For consistency, this dissertation employs the word attribute rather than criterion.

2.1 Aircraft-based Weather Data and Its Impact

Developing an effective valuation scheme for TAMDAR requires an understanding of aircraft-based weather data and its impact on weather forecasts. TAMDAR data extends the capability of the current aircraft-based weather data collection system, which is known as Meteorological Data Collection and Reporting System (MDCRS) data. Among its several advantages over MDCRS, the main distinction of the TAMDAR system is that it provides a more comprehensive set of meteorological data sensors. For example, unlike the TAMDAR system, most of the MDCRS sensors do not measure and report turbulence, icing, and humidity information. In addition, TAMDAR is designed to be installed in aircraft that fly below 25,000 feet, which provides more valuable data for short term weather forecasts.

TAMDAR is designed to support various weather forecast products and the following categorization is helpful for identifying the areas, in which TAMDAR data has potential to contribute most. Weather forecast products can be divided into three main groups according to their forecast lead-times: Hazardous weather event prediction, longer range forecasts and very long range forecasts.

Hazardous weather events such as thunderstorms and tornadoes take place in relatively short time intervals. These events can show significant changes on very short time and space scales and cause considerable damage to life and property. Longer range forecasts provide day-to-day weather information for the general public and commercial users. These forecasts are generally developed up to one week in advance, but they can extend to two weeks. Longer range forecast products are widely used in the economic activities of the nation. Very long-range forecasts span months to seasons and help national, regional and local agencies plan for the impacts of weather (NCEP 2000). It is anticipated that the TAMDAR data has the highest utility for shorter range forecasts, whose maximum lead times are typically up to 2 hours. Table 2 provides a summary of these forecast groups.

Table 2 Forecast Product Groups

Weather Products	**Scope**
Hazardous Weather Events	*Thunderstorms, Tornadoes*
Longer Range Forecasts	*Day-to-day weather information*
Very Long Range Forecasts	*Span months to seasons*

The aviation sector relies on timely and high quality weather forecasts. Since many operational activities are dictated by short term forecasts, the TAMDAR data has a high utility for users in the aviation community and the next section provides a more detailed analysis of these benefits.

2.1.1 Aviation Sector Benefits

A primary beneficiary of aircraft-based weather data is the aviation sector. Aviation is vital to the U.S. economy providing large number of jobs and generating federal, state and local tax revenues. For example, aviation's 1998 contribution to Gross Domestic Product (GDP) was 4.7%, aviation-related economic activity totals $975.7 billion annually and aviation employment totals 10.9 million people who earn $278.4 billion annually (Zuelsdorf, 2000).

One can divide the benefits of TAMDAR data for the Aviation Sector into two main groups: safety benefits and system efficiency benefits. Safety related improvements involve reducing aircraft accidents and achieving higher safety records. System efficiency benefits include operational improvements in airlines and airports such as reductions in delays, lower fuel costs, and better runway allocation. The next sections discuss these savings in more detail.

2.1.1.1 Potential to Increase Air Safety

Weather was either a cause or factor in 3,978 aviation accidents between 1989 and 1997. To address this issue, the FAA's current safety goal is to reduce aviation fatal accident rates by 80 percent from 1996 levels. Since better weather forecasts may reduce weather related aircraft accidents, it is anticipated that TAMDAR data will contribute to reduction of the accident rate in the aviation sector. Weather factors, which play role in weather related aircraft accidents include (Keel, 2000):

- Thunderstorm
- Turbulence
- Visibility/Ceiling
- Winds
- Wind shear
- Density Altitude
- Icing
- Precipitation

An example of TAMDAR's possible impact can be seen in thunderstorm forecasts, also known as convective weather forecasts. Thunderstorms usually produce significant weather phenomena that may cause aviation hazards, including turbulence, icing, hail, heavy rain, lightning, tornadoes, gusty surface winds (including low-level wind shear), effects on the altimeter (by causing faulty altimeter readings due to the sudden changes in atmospheric pressure), and low ceilings and visibility (Lankford, 1998). Experts believe that TAMDAR has the potential to improve the quality of the thunderstorm forecasts.

TAMDAR has safety implications for pilots in the terminal area. For example, when approaching the destination, pilots choose whether to penetrate into thunderstorms or deviate around them by assessing the risk. A study conducted by MIT Lincoln Laboratory (Rhoda, 1999), showed that pilots are more likely to penetrate intense thunderstorms near the destination airport than farther away. They are also more likely to choose to penetrate into the storm if another aircraft recently penetrated and performed well. If an aircraft is behind schedule, it is more likely to penetrate into the storm and the reports of the pilots of the preceding aircraft play important role in this decision process. TAMDAR data (which also includes turbulence readings) will have a high value for pilots to have the capability to see the weather readings of the leading aircraft and make improved route approach decisions.

2.1.1.2 Improvements in System Efficiency

Aviation sector efficiency improvements can be studied in two main groups according to the location of their occurrence: improvements in the terminal area and improvements en route. Better weather forecasts can improve efficiency in terminal area operations, which have become very sensitive to weather events due to the tight schedules of airports. Major airports often operate at near-capacity levels with numerous flights spaced closely together. When weather slows the arrival and departure rate of these flights, operations quickly back up, resulting in missed connection, long delays, flight diversions, and flight cancellations

There are two main types of weather events, which cause airport closures: snow (or ice) storms and thunderstorms. An important portion of weather related airport closures is avoidable if more accurate short term forecasts are achieved. Real-time aircraft-based weather data can contribute significantly to the accuracy of airport closure decisions. For example, the abundant MDCRS data from the Chicago O'Hare vicinity has allowed forecasters to more accurately predict the precipitation type of winter storms, high and low temperatures, lake effect snow and strong winds. The data had very important applications in an environment favorable for thunderstorm development, allowing real-time assessment of vertical wind shear and stability and forecast improvement (Mamrosh, 2000).

Inability to predict the weather as accurately as needed, causes airports to experience unnecessary capacity reductions that cause a number of problems including decreases in airport acceptance rates, delay increases, and extra strains on air traffic control (ATC). All these factors increase operational costs and TAMDAR data can potentially mitigate these additional costs by improving the terminal area forecasts. Table 3 summarizes the major weather phenomena that cause capacity reductions in select airports.

Table 3 Major weather types that cause capacity reductions in different airports

Airport	Major Delay-inducing Weather Type	Source
Atlanta Hartsfield International Airport	1. Heavy fog 2. Thunderstorms 3. Reduced visibility	Robinson (1989)
Chicago O'Hare International Airport	1. Thunderstorms 2. Heavy fog 3. Reduced visibility	Weber. et al. (1991)
San Francisco International. Airport	Reduced visibility (however, climatologically few days with thunderstorms)	Clark and Wilson (1997)
Newark International Airport	1. Ceiling & visibility 2. Thunderstorms 3. High wind	Allan & Gaddy (2000)

TAMDAR data also contains wind speed and direction readings and accurate wind measurements play an important role in terminal operations. A specific horizontal distance must be maintained between each aircraft during landing. When head winds increase, aircraft's ground speed decreases and because of the reduced speed, some aircraft perform their landings in longer time intervals causing delays in landing queue (Wilson, 1997). Airport controllers are able to maintain a smooth flow of air traffic into major air traffic hubs by monitoring wind aloft data gathered from MDCRS-installed aircraft (Martin 2000) and TAMDAR has potential to further such improvements.

Despite great improvements in fuel efficiency in modern aircraft, airlines still consume enormous amount of fuel; this is one of the major cost drivers for the airlines. Before take-off an aircraft must specify an alternate airfield and load fuel accordingly (O'Connor, 1989). A fixed percentage of this unused contingency fuel is burned each hour in order to carry the unused contingency fuel. Extra fuel needed for holding at the destination is loaded if the destination is forecast to be at the aircraft's limits or worse. Due to these factors aircraft take unnecessary fuel when destination forecasts are not accurate. Frequent TAMDAR data points provide flight planners with more accurate current and forecast weather at the destination point and contribute to fuel cost reduction.

Rerouting is necessary if the planned route of the aircraft is blocked by a line of thunderstorms and most of the en route delays are caused by this problem. En route delays, in excess of one hour can be experienced in the case of long lines of thunderstorms. The TAMDAR data can help forecasters to better predict the formation and behaviors of thunderstorms.

2.1.2 MDCRS Data

Studying similar data sets provides a foundation for evaluating the impact of the TAMDAR system. Since the MDCRS data set is similar to the TAMDAR concept, this section summarizes previous studies regarding the use of MDCRS data.

MDCRS data is used in wide variety of weather products and has become an important source of data in many forecast products (Mamrosh, 2000). It is also used as source information for initial analyses of numerical forecast models and it is an important data source for the Rapid Update Cycle, a computer-based weather forecast model. However, there are gaps in MDCRS data coverage.

Jamison and Moninger (2001) looked in detail at world-wide and Continental U.S. coverage of aircraft weather data. They stratified the data by day of week, time of day, and altitude and found that most data below 25,000 ft, data are concentrated near major hubs. Since TAMDAR sensors will be installed on aircraft that fly below 25,000 ft, they will improve the spatial coverage of the aircraft-based weather data.

MDCRS data is very useful in forecasting convective weather. The availability of frequent soundings allows the forecaster to monitor the degree of instability and wind shear throughout the day, and issue improved forecasts of convective initiation, severity, and dissipation. (Mamrosh, 1997, 1998). TAMDAR has potential to further the advantages of aircraft based weather data by improving the spatial and temporal coverage.

MDCRS complements radiosonde data by providing frequent soundings from locations that are far from radiosonde sites. Martin (2000) studied the utilization of MDCRS data and concluded that it has the advantage of providing greater spatial and temporal sounding detail in the vicinity of areas with significant commercial air traffic and at times of day when such flights are greatest. For example, aircraft near Chicago O'Hare Airport sometimes transmit soundings of wind and temperature every 15-30 minutes during the busiest times of the day. Such data can be a useful supplement to upper-air data from the more widely spaced and less frequently available radiosonde soundings.

It is clear that TAMDAR data has wide application and provides additional data from regions that are not covered by MDCRS. In addition, the TAMDAR system includes sensors, which are not included in most MDCRS-equipped aircraft such as humidity, icing, and turbulence sensors. Consequently, TAMDAR will complement MDCRS data and enhance the value of aircraft based weather data collection.

2.2 Financial Impact of Forecasts

Previous sections have discussed the weather forecast impact on the aviation sector. A number of additional examples are given below to illustrate the general approaches used in weather information valuation and the level of financial impact.

Rodney, Evans and Rhoda (1997) studied delay reduction due to the Integrated Terminal Weather System (ITWS) Terminal Winds Product (TWP). In this study several Dallas-Ft. Worth Traffic Control Management Coordinators were interviewed to determine the terminal weather products use and their impact on air traffic flow rates at the airport. Findings indicate that TWP is particularly beneficial during times when the capacity is reduced by a combination of low ceilings and/or visibility coupled with a strong vertical shear of the horizontal winds. An analysis using a deterministic queuing model valued the benefit of the TWP at Dallas-Ft Worth at approximately $17M/year.

Patton, Halsey and Lunnon (1997) investigated ceiling and visibility impacts from incorrect terminal forecasts. They measured the cost to the user of an incorrect forecast by constructing a benefit/cost measure based on the fuel loading costs of commercial aircraft. The study found that depending on the accuracy of the forecasts of ceiling and visibility at the destination and diversion airports, unnecessary costs are incurred at the planning stage through incorrect fuel loading computations. The study identified that, for 77% of the aircraft, the average cost to airlines of inaccurate ceiling and visibility forecasts is between $100 and $160 per flight.

Wilson and Clark (1997) estimated the avoidable cost of ceiling and visibility events and considered two airport situations, a realistic situation at San Francisco International Airport (SFO), and a synthesized case for two very large airports. They developed a simple queuing model and applied this to cases of airport arrival capacity reductions that are typical of many ceiling and visibility impacts based on accepted FAA accounting data ($1000/hour for airborne holding and $3,800/hour for delay). According to the results of this study a cost reduction between $100K and $200K per delay event can be achieved by using an efficient weather product at SFO.

2.3 Standard Approaches in Weather Data Valuation: Expected Value Analysis and The Bayesian Approach

The most widely applied decision models to value weather information employ expected value analysis and the Bayesian approach as the most widely applied techniques, to value information. This section describes these standard approaches in weather data valuation by studying a hypothetical example. It then evaluates them as tools for integration into the TAMDAR DSS.

Example: Managers of Airport X are considering the reduction of airport arrival capacity due to predicted low visibility conditions for the next two hour time period. In the past, in similar decision situations, 60% of the time low visibility conditions occurred while normal conditions were observed 40% of the time. Before the decision is made, available weather reports are examined and airport meteorologists predict the visibility conditions in the terminal area. Based on their predictions, airport managers either reduce the arrival capacity of the airport or do not act. In the past, low visibility conditions did not occur 20% of the time when the meteorologists recommended capacity reduction. Low visibility conditions were recorded 8% of the time when they forecasted normal conditions. Airport officials are considering use of TAMDAR data in their forecasts and it has been estimated that their forecast accuracy will increase by 5% using this new data. The following methodology can be used to calculate the savings resulting from TAMDAR data.

Let

Event V = normal conditions — event F = normal capacity

Event V' = low visibility — event F' = reduced capacity

and

$P(V) = 0.40$ — $P(F \mid V) = 0.80$ (= 0.85 if TAMDAR data is used)

$P(V') = 0.60$ — $P(F \mid V') = 0.08$ (= 0.03 if TAMDAR data is used)

Figure 2 shows the decision tree that provides a way to view the breakdown of the possibilities into four cells. There are two branches according to whether or not the low visibility conditions occur. Each of these branches has two sub-branches, corresponding to whether the visibility forecast is accurate or not. The probabilities at the end of each of the four sub-branches represent the joint probability for each combination of events.

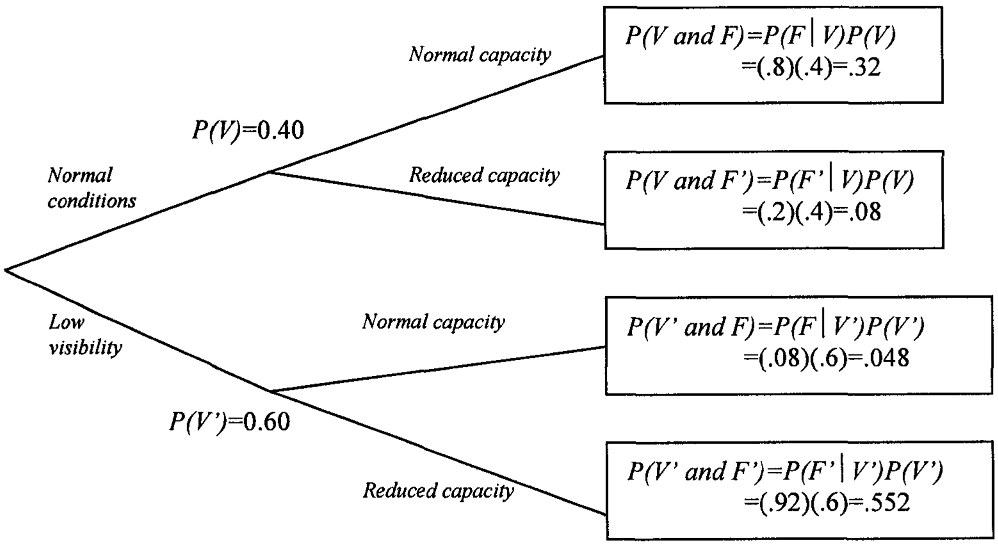

Figure 2 Decision tree for the airport arrival capacity problem.

The information, valued in this example is the weather forecast, which is in the form of “low visibility” or “normal conditions” for the next two-hour time period. Airport operations cost total \$50,000 on average and it costs \$150,000 to reduce the airport arrival capacity due to the increases in delays. If managers do not reduce the capacity and low visibility conditions occur, then estimated delay costs total \$550,000. Table 4 summarizes the pay off matrix.

Table 4 The payoff matrix.

Nature	1-Low Visibility	2-Normal Conditions
Decisions: 1. Reduce the airport arrival capacity	-\$200,000	-\$200,000
2. Do not reduce airport arrival capacity	-\$600,000	-\$50,000

The expected monetary value (EMV) for a course of action j is given by

$$EMV_j = \sum_{i=1}^{N} x_{ij} P_i \tag{2.1}$$

where EMV_j, is the expected monetary value of action j, x_{ij} represents the payoff that occurs when course of action j is selected and event i occurs, and P_i is the probability of occurrence of event i. Monetary values are negative in our example since costs are considered.

By using equation (2.1) total expected monetary costs incurred by the different states of the nature for our decision problem can be computed as:

$$EMV_A = (.8)(.4)(\$-50K)+(.2)(.4)(\$-200K)+(.08)(.6)(\$-600K)+(.92)(.6)(\$-200K) \tag{2.2}$$
$$=\$-171,200$$

If the airport meteorologists use TAMDAR data expected costs would be as follows:

$$EMV_B = (.85)(.4)(\$-50K)+(.15)(.4)(\$-200K)+(.03)(.6)(\$-600K)+(.97)(.6)(\$-200K) \tag{2.3}$$
$$=\$-156,200$$

Therefore, savings resulted by the use of TAMDAR data can be computed as follows:

$$\text{Savings} = EMV_A - EMV_B = \$-171,200 - \$-156,200 = \$15,000. \tag{2.4}$$

The Bayesian view, which is widely used in weather data valuation, postulates that the probability of an event is the degree of belief that a person has, given some state of knowledge that the event will occur. In the classical view, the probability of an event is the frequency with which an event occurs given a long sequence of identical and independent trials. In many value of information problems, directly representative and complete data sets are rarely available and inferences in these situations are inherently subjective.

The feasibility of using a Bayesian approach is based on the available data and the level of subjectivity that is acceptable to the decision makers. Bayesian approaches have been used to value information in a variety of applications. To illustrate, Claxton (1999) used a Bayesian framework to evaluate health care programs and other areas of research include engineering (Howard 1996) and environmental risk assessment (Thompson and Evans, 1997).

These standard data valuation techniques (expected analysis and Bayesian approaches) focus on individual decision scenarios encountered by single decision making agents. In other words, a pay-off table is developed for each scenario. In the case of the TAMDAR problem, there are numerous decision-making entities such as pilots, airport authorities, airline dispatchers, and aviation weather forecasters. To apply these techniques, pay-off tables and decision trees must be constructed separately for each possible decision scenario that is likely to be encountered by these entities. Such an analysis is impractical and, in addition, the required information regarding the subjective probabilities of events is not available to conduct Bayesian and expected value analysis. As a result, these methods are not appropriate for the TAMDAR DSS. The next section develops an alternative approach to value TAMDAR data.

2.4 Multi-attribute Utility Theory: an Alternative Method to Value Weather Data

Multi Attribute Utility Theory (MAUT) provides an alternative valuation technique that has been used in wide variety of applications. It provides a flexible valuation scheme, which can meet the requirements of the TAMDAR DSS and this section provides an overview in this area.

2.4.1 Concept of Utility

The notion of utility is a key foundation for application of MAUT and is defined as the ability or power of a good or service to satisfy a want. Utility concepts were used by the classical economists of the eighteenth and early nineteenth centuries. Neoclassical economists introduced the mathematical formulation of utility in the late nineteenth century. Marginal utility, a natural development of the utility concept, is defined as the change in total utility resulting from a unit change in the quantity of the product consumed.

Although the theory of utility provides one of the most fundamental tools used by economists, it has two main shortcomings. The first is indivisibility of products. The theory generally assumes that commodities are sufficiently divisible to be consumed in separate and relatively small units, but not every product or service is divisible or quantifiable. The second shortcoming of the utility theory is that there is not a definite method to measure utility. Utility can not be measured in the same way we measure physical entities. In other words, we can not measure it in terms of cardinal numbers (Spencer 1986).

Management scientists have applied the theory of utility to decision problems, and as a result, the fields of operation research and decision theory have extended the meaning of utility. For example, decision science defines utility as an alternative way of measuring the attractiveness of the result of a decision (Eppen et al. 1998). Flexibility of utility theory led decision scientists to define multi-dimensional utility structures, which are introduced in the next section.

2.4.2 Multi-attribute Utility Functions

Multi-attribute utility derives from the work of von Neumann and Morgenstern (1947), and of Savage (1956) and provides a model, which examines how individuals should make multicriteria choices. Multi-attribute utility theory has gained wide acceptance based on numerous applications to a wide variety of problems. Keeney and Raiffa (1976) elevated the usability of the theory by developing a set of procedures, which allow decision makers to evaluate multicriteria options in practice. To build multidimensional utility functions, they developed a five step process (Keeney and Raiffa 1972, 1976), summarized in Figure 3.

Multi-attribute utility theory postulates that utility of an entity can be multi-dimensional since it is composed of a number of elements (or attributes), which may be independent or dependent to each other. Therefore, for each utility attribute, we can develop a single attribute utility function and then all utility components can be combined by using appropriate weighted mathematical functions. According to Keeney and Raiffa (1976), one can build a one-to-one relationship between decision makers' objectives and utility attributes and the resulting attribute set reflects the hierarchy of the decision makers' objectives.

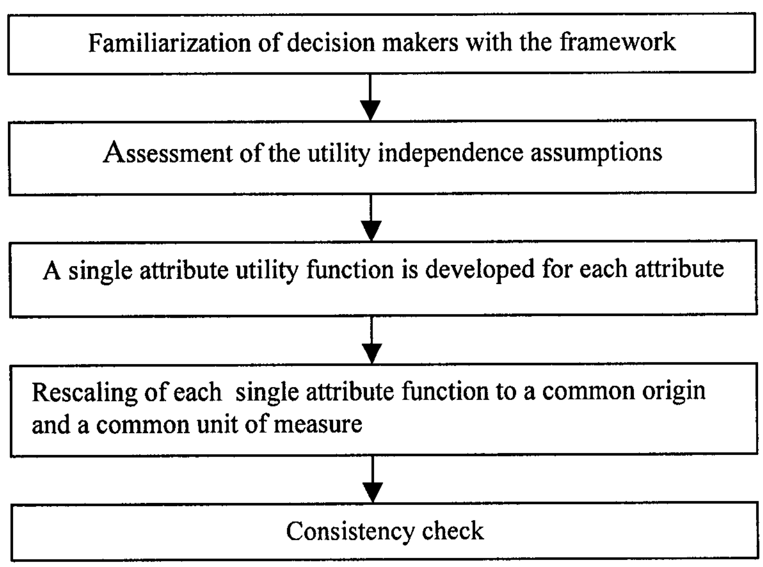

Figure 3 Keeney Procedure: Five step approach for assessing multidimensional utility functions.

The Keeney and Raiffa approach to decision support has been applied to many real decision problems. Although well-established and effective, it is relatively complex and it requires subject matter experts and significant time for successful implementation. A number of applications are presented below in order to illustrate the use of the concept and range of applications.

Baker et al. (1984) applied multi-attribute utility theory to the planning of emergency medical services to patient outcome, and considered both response time and on-the-scene care. Response time and desired personnel requirements were decision variables and they constructed their multi-attribute utility functions based on assessments of a group of 3 experts.

Brinck et al. (1986) used multi-attribute utility functions to model preferences among outcomes of alternative reclamation schemes typical of stripmined lands in the western USA. Their model represents the preference function of an assumed group of decision-maker and ranks the reclamation schemes on the basis of the preference structure. They formed their attribute set based on the main objectives of their proposed system. They also used standards and regulations in forming the attributes.

Rinks et al. (1987) used multi-attribute utility functions in stochastic capacity planning for uncertain demand. They constructed utility functions to reflect the decision makers' trade-off cost and risk and concluded that a significant advantage of the multi-attribute utility approach is that it allows for nonlinear trade-offs of cost and risk.

Chen et al (1999) used multicriteria utility approaches to assist decision making in quality engineering and the applications of robust design. They developed a robust design procedure that allows designers to express their preference structure of multiple aspects of robust design. They obtained a set of utility functions and used them to explore the set of efficient solutions in a neighborhood of the candidate solution.

Zopounidis and Doumpos (1999) adapted multicriteria decision analysis techniques to sorting problems. Sorting problems constitute a major part of real world decisions, where a set of alternative actions (solutions) must be classified into two or more predefined classes. They studied two real world classification problems concerning the field of financial distress. In a similar application, Bugera et al (2002) developed a multicriteria utility based methodology that separates specific subgroups in a population of objects and applied it to a credit cards scoring problem.

This range of examples indicates that MAUT provides a generalized and flexible scheme that may be applied to meteorological data valuation. In this application, instead of analyzing the problem in terms of individual cases and their specific outcomes like expected value and Bayesian methods, one can view TAMDAR data as an ingredient used in a wide variety of weather forecasts and evaluate the level of its positive impact in the final products resulting from varying levels of its attributes.

To conduct such an analysis, system designers can collect information about the value of TAMDAR data by studying the current use of aircraft-based meteorological data (MDCRS). This information will identify the attributes, which characterize the utility of TAMDAR. Once the attribute set is formed, single attribute utility functions are determined for each using the available expert knowledge and data. Then, each single attribute function is rescaled to a common origin and a common unit of measure. Utilization of MAUT for the TAMDAR DSS is explained in more detail in Chapter 4.

2.5 Summary

This chapter provided the necessary background to develop a valuation approach for TAMDAR data that is suitable for use in a DSS. In the first section, the impact of aircraft-based weather data was explained. The second section discussed the utilization of MDCRS weather data, which is similar to TAMDAR data and described the advantages of TAMDAR data based on the assessment of the current MDCRS data impact. The third and fourth sections focused on developing a feasible valuation technique for TAMDAR data. The third section concluded that the expected value analysis and Bayesian approach are not applicable to the TAMDAR problem and the fourth section concluded that the multi-attribute utility functions present a desirable approach for the requirements of this research. The next chapter develops a framework, which integrates MAUF into a spatial decision support system.

3. MULTICRITERIA SPATIAL DECISION SUPPORT SYSTEMS

Spatial multicriteria decision problems involve a set of geographically defined alternatives from which choices are made based on a given set of evaluation criteria (Jankowski, 1995; Malczewski, 1996). This chapter studies multicriteria spatial decision support systems (MC-SDSS) and describes the underlying technologies and theoretical background. The first section defines the MC-SDSS and identifies GIS as a key technology employed in such systems. The second section describes the architecture of MC-SDSS and discusses its implications for the TAMDAR DSS. The third section examines the range of applications in this area and the fourth section introduces the TAMDAR DSS concept by explaining its basic elements. Finally, the remaining sections discuss the advantages of the TAMDAR DSS model over the existing MC-SDSS and conclude the chapter.

3.1 Multicriteria Spatial Decision Support Systems

The TAMDAR DSS is a multicriteria spatial decision support system (MC-SDSS) that provides a framework to combine and transforms spatial and non-spatial data into a resultant decision. Since MC-SDSS can be viewed as a part of a broader field of decision support systems (DSS), this section begins by explaining the basic characteristics of DSS, applicable to MC-SDSS, before focusing on the specific elements of MC-SDSS.

DSS can be considered a subset of computer-based information systems and includes a variety of familiar systems such as office automation systems, transaction processing systems, management information systems, and management support systems. DSS are often referred as a type of management support system and have two main elements: human decision makers and computer systems. Based on definitions that have been developed by Alter (1980), Bonczek et al. (1981), Keen and Scott-Morton (1978), and Sprague and Carlson (1982), a DSS can be defined as a computer-based, human-computer decision-making system that supports decision makers to solve problems with varying degrees of structure (e.g. from non-structured or ill-structured to very structured) by using data and analytical models.

Since the main advantage of using DSS is facilitation of decision processes, DSS focus on effectiveness rather than efficiency in decision processes. Unlike *expert systems*, which mimic human decision makers in making repetitive decisions in a narrow domain, DSS do not replace decision makers but rather support them in solving different decision problems, which are often not well-structured.

Decision problems that involve geographical data are referred to as geographical or spatial decision problems. Spatial decision support systems are a subgroup of DSS and are generally employed in problems, in which spatial dimensions play a significant role. Since almost every modern spatial decision support system relies on a geographical information systems (GIS) component, it is important to develop a sound understanding of GIS concepts in order to design successful spatial DSS. In fact, most experts see GIS as a form of DSS. For example, Cowen (1988) defined GIS "as a decision support system involving the integration of spatially referenced data in a problem solving environment".

GIS were originally developed to automate cartography and map production. Early implementations in the 1970s were not able to deliver the benefits of GIS systems effectively, because of the limited computational power available at that time. In the mid 1980s, software integration and more powerful computers were combined to create packaged GIS offering usable digital mapping functionality. Utility companies and mapping agencies were among the first users of GIS systems (Raper, 2000).

A GIS system is composed of a geographical data base, an input/output process, a data analysis method, and a user interface. The terms *spatial* or *geographical data* are often used interchangeably and describe objects based on two types of characteristics: location and attributes. Location-related data provides spatial position of the object and attribute data includes all other properties of the objects. The data in GIS systems are usually organized by thematic maps or sets of data.

Although GIS provide extensive spatial analysis and data visualization power to their users, such systems offer a limited capacity for tackling complex, ill-defined, spatial decision problems. Spatial decision support systems (SDSS) augment the problem-solving capacity of GIS by integrating analytical models into the decision process (Densham and Goodchild, 1989). There has been considerable growth in research, development and application of SDSS in the last decade (NCGIA, 1990, 1996).

The next section focuses on the spatial multicriteria decision analysis and provides a general architecture.

3.2 Developing a Design Methodology for the TAMDAR DSS

A number of frameworks for designing MC-SDSS have been proposed including Diamond and Wright (1988), Carver (1991), Eastman et al. (1993), and Jankowski et al. (1997). Despite differences in GIS capabilities and multicriteria decision making (MCDM) techniques, the generic framework contains three major components: a user interface, MCDM models (includes tools for generating a value structure, preference modeling, and multiattribute decision rules), and geographical data analysis and management capabilities.

Malczewski (1999) provides a framework for spatial multicriteria decision analysis. According to this framework, shown in Figure 4, there are three main phases of MC-SDSS: intelligence, design, and choice. This three-phase process is the most widely accepted generalization of the spatial multicriteria decision making and is described in more detail in the following paragraphs.

The *intelligence phase* includes the definition of the problem, constraints, and evaluation criteria. Once the decision problem is identified, spatial multicriteria analysis focuses on the set of *evaluation criteria*. This step involves specifying a comprehensive set of objectives that reflects all concerns relevant to the decision problem and the measures (or attributes) for achieving those objectives.

Attributes that address the system objectives are converted to *criterion maps*, which are two-dimensional representations of evaluation criteria in GIS database. The set of criterion maps represents a particular decision situation related to a particular segment of the real-world geographical system. Evaluation criteria form the basis for the decision matrix and each criterion can have different importance to the decision makers. Consequently, information about the relative importance of the criteria is necessary. One way of deriving criterion maps is to use *value/utility approaches* that assign to each criterion a weight that indicates the criterion importance relative to the other criteria under consideration. At this stage, multi attribute utility functions can be integrated into the system by using these criterion maps, therefore, Malczewski's framework can accommodate the TAMDAR data valuation approach, derived in the previous chapter.

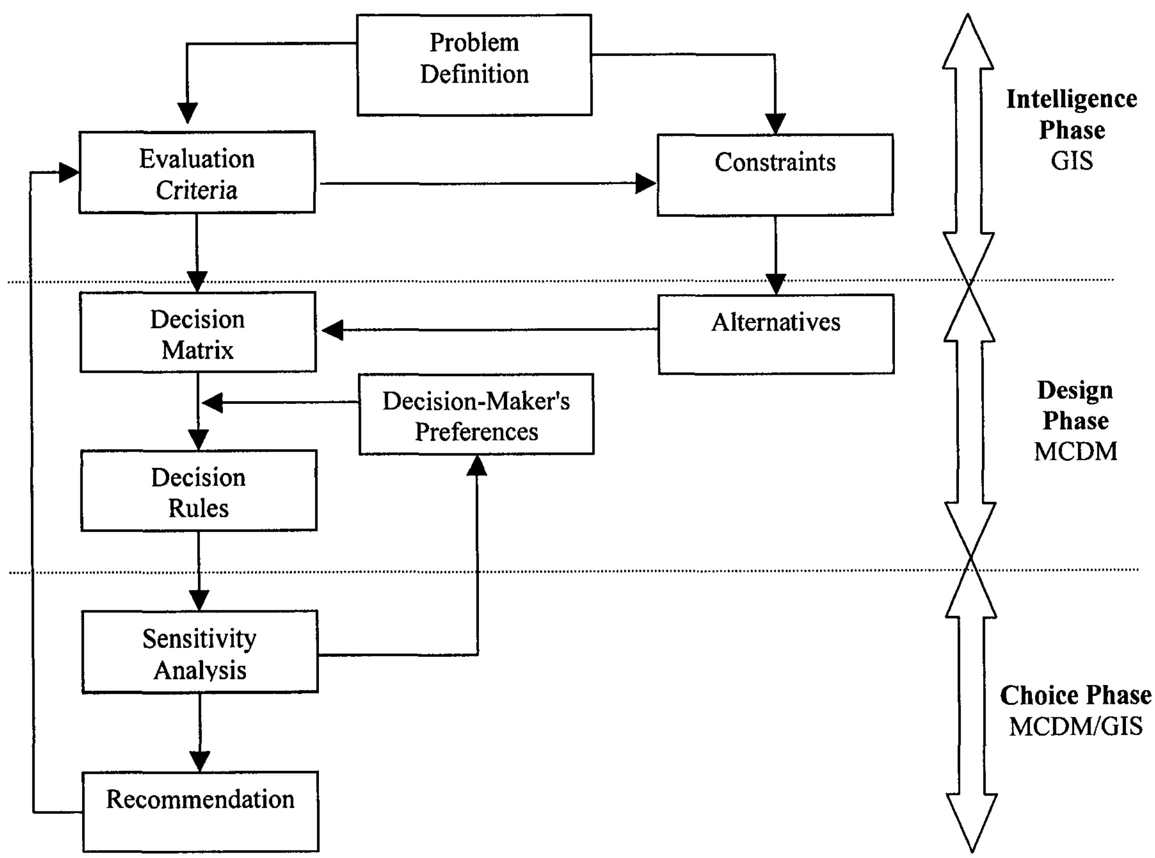

Figure 4 General architecture of spatial multicriteria decision analysis.

The *design phase* integrates decision makers' preferences into the system. *Decision alternatives*, *decision rules*, and the *decision matrix* structure the design phase to accommodate the required functionality. *Decision alternatives* are the alternative courses of action among which the decision maker must choose. The process of generating decision alternatives should be based on the value-structure and be related to the set of evaluation criteria. The *decision matrix* compiles feasible decision alternatives while *decision rules* provide a procedure that allows for ordering alternatives. The values provide a basis for the integration of the criterion map layers and judgments in order to provide an overall assessment of the alternatives. Specifically, the decision rules order the decision space via a one-to-one or one-to-many relationship of outcomes to decision alternatives.

The *choice phase* includes sensitivity analysis in the optimization. In the final step of this phase, recommendations are formed based on the findings of the sensitivity analysis. The framework for this step is an iterative process, which allows the readjustment of the decision rules and evaluation criteria based on the outcomes of the recommendations and sensitivity analysis (Malczewski,1999).

The three stages of multicriteria spatial decision making do not necessarily follow a linear path from intelligence, to design and to choice and they can be adapted to different decision situations. The next section demonstrates this by examining the scope and range of applications in MC-SDSS.

3.3 Applications of Multicriteria Spatial Decision Support Systems

Examination of MC-SDSS applications provides an understanding of the usefulness of this method and this section presents a number of representative examples. They are selected to cover different fields and address the significant aspects of MC-SDSS. The examples also illustrate typical approaches used in MC-SDSS.

MC-SDSS have been applied for a variety of problems, including land use planning (Diamond and Wright, 1988) (Thill Jean-Claude, Xiaobai Yao, 1999) (MacDonald and Faber, 1999), nuclear waste disposal facility location (Carver, 1996), water resource management (Bender and Simonvic, 1995), habitat site development (Jankowski et al., 1997), health care resource allocation (Jankowski and Ewart, 1996), land suitability analysis (Eastman et al., 1995; Fischer et al., 1996), highway planning (Morin, David M., 1997), and retail location selection problems (Arentze, Borgers and Timmermans, 1997). Table 5 provides an overview of the literature search on MC-SDSS applications.

Table 5 Summary of MC-SDSS Examples

Application Area	**Examples**
Land use planning	(Diamond and Wright, 1988) (Thill Jean-Claude, Xiaobai Yao, 1999) (MacDonald and Faber, 1999) (Eastman et al., 1995; Fischer et al., 1996)
Retail location selection	(Arentze, Borgers and Timmermans, 1997)
Habitat site development	(Jankowski et al., 1997)
Highway planning	(Morin, David M., 1997)
Health care resource allocation	(Jankowski and Ewart, 1996)
Nuclear waste disposal facility location	(Carver, 1996)
Solid waste planning	(MacDonald, 1996)
Water resource management	(Bender and Simonvic, 1995)
Spatial analysis of coral reef	(Freire, 2001)
Forest planning	(Sugamaran, 2000)
Watershed planning	(Bealieu, 2000)

Most of the MC-SDSS, listed on Table 5, focus on static spatial decision analysis without providing a temporal analysis capability. The necessity to integrate simulation models into spatial decision support system was articulated by Burrough et al. (1988). In many MC-SDSS, temporal decision analysis necessitates the development of simulation models. However, the integration of simulation models poses significant challenges and successful applications are scarce (Colombo, 1992). Ideal integrated systems should feature seamless transitions between simulation modules and other system components and they should also offer user-friendly environments to analyze different scenarios effectively.

As illustrated by the applications, given above, MC-SDSS have a satisfactory record in a wide range of problems and in various circumstances. On the other hand, most of these systems lack the temporal analysis features that are desired by the users. The next section addresses this issue by identifying the role of the simulation module in the TAMDAR DSS and also describes the model in general terms.

3.4 System Architecture of the TAMDAR DSS

This section introduces the TAMDAR DSS architecture and explains its basic elements. In the TAMDAR DSS, the decision variable is the binary status of the weather data sensor in each flight segment, the "on" or "off" condition controls data acquisition for each flight segment: ascent, en route and descent. The ascent phase starts when the pilot begins the take-off procedure and ends when aircraft reaches the designated cruise altitude. The en route phase includes the interval between the ascent and descent segments. Finally, descent phase starts when the aircraft begins to decrease its altitude to perform a landing approach and ends when the aircraft touches down.

Describing a flight pattern in terms of these three phases has several advantages. First, it simplifies and clusters the data selection process, since it is not feasible to analyze the exact characteristics of every possible individual flight data point. Another advantage is that the aviation community is acclimated to thinking in terms of these flight segments since they are used in many flight planning activities. Finally, meteorologists consider ascent, en route, and descent aircraft data as similar to weather balloon soundings that are viewed as integrated data groups.

The status of a sensor is the direct decision variable, which stipulates a number of indirect decision variables including the expected data volume and geographical distribution. Several constraints limit the number of data points (data volume), collected. Economic concerns, related to data collection and processing are the most obvious. In addition, spatial and temporal distributions of data points are constrained by the discrete choices of aircraft flights. Airlines are motivated to choose flight routes to serve passengers not to gather weather data. As a result, TAMDAR decision makers must choose the flight routes which are likely to provide the best match to the desired coverage. There are also density considerations for TAMDAR data. For example, over-sampling of a geographical region is not desirable. On the other hand, temporal and spatial data gaps in the geographical coverage must be avoided. Finally, the TAMDAR system should maintain a consistent daily minimum data rate in order to meet the forecasters' expectations and forecast model needs.

The TAMDAR DSS has four main components (see Figure 5):
-GIS-based data visualization and user Interface Unit
-Multicriteria optimization model
-Data pattern simulator
-Multi-attribute utility estimator

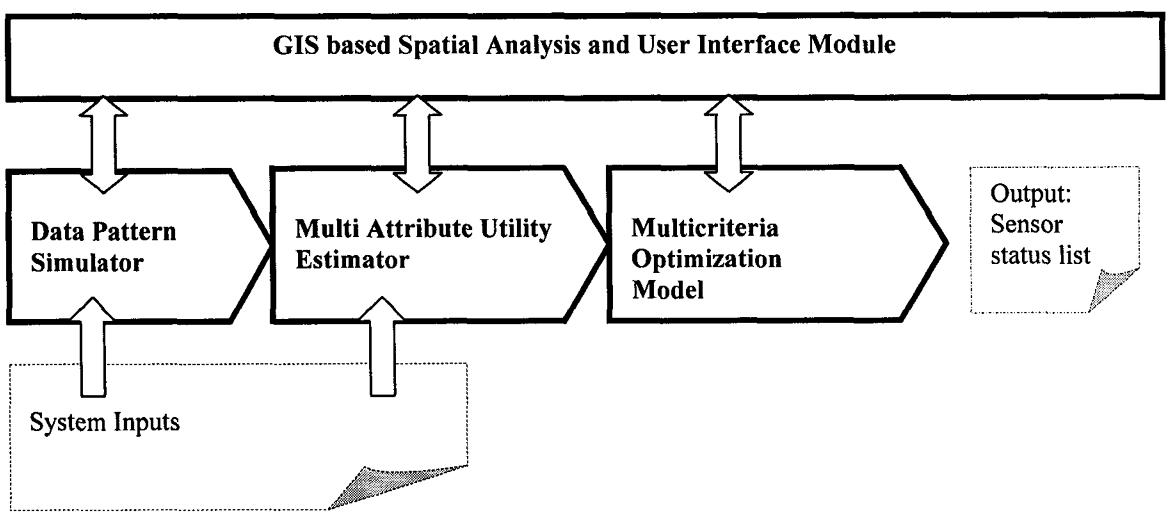

Figure 5 The TAMDAR DSS architecture

The GIS and user interface facilitates the user interaction with the system and coordinates the functions of all other modules. A GIS based analysis engine provides data analysis, visualization and data storage capabilities and also communicates with the other system components. The user interface is integrated into the same module and provides a user friendly environment for the interaction of the operator with the DSS.

The data pattern simulator develops the spatial and temporal distribution of the possible data using daily flight schedule and other inputs. Its output is fed to the multi-attribute utility estimator that values the individual weather data points by employing multi-attribute utility functions.

The multi-attribute utility estimator sends its output of utility scores for all flight phases to the optimization module whose objective is to maximize the utility of the data set subject to budgetary constraints.. The optimization module ranks all alternatives and selects the best data collection combination. The system output is a digital text file listing proposed sensor status per each flight segment.

3.5 Novelty of the TAMDAR DSS

The TAMDAR DSS differs from most of the applications that were cited in Section 3.3 in a number of ways that make it a unique tool and enable it to advance the state-of-the-art of MC-SDSS. Based on the comparison made between the TAMDAR problem and the examples, found in the literature, the following advantages of the TAMDAR DSS were identified:

-Spatial-temporal analysis capability: Most of the current MC-SDSS applications focus on the spatial data analysis. It is anticipated that future generation MC-SDSS will be not only spatial but also spatial-temporal (Ascough II, 1998). Since the TAMDAR DSS processes both spatial and space-time data, it extends the current methods of analyzing spatial decision situations.

-Defining a new application area: Although MC-SDSS applications cover wide variety of areas, there is no previous research that focuses on the economic analysis of meteorological data collection systems. There is a substantial need for development of systems that optimize the weather information gathering and the TAMDAR DSS is the first spatial decision support system that demonstrates the feasibility of such systems.

-Innovative approach for a simulation component: Although many MC-SDSS include a simulation element, the simulation module of the TAMDAR DSS features unique characteristics. Most of the spatial decision support systems employ simulation to analyze the error propagation and uncertainty while the TAMDAR DSS simulation module was designed to generate the decision alternatives. The TAMDAR DSS simulates the spatial and temporal distribution of TAMDAR data before it is collected and makes recommendations based on the simulated data. This approach provides a clear advantage for decision problems involving situations in which decision alternatives of a system must be predicted.

3.6 Summary

This chapter examined existing research in MC-SDSS and identified the approaches applicable to the context of the TAMDAR DSS. It provided a general view of the underlying technologies used in the field of MC-SDSS and examined a number of research applications, which illustrate the scope of the field. This chapter also demonstrated that the TAMDAR problem constitutes an original case, which differentiates it from most of the existing examples while it still carries the common characteristics of the MC-SDSS.

4. TAMDAR DECISION SUPPORT SYSTEM (TAMDAR-DSS)

This chapter explains the TAMDAR DSS model and begins with a conceptual description of the system operation to provide context for the DSS. The second section focuses on the system components and provides detailed technical information about each.

4.1 System Description

The TAMDAR DSS envisions a number of regional decision centers for controlling data collection throughout the continental U.S. This distributed decision making is necessary, since different geographical regions present different meteorological characteristics. Figure 6 shows a division of regional command centers that is suitable for the TAMDAR DSS. Command centers, in these regions, are currently used by the Aviation Weather Center of the National Weather Service (NWS) to generate area forecasts for multi-state areas. This partition, therefore, reflects actual operational divisions, which are already in use that could support the operational objectives of TAMDAR. The examples that follow will be based on the North-East Region.

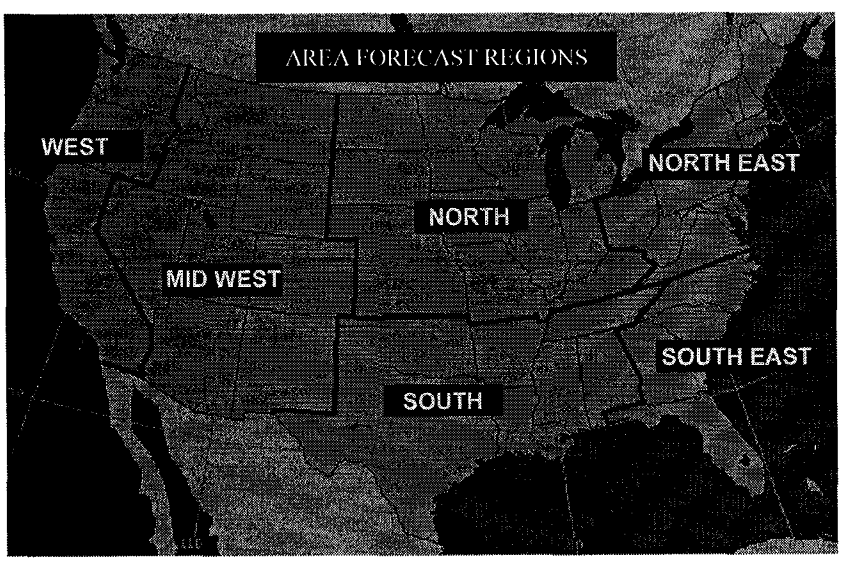

Figure 6 Operational divisions of TAMDAR DSS.

Figure 7 describes the system architecture for the decision centers. At the heart of the system is the TAMDAR DSS operator, who uses the TAMDAR DSS to compose the list of flight segments in which the TAMDAR sensor will be activated. The operator is also responsible for gathering inputs, required for the tool. The TAMDAR DSS may be run as frequently as needed from daily to weekly or monthly.

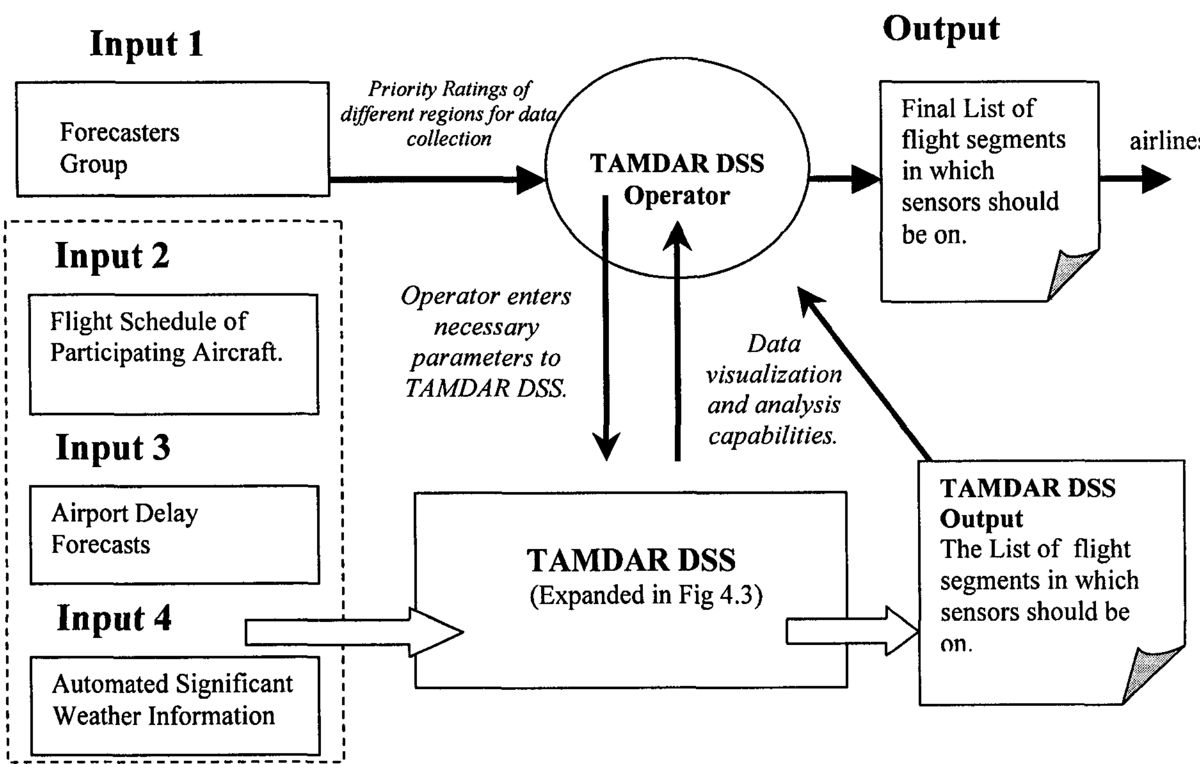

Figure 7 The TAMDAR DSS Architecture.

The model provides for four system inputs: forecasters assessments (input 1), daily flight schedule (input 2), aviation delay forecasts (input 3), and significant weather information (input 4). Forecasters' assessments (input 1) include the information, which defines the priority regions for data collection. The daily schedule (input 2) contains the timetable of the flights that are flown by TAMDAR-equipped aircraft. Airport delay forecasts (input 3) convey expected delays in the Nation's airports. Automated significant weather forecasts (input 4) contain information about predicted significant weather events and their geographical location.

Only input 1 requires direct human involvement while inputs 2, 3 and 4 are generated and received automatically without requiring any human intervention. In the future the forecasters' group data (input 1) may also be automated since , in many cases, automated weather forecasts can provide most of the required inputs. The forecasters group informs the TAMDAR DSS Operator about the priority regions for required data based on different forecasting processes such as the current status of the weather and/or climatologic data needs for their forecasts. These assessments may be generated seasonally, weekly or daily based on the desired level of human intervention in the system. This forecaster group is composed of experts who represent the meteorological data needs of different forecasting processes. They designate temporal and spatial regions, which have higher priority for data collection. The TAMDAR DSS operator then translates these assessments into a format, which can be processed by the TAMDAR DSS.

The final product of the TAMDAR DSS is the optimum list of flight segments for data collection. The operator analyzes this list and makes necessary modifications using the data visualization features of the TAMDAR DSS. After composing the final list, the operator sends it to the appropriate centers (e.g. Airline command and control facilities and/or Aircraft communication centers), which are capable of activating (or deactivating) TAMDAR sensors on the selected flight segments. The activation process may differ from airline to airline and with different aircraft models and avionics equipment.

Three primary software packages were integrated to implement the TAMDAR-DSS: *S-PLUS, Arc View,* and *Visual Basic.* Figure 8 indicates the specific software used in each module. S-Plus is statistical analysis software that was utilized in combination with additional modules: S+SpatialStats, NuOpt, and S-Plus for ArcView GIS. S+SpatialStats is an add-on module to the S-Plus system for data analysis and graphics that provides a comprehensive set of tools designed for the statistical analysis of spatial data. NuOpt is a numerical optimization software package and S-Plus for Arc View provides the software link between S-Plus and Arc view environments. It facilitates data transfer between the two software environments. Arc View presents extensive GIS based analysis capabilities and cartographic data presentation functionality. Finally, Visual Basic is used for developing additional custom functionality such as the flight pattern simulation, the data input/output operations, and user dialog design.

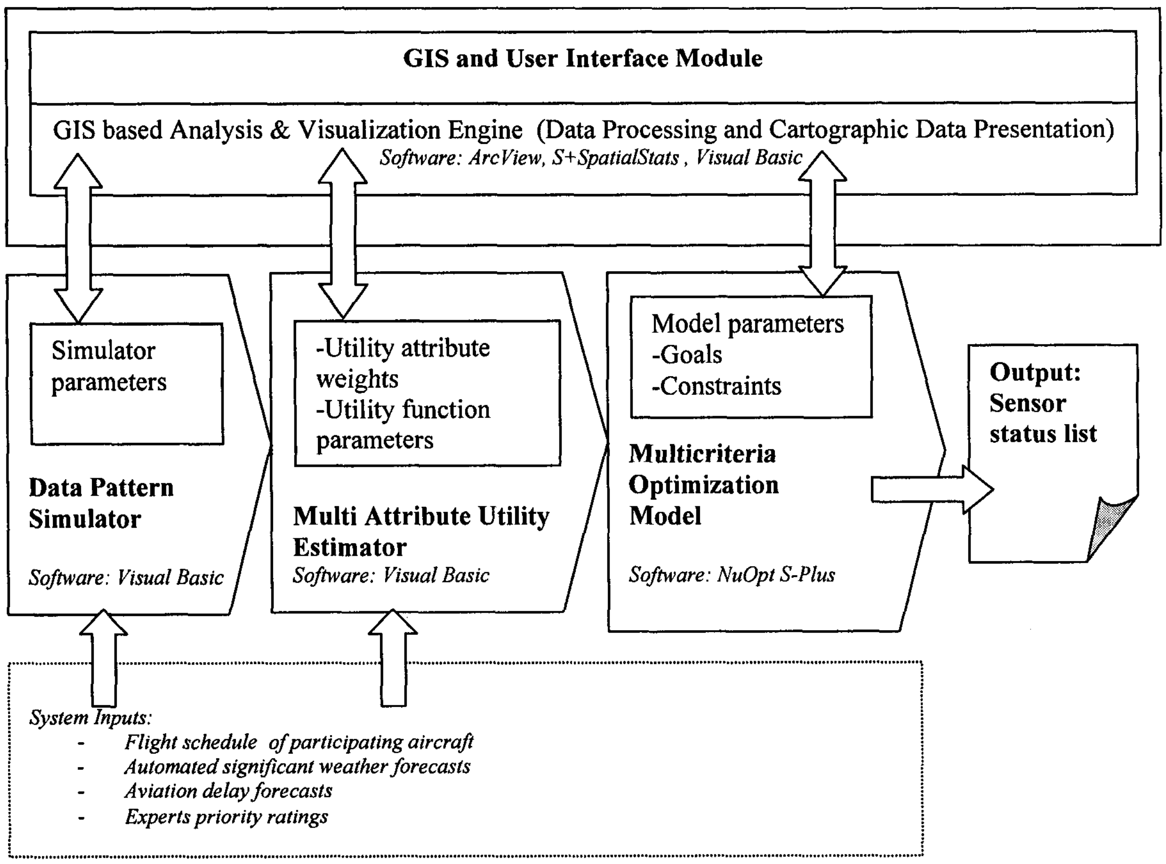

Figure 8 Components of TAMDAR DSS architecture

4.2 Components of the TAMDAR DSS

This section explains the four components of the TAMDAR DSS: data pattern simulator, multi-attribute utility estimator, multicriteria optimization module, and GIS-based data visualization/user interface.

4.2.1 Data Pattern Simulator

An essential first step for the model is the capability to convert flight information into the related spatial and temporal data pattern. The flight pattern simulator module achieves this by generating a prediction of flight trajectories together with the related geographical data point location and acquisition time. The geographical location information includes latitude, longitude and altitude for possible data points collected during each candidate flight segment. The input file, which is fed to the flight pattern generator, includes the daily list of the candidate flights and related information such as:

1-Codes of originating and destination airports

2-Departure time

3-Aircraft type

4-Airport delay forecasts

Aircraft can be divided into four groups for the consideration of the TAMDAR DSS simulator as shown in Table 6. Each aircraft type on this table shows similar characteristics and speeds during different flight segments. These parameters can be approximated based on the aircraft type (Xavius Software. 2001). Table 7 shows the average aircraft speed for different flight segments based on the aircraft type. For simplification this model assumes that all velocities (vertical and horizontal) are constant during each flight phase. Similar to aircraft speed values, typical flight altitudes can also be related to aircraft types as shown in Table 8(Xavius Software. 2001).

Table 6 Classification of aircraft for the simulator.

Type	Typical Examples
Jets	Boeing 737, Boeing 757, Boeing 767, Airbus 320
Jumbo jets	Boeing 747, DC10, MD11
Turboprops	Saab 340, Bomabardier Q100, Q200, Q300, Q400
Piston	Baron 58

Table 7 Aircraft speeds versus aircraft type

	Ascent Phase		En Route Phase		Descent Phase	
	Horizontal Speed V_{AH} (ft/min)	Vertical Speed V_{AV} (ft/min)	Horizontal Speed V_{EH} (knots)	Vertical Speed V_{EV} (knots)	Horizontal Speed V_{DH} (knots)	Vertical Speed V_{DV} (ft/min)
Jets	300	1,500	450	0	300	-1,000
Jumbo Jets	300	1,000	450	0	300	-1,000
Turboprops	200	1,000	250	0	200	-1,000
Piston	100	1,000	140	0	100	-1,000

Aircraft speed and flight altitude characteristics are identified based on the average values determined by analyzing the FAA radar data. Average flight duration of TAMDAR-equipped aircraft is estimated as 1.2 hours (Kauffmann and Ozan 2002), therefore, data shown in Tables 7 and 8 reflect the characteristics of short range flights, which may necessitate lower flight altitudes.

Table 8 Aircraft type versus flight altitude.

Type	h_E, Average Flight Altitude
Jets	30,000 ft
Jumbo jets	35,000 ft
Turboprops	20,000 ft
Piston	10,000 ft

Figure 9 relates aircraft speed (vertical and horizontal) and the altitude to the different flight phases. T_A, T_D, and T_E represent times spent during ascent, descent, and en route phases respectively. To calculate T_A, T_D, and T_E, one needs to compute the distance between two airports (*D*). Considering the spherical geometry of the earth's surface, the following equations, based on an approach, known as *great circle path,* provide a simple method for this calculation. If *latitude1, latitude2, longitude1, and longitude2* represent the geographical coordinates of two airports, the following equations calculate the great circle path distance (*D*) between two points as shown in Figure 10:

$$\alpha = 90 - latitude1 \quad (4.1)$$

$$\beta = 90 - latitude2 \quad (4.2)$$

$$\phi = longitude1 - longitude2 \quad (4.3)$$

$$\cos\tau = (\cos\alpha)(\cos\beta) + (\cos\phi)(\sin\beta)(\sin\alpha) \quad (4.4)$$

$$D = 60 * \cos^{-1}\tau \quad (4.5)$$

After computing D, we can compute times spent during ascend (T_A), descend (T_D), and en route (T_E) as follows:

$$T_A = h_E / V_{AV} \tag{4.6}$$

$$T_D = h_E / V_{DV} \tag{4.7}$$

$$T_E = (D - T_A V_{AH} - T_D V_{DH}) / V_{EH} \tag{4.8}$$

where h_E represents flight level and is determined based on the aircraft type (see Table 1).

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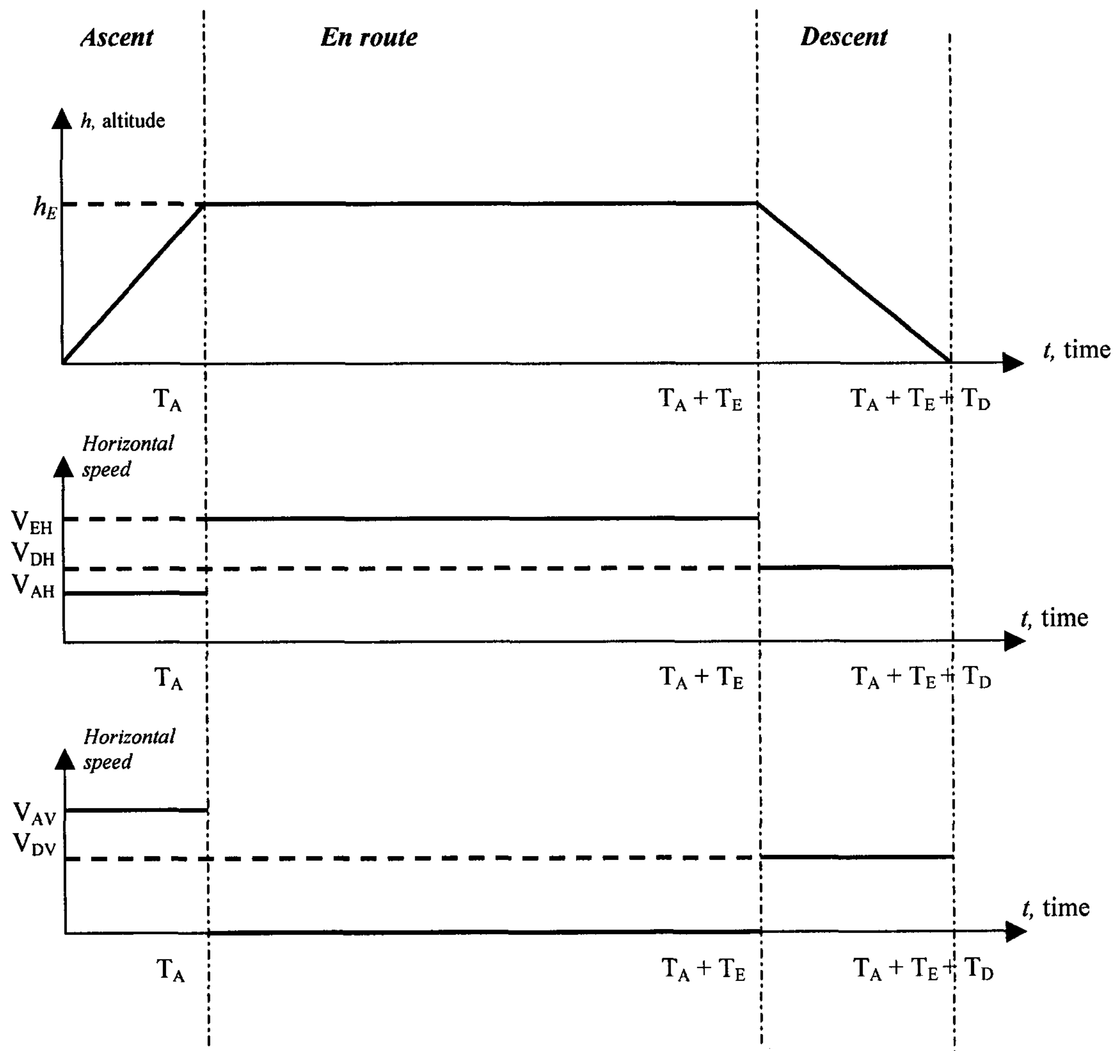

Figure 9 Altitude, horizontal and vertical aircraft speed characteristics.

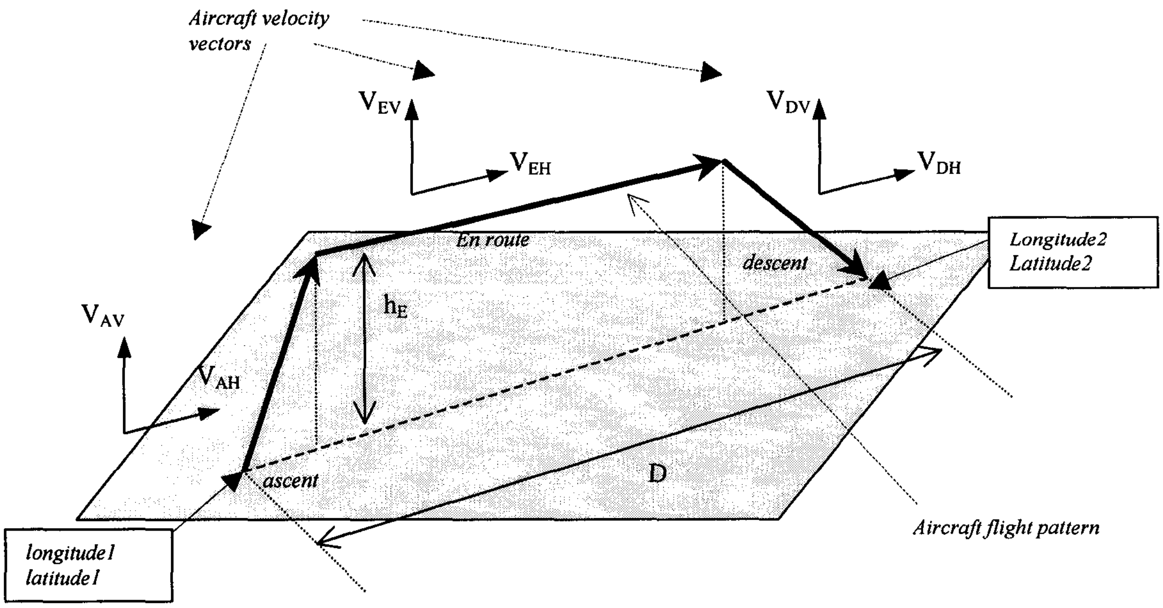

Figure 10 Explanation of the variables, used in the simulator.

Table 9 Flight segments and their mathematical representation.

Flight Phase	Interval
Ascent	$T_A \geq t$
En route	$T_A + T_E \geq t > T_A$
Descent	$T_A + T_E + T_D > t > T_A + T_E$
End of flight	$t \geq T_A + T_E + T_D$

Table 9 shows the mathematical representation of different flight phases and traveled distance $d(t)$ at time t can be calculated as follows:

$$d(t) = \begin{cases} V_{AH}.(t) & \text{for } t < T_A \\ V_{AH}.T_A + V_{EH}.(t - T_A) & \text{for } T_A \leq t < T_A + T_E \\ V_{AH}.T_A + V_{EH}.T_E + V_{DH}.(t - T_A - T_E) & \text{for } T_A + T_E \leq t < T_A + T_E + T_D \\ D & \text{for } t \geq T_A + T_E + T_D \end{cases} \qquad (4.9)$$

The altitude of the aircraft, *h(t)* at time *t* can be calculated as follows:

$$h(t)=\begin{cases} V_{AV}.t & \text{for } t<T_A \\ h_E & \text{for } T_A \le t < T_A + T_E \\ h_E - V_{DV}.(t - T_A - T_E) & \text{for } T_A + T_E \le t < T_A + T_E + T_D \\ 0 & \text{for } t \ge T_A + T_E + T_D \end{cases} \tag{4.10}$$

Let

$$\Delta lat = lat2 - lat1 \tag{4.11}$$

$$\Delta long = long2\text{-}long1 \tag{4.12}$$

The TAMDAR DSS calculates the geographical coordinates, indicated by *Lat(t)* and *Long(t)* of the aircraft for a given time value *t* as follows.

$$Lat(t) = lat1 + [\,(\,d(t) \;*\; \Delta lat\,)\,/\,D\,] \tag{4.13}$$

$$Long(t) = long1 + [\,(\,d(t) \;*\; \Delta long\,)\,/\,D\,] \tag{4.14}$$

where *lat1, long1, lat2,* and *lat2* are the coordinates of originating and destination airports respectively and *d(t)* represents the traveled distance.

The flight pattern simulator uses the time relationships in Table 9 with the distance and altitude equations to generate the expected TAMDAR data pattern. Figure 11 shows an ArcView image of simulated data point patterns for hypothetical flights between seven airports (Chicago O'Hare, Cincinnati, Cleveland, Norfolk, Washington Dulles, Newark, and New York JFK). During the flight planning phase, major factors such as thunderstorms and winds are considered by the planners. Future accuracy of the data pattern simulator can be improved by the inclusion of the filed flight plans, which provide requested flight altitudes and the planned flight routes.

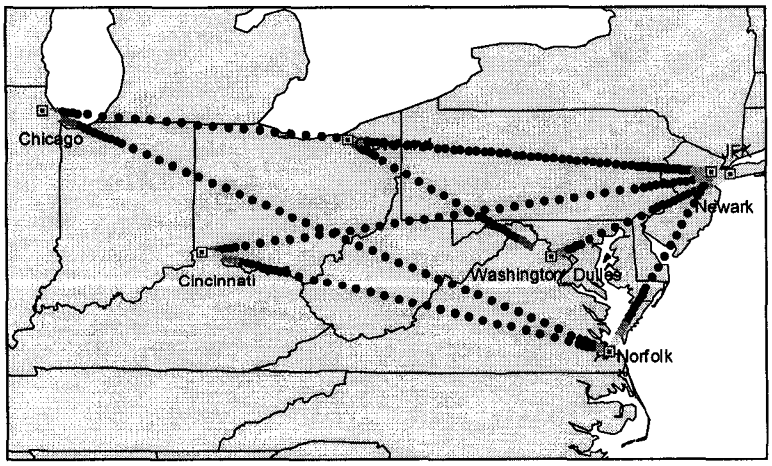

Figure 11 An example of TAMDAR-DSS flight pattern simulator's output.

Table 10 shows an example of the output of the data pattern simulator. The simulator calculates the predicted values for longitude, latitude, altitude, and time of data reporting together with the flight numbers and phases. Ascent, en route, and descent phases are represented with 1,2, and 3 respectively.

Table 10 An example of the output of the data pattern simulator.

Index no.	Flight no.	Phase	Time	Altitude (feet)	Longitude	Latitude
1	1	1	10:00:00	1,000	58.3	-68.09
2	1	1	10:01:00	2,000	58.4	-68.12
3	1	1	10:02:00	3,000	58.5	-68.30
...	...	...	...	...	...	...
232	6	2	12:08:00	18,000	56.43	-80
233	6	3	12:14:00	17,500	56.9	-80.5
...	...	...	...	...	...	...

The output of the simulator can be presented in a matrix form in which the expected data pattern for each flight segment is contained in a matrix. Therefore, the simulator output can be represented by a matrix $[D]_{N,6}$ as follows:

$$D = \begin{bmatrix} d_{11} & d_{12} & d_{13} & d_{14} & d_{15} & d_{16} \\ d_{21} & d_{22} & d_{23} & d_{24} & d_{25} & d_{26} \\ d_{31} & d_{32} & d_{33} & d_{34} & d_{35} & d_{36} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ d_{N1} & d_{N2} & d_{N3} & d_{N4} & d_{N5} & d_{N6} \end{bmatrix} \tag{4.15}$$

Where N is the number of expected number of data points, gathered and the d_{ik} element of a data point respectively. In matrix D every row corresponds to an individual data point and each column includes separate elements of data points (flight number, flight segment, data acquisition time, longitude, latitude, and altitude).

Each row of the matrix $[D]_{N,6}$ represents a TAMDAR data point in the form of a row vector, d_p , which is a 1x6 matrix.

$$d_p = \lfloor d_{p1} \quad d_{p2} \quad d_{p3} \quad d_{p4} \quad d_{p5} \quad d_{p6} \rfloor \tag{4.16}$$

d_{p1} , d_{p2} , d_{p3} , d_{p4} , d_{p5} , d_{p6} represent the flight number, flight phase, time, longitude, latitude, and altitude of data point p. d_{p3} equals to 1 for ascent phase, 2 for en route, and 3 for descent phase.

Some of the flights may not have all three flight phases, completed in the same region. In other words, they may cross a number of regions. For example, an aircraft may take off from an airport in the North Eastern Region, flies through the Southern Region and lands to an airport in the South Eastern Region. For such cases, there should be a mechanism that defines which flight segments are controlled by which centers. To address this problem, the TAMDAR DSS data pattern simulator processes the flight segments whose greater portions are located in the specified region.

In summary, the data pattern simulator provides a detailed picture of the selected data before it is collected. Temporal and spatial distribution characteristics of the data can be studied by using different visualization tools of the TAMDAR DSS. The output of the data pattern simulator becomes the input to the multi attribute utility estimator, which is explained in the next section.

4.2.2 Multi Attribute Utility Estimator

Multi attribute utility functions (MAUF) provide an effective way to measure the value of weather data. A MAUF model defines a method to combine several criteria into one overall value. This is accomplished by multiplying the value score on each attribute by the weight of that attribute and adding the weighted scores together.

Based on common meteorological practices and information gathered from experts, four main attributes were selected. The utility of a meteorological data package is related to the following attributes:

-Spatial Coverage (x_1)

-Temporal Coverage (x_2)

-Altitude Attribute (x_3)

-Priority Attribute (x_4)

The weighted additive multi attribute utility function, $u(d_p)$ of a TAMDAR data point p can be expressed as

$$u(d_p) = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4, \quad (4.17)$$

where d_p is a vector, which represents the p'th data point and x_i is the assessed value (utility) of the ith attribute. w_i, $i=1,..,m$, are scaling constants or weights of attributes (Malakooti,1991).

Each of these four attributes (x_i) is used to calculate a utility score in the TAMDAR DSS. After building utility scores for each attribute, decision makers can determine the weights (w_i) of each layer depending on their judgment.

Finally, utility values are calculated by using special single utility functions (f_i) for each attribute:

$$x_1 = f_1 (d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}) \quad (4.18)$$

$$x_2 = f_2 (d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}), \quad (4.19)$$

$$x_3 = f_3 (d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}), \quad (4.20)$$

$$x_4 = f_4 (d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}) \quad (4.21)$$

Next sections will focus on the derivations of $f_1, f_2, f_3,$ and f_4 and the descriptions of each attribute.

4.2.2.1 Spatial Coverage

Weather forecasters prefer homogenous and continuous data coverage. Under-sampling and over-sampling (because of data acquisition cost and data quality concerns) are not desired and should be avoided. In the TAMDAR-DSS, the spatial coverage attribute is integrated by a 2D map, based on data point density. Spatial utility value is calculated for each data point d_p by considering an imaginary 3-dimensional box formed around the data point (see Figure 12) whose spatial coverage utility is measured as shown with d_p in Figure 12. Horizontal box dimensions are 2° (longitude) by 2° (latitude) and the vertical edge measures 2,000 feet.

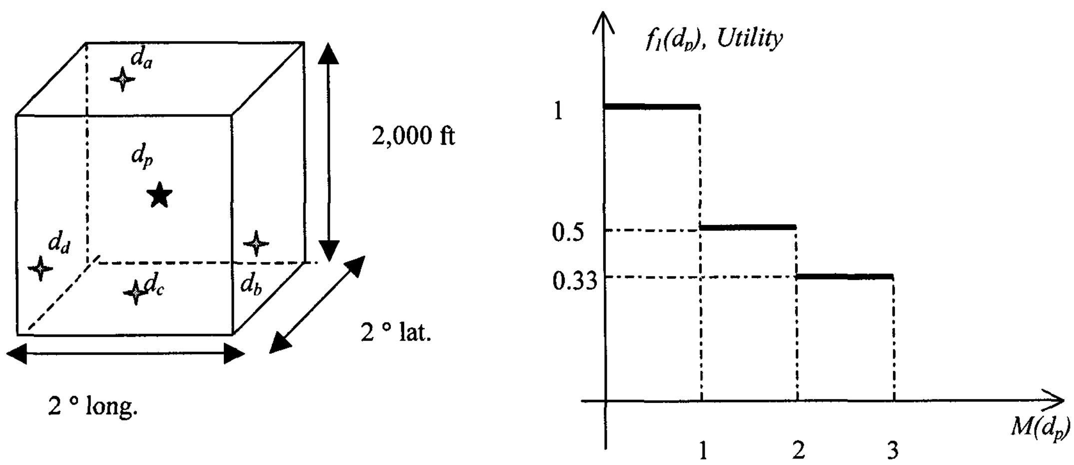

Figure 12 Calculation of the spatial data coverage attribute.

$M(d_p)$ is the count of the data groups whose time stamps are less than or equal to d_{p3} (time, data p is gathered) in the box. The spatial utility value of point d_p is established using the following function:

$$x_1 = f_1\,(d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}) \tag{4.22}$$

$$f_1\,(d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}) = 1 \,/\, M(d_p) \tag{4.23}$$

Mathematical representation of $M(d_p)$ can be derived as follows. $\kappa(d_x, d_p)$ represents the function that tests whether data point d_x resides inside the close spatial temporal neighborhood of the data point d_p, i.e., whether d_x is enclosed by the box shown in Figure 12.

$$\kappa(d_x, d_p) = \begin{cases} 1 & \text{if } [d_{x1} \neq d_{p1}] \text{ and } [d_{x3} \in (0, d_{p3})] \text{ and } [d_{x4} \in (d_{p4} - 1, d_{p4} + 1)] \text{ and } \\ & [d_{x5} \in (d_{p5} - 1, d_{p5} + 1)] \text{ and } [d_{x6} \in (d_{p6} - 1000, d_{p6} + 1000)] \\ 0 & \text{if } [d_{x1} = d_{p1}] \text{ or } [d_{x3} \notin (0, d_{p3})] \text{ or } [d_{x4} \notin (d_{p4} - 1, d_{p4} + 1)] \text{ or } \\ & [d_{x5} \notin (d_{p5} - 1, d_{p5} + 1)] \text{ or } [d_{x6} \notin (d_{p6} - 1000, d_{p6} + 1000)] \end{cases} \quad (4.24)$$

Therefore, $M(d_p)$ can be derived as follows:

$$M(d_p) = \sum_{x=1}^{N} \kappa(d_x, d_p) + 1 \quad (4.25)$$

As a result of the scheme provided above, regions where data points are abundant have lower utilities while regions and locations where data points are scarce have higher utility values. This layer is designed to ensure the inclusion of spatial coverage concerns in the final computation of the utility values.

4.2.2.2 Temporal Coverage

Forecasters also need temporally distributed data and the temporal coverage attribute is integrated into the utility function by calculating point density values in a close temporal neighborhood of each data point.

Temporal utility value is calculated for each data point $(D_{i,j})_{k,l}$ by using an algorithm, which employs a 4-dimensional imaginary box, formed around the data point as shown with $(D_{i,j})_{k,l}$ in Figure 13. Horizontal dimensions are 2° by 2° (latitude/longitude) and the vertical edge measures 2,000 feet with a time dimension of 1 hour.

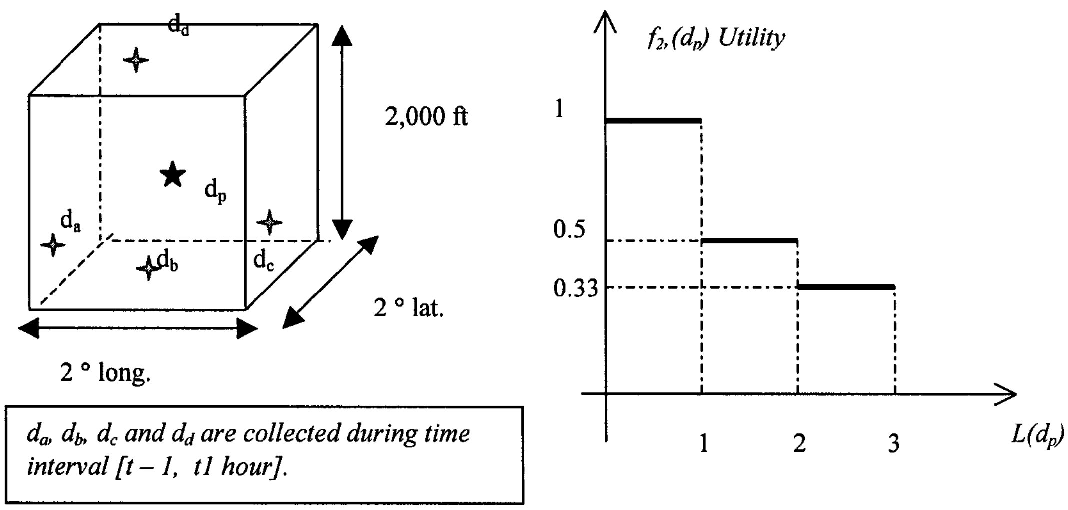

Figure 13 Calculation of the temporal data coverage attribute.

$L(d_p)$ is the count of the data groups whose time stamps are between (d_{p3}-1 hour) and d_{p3} (d_{p3} is the time, data p is gathered) in the box. The spatial utility value of point d_p is established using the following function:

$$x_2 = f_2(d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}) \tag{4.26}$$

$$f_2(d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}) = 1 / L(d_p) \tag{4.27}$$

Mathematical representation of $L(d_p)$ can be derived as follows. $\gamma(d_x, d_p)$ represents the function that test whether data point d_x resides inside the close spatial-temporal neighborhood of the data point d_p, i.e., whether d_x is enclosed by the box shown in Figure 13.

$$\gamma(d_x, d_p) = \left\{ \begin{array}{ll} 1 & \text{if } [d_{x1} \neq d_{p1}] \text{and} [d_{x3} \in (d_{p3} - 1, d_{p3})] \text{and} [d_{x4} \in (d_{p4} - 1, d_{p4} + 1)] \text{and} \\ & \quad [d_{x5} \in (d_{p5} - 1, d_{p5} + 1)] \text{and } [d_{x6} \in (d_{p6} - 1000, d_{p6} + 1000)] \\ 0 & \text{if } [d_{x1} = d_{p1}] \text{or} [d_{x3} \notin (d_{p3} - 1, d_{p3})] \text{or} [d_{x4} \in (d_4 - 1, d_{p4} + 1)] \text{or} \\ & \quad [d_{x5} \notin (d_{p5} - 1, d_{p5} + 1)] \text{or } [d_{x6} \notin (d_{p6} - 1000, d_{p6} + 1000)] \end{array} \right\} \tag{4.28}$$

Therefore, $L(d_p)$ can be derived as follows:

$$L(d_p)=\sum_{x=1}^{N}\gamma(d_x,d_p)+1 \tag{4.29}$$

As a result of the scheme provided above, regions that has frequent samplings, have lower utilities while spatial-temporal regions where data points are scarce have higher utility values. This layer is designed to ensure the inclusion of temporal coverage concerns in the final computation of the utility values.

4.2.2.3 Altitude Priorities

The utility of TAMDAR data points is also related to the altitude of the reading and this can also be represented by a utility function. Data from a recent study is employed to develop a single utility function for the altitude of a data point. Ozan and Kauffmann (2002) summarized responses to a survey administered to 133 forecasters during the 1999- 2000 period. One of the questions examined the priority of data from various altitude ranges. Figure 14 summarizes those responses: 83 participants rated the 0-6000 ft altitude range as the most valuable to have a vertical sounding, 39 marked the 6000-12000 ft. interval, 29 the 12000- 18000 ft. interval, 19 the 18000-25000 ft. interval and 12 indicted altitudes above that. The utility of sounding data decreases with increasing altitude and the majority of the participants showed that trend.

To develop an altitude attribute utility function (f_3) for the data point d_p, survey data shown in Figure 15 is normalized and the following equation is developed:

$$f_3\,(d_{p1}, d_{p2}, d_{p3}, d_{p4}, d_{p5}, d_{p6}) = 1 - 0.53\,\theta(d_{p6} - 6{,}000) - 0.12\,\theta(d_{p6} - 12{,}000) - 0.13\,\theta(d_{p6} - 18{,}000) - 0.08\,\theta(d_{p6} - 25{,}000). \tag{4.30}$$

Where d_{p6} represents the altitude of the data point p and θ(x) is the step function such that

$$\theta(x)=\begin{cases}1 \text{ if } x \geq 0\\ 0 \text{ if } x < 0\end{cases} \tag{4.31}$$

Figure 15 depicts the graphical representation of the altitude utility function (f_3).

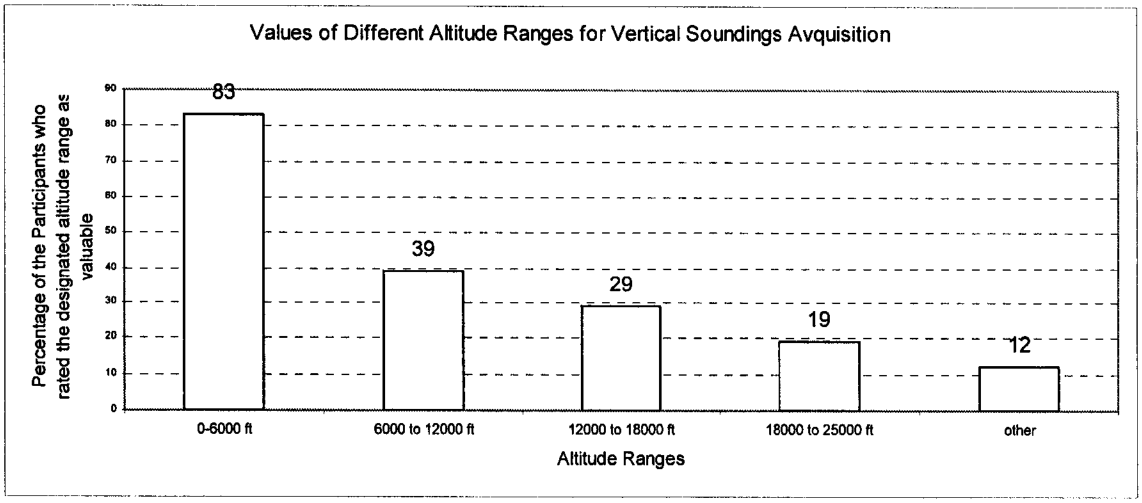

Figure 14 Relative importance of data gathered at different altitudes.

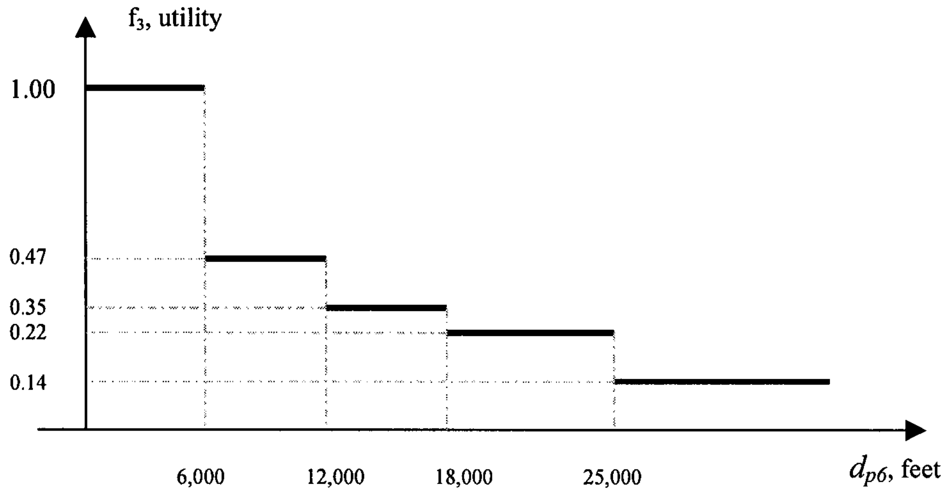

Figure 15 Altitude utility function.

4.2.2.4 Priority Ratings Attribute

The first three attributes are designed to achieve static data acquisition goals. However, there are also dynamic data collection requirements, imposed by developing weather events or other factors and the TAMDAR DSS should have an attribute to address them. The priority rating attribute accommodates these dynamic factors by designating high priority regions that require more frequent samplings.

Weather is a dynamic phenomenon and some weather events may necessitate higher sampling rates within their proximities. Significant weather events such as thunderstorms, fog, and snowstorms should be monitored closely since they have considerable economic impacts on society. For example, accurate prediction of the trajectory of a snow storm may reduce the associated weather related costs. Therefore, data points, which are close to such events should have higher utility values. In the TAMDAR DSS, weather events are encoded in terms of polygons, which are generated based on current weather conditions. To compute these polygons, data regarding daily significant weather events should be entered into the system. These data include the spatial and temporal distribution, type and intensity of the events.

Entry of significant weather events into the system can be done automatically by using weather forecast products issued by Aviation Weather Center (AWC). AWC issues a number of forecast products, which serve the needs of the aviation community. A convective SIGMET is an example of an AWC product that can be used to prioritize the weather regions for the TAMDAR DSS. Convective SIGMETs, which are accessible from http://adds.aviationweather.noaa.gov/projects/adds/airmets/ are provided in text formats that include all the relevant information about the convective activity such as location, altitude coverage, and expected time of applicability. A typical convective SIGMET text report (Source: http://www.aviationweather.noaa.gov/awc/fltfldr/6406.txt) and its map-based representation are shown in Figure 16 and Figure 17 respectively.

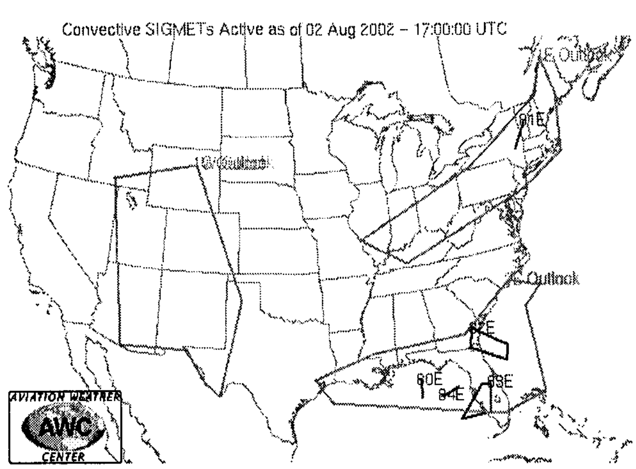

Figure 16 An example of a convective SIGMET

```
CONVECTIVE SIGMET 80E
VALID UNTIL 1855Z
FL CSTL WTRS
FROM 100S CEW-170S CEW
LINE TS 20 NM WIDE MOV FROM 02015KT. TOPS TO
FL450.
CONVECTIVE SIGMET 81E
VALID UNTIL 1855Z
VT NY
FROM 20SSW MPV-30SW ALB
LINE TS 30 NM WIDE MOV FROM 28030KT. TOPS TO FL420.
```

Figure 17 A convective SIGMET report.

AIRMET reports are similar to SIGMET and they can also be used in the TAMDAR DSS to define the priorities of regions for data collection. They are available in text or map formats. AIRMETs report hazardous weather conditions such as low visibility, icing, turbulence, and hazardous winds. Both AIRMET and SIGMET identify the spatial and temporal regions in which significant weather activities are expected. Therefore, acquiring additional TAMDAR data from these regions can improve the accuracy of the forecasts that are critical for aviation safety.

In addition to the examples mentioned above, there are other weather forecasting activities that require subjective evaluations. For example, geographical locations may present extra importance for forecasters because of their climatologic characteristics. To illustrate, jet streams play an important role in weather events in the Continental U.S. Therefore, forecasters monitor the behavior of this atmospheric phenomenon and hence geographical locations, which are close to this phenomena may have higher priority for sampling. Since climatologic data needs should span longer time ranges. They can be planned well ahead of data collection, therefore, they do not need to be updated frequently. A typical update frequency may be seasonally. In the TAMDAR DSS, a group of forecasters evaluate the data collection priorities regularly and communicate their assessment to the operator verbally or in written form. The TAMDAR DSS operator translates this assessment to a format that can be processed by the software.

The format of the priority ratings is in the form of a set of polygons defining regions of interest. Polygons can be defined by the latitude, longitude positions of their vertices. Users can describe a wide variety of geographical shapes by using polygon and this is a convenient way to communicate the priority regions. The TAMDAR DSS provides GIS capabilities, which help users to draw and define these polygons.

In summary, a typical priority rating scheme includes a set of polygons along with their altitude and times of applicability. Table 11 depicts an example, which describes how a priority region is defined. The cartographic representation of the same region is shown at Figure 18.

Table 11 An example, which explains how priority regions are coded by polygons.

Positions of Vertices (longitude, latitude)	Time Range	Altitude Range	Utility Score
(-83.10, 40.70), (-78.91, 41.26), (-78.30,39.04), (79.89, 37.03), (-82.74, 38.17), (-83.10, 40.70)	10.00AM-12.00AM	6K – 12K	0.8

Priority ratings are integrated into the TAMDAR-DSS by using a function f_4, which returns the priority attribute utility score of a data point. Assessed utility (x_4) of data point d_p is given as follow:

$$x_4 = f_4\,(d_{p1}\,,\, d_{p2}\,,\, d_{p3}\,,\, d_{p4}\,,\, d_{p5}\,,\, d_{p6}) \qquad (4.32)$$

f_4 is a temporal-spatial function, which returns the utility value of a geographical data point based on its spatial and temporal location.

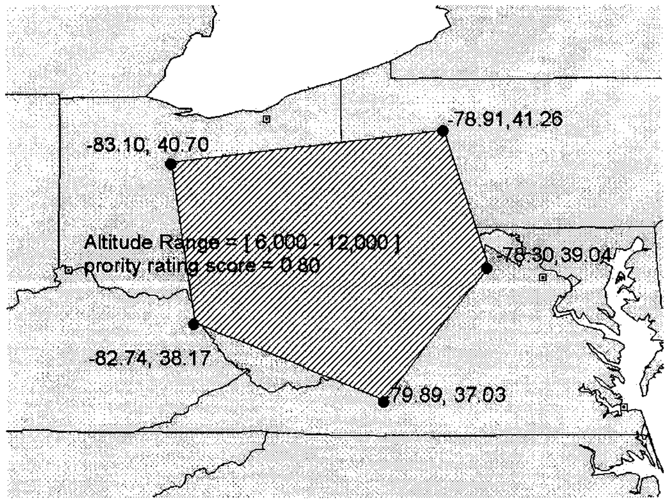

Figure 18 An example of the designation of a priority region.

In the TAMDAR DSS, each priority region is recorded in the form of a polygon and accompanying parameters. To define a priority region the following elements are identified: priority score of the region, coordinates of the polygon vertices (longitude and latitude) and altitude range (minimum and maximum), and the time interval.

Both automated significant weather reports and forecasters assessments are characterized by polygons. For example, the region, which is shown in Figure 18 can be described by its vertices, which are five geographical points, (as it is tabulated on Table 11) its altitude range (between 6,000 and 12,000 feet), and its priority score, which is 0.80.

To calculate the priority rating utility attribute of a TAMDAR data point, the model checks whether it resides inside one of the polygons, that designate priority regions. Bourke (1987) provides a simple solution to this problem of determining whether or not a point (x,y) lies inside or outside a polygon, which is often encountered in computer graphics. The solution of this problem and the software is included in Appendix B.

Once utility values are composed for each attribute and every data point for every flight, the TAMDAR DSS is ready to combine these values to form a single utility score for each flight segment. The next section describes how the TAMDAR DSS calculates the total utility value of a flight segment.

4.2.2.5 Total Utility for Segment p of Flight i

Flight segments (or phases) are the entities, which are considered the smallest decision units in the TAMDAR DSS. In other words, the model selects the flight phases but not the individual data points. Therefore, we need to calculate the utility values for each flight segment. The utility value of a flight segment j of flight i is given as follows:

$$U_{i,j} = \sum_{k=1}^{N} u(d_k) \quad \text{for all } k \text{ such that } d_{k1} = i \text{ and } d_{k2} = j. \tag{4.33}$$

where $u(d_p) = w_1 . f_1(d_p) + w_2 . f_2(d_p) + w_3 . f_3(d_p) + w_4 . f_4(d_p)$, and N is the total number of data points collected.

4.2.3 Optimization Model

The goal of the optimization engine is to maximize the total utility of TAMDAR data without exceeding the budgetary constraints. We can formulate our optimization model as follows:

$$\text{Maximize} \sum_i \sum_p U_{i,p} s_{i,p} \tag{4.34}$$

subject to:

$$\sum_i \sum_p n_{i,p} s_{i,p} < \mathrm{N} \tag{4.35}$$

where $s_{i,p}$ is an integer and $s_{i,p} = 0$ or 1. (4.36)

N is the limit for daily total number of data points collected and $U_{i,p}$ represents the total utility rate calculated for segment p of flight i. If flight i is selected for data collection $s_{i,p}$ equals to 1, meaning the sensor should be activated during that flight leg. If it is not selected $s_{i,p}$ equals 0 meaning the sensor should be switched off during that particular flight segment. The number of data point collected during flight segment i,p is given by n_i. The output contains all $s_{i,p}$ values and it can be seen as a daily list of sensor status (on or off) for all flights.

4.2.4 GIS-based Data Visualization and User Interface Module

The TAMDAR DSS provides extensive data visualization capabilities through embedded GIS components that facilitate the spatial-temporal data analysis. There are two types of GIS data visualization tools within the TAMDAR DSS: 2-dimensional and 3-dimensional. 2D data visualization is implemented by using the geographical and statistical data presentation capabilities, provided by ArcView and S-Plus software packages. With ArcView users work with geographic data in interactive maps called views and ArcView's layouts let users create full color maps by first arranging the various graphic elements on-screen the way users need them. Layouts have a live link to the data they represent. Any changes to the data are automatically included, therefore, everything on the map will be up-to-date. S-Plus complements ArcView by providing an extensive suite of spatial-temporal data visualization options.

The TAMDAR DSS also provides 3D data visualization capability, which is implemented by using the Virtual Reality Modeling Language (VRML). The VRML technology integrates three dimensional data, text, and multimedia outputs into a coherent model (Web 3D Consortium, 2000). Different layers of data can be observed in VRML viewers with an enhanced 3D spatial awareness (VRML, 1996). Figure 19 shows a screenshot that illustrates a data pattern in a 3D setting.

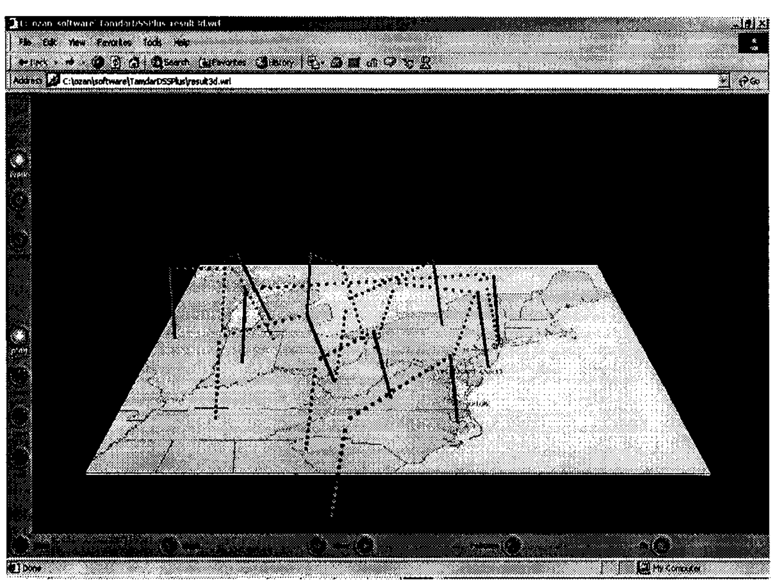

Figure 19 A screenshot showing 3D VRML data visualization

VRML viewers are useful for studying selected flight patterns in a 3D setting. Input and output flight pattern data files are converted to VRML files by using simple scripts (Kim et al., 1998, Huber, 2000). VRML also provides a rich environment to decision makers for exploratory analysis.

The example shown in Figure 20 depicts how a TAMDAR data point is coded in VRML. Each data point is represented by a sphere, centered on the geographical location of the point. The code, given in this example, also allows the use of different colors for different flight phases in order to make the output graphics more readable.

The graphical user interface (GUI) of the TAMDAR DSS is designed with Visual Basic. This provides a simple mechanism to customize features of the tool under a single module. The following functions can be invoked by using the TAMDAR DSS GUI:

- Simulation of the TAMDAR data
- GIS data visualization
- Defining weights of the utility attributes
- Modification of the utility functions
- Defining goals and constraints of the optimization
- Activation of the optimization process and report generation

```
DEF Sphere01-ROOT Transform {
 translation   712.024410426148          0           -
302.229210342418
  rotation -1 0 0 -1.571
  scale 1 1 1
  children [
   Shape {
    appearance Appearance {
     material Material {
      diffuseColor 0.2667 0.1922 0.5451
      shininess 0.25
     transparency 0
     emissiveColor 0.2667 0.1922 0.5451
     }
   }
   geometry Sphere { radius 3 }
  }
```

Figure 20 A VRML code that encodes a TAMDAR data point.

The TAMDAR DSS GUI is described in the users' manual, contained in Appendix A. An example of the main TAMDAR DSS control window is shown in Figure 21. By using the buttons and text boxes, provided on this window, users can modify different parameters of the modules such as attribute weights, utility function characteristics, and data pattern simulator parameters. As users advance through the optimization process, new windows automatically pop up requesting user input. For example, when the decision maker clicks on the "Optimize!" button, another window pop ups and asks the user to enter optimization model parameters (constraints and optimization goals).

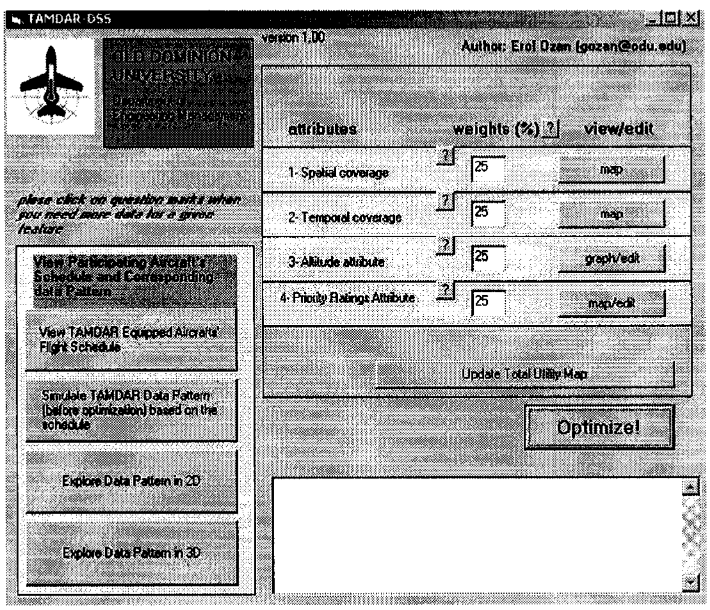

Figure 21 The TAMDAR DSS Main Window.

4.3 Summary

This chapter introduced the TAMDAR DSS model and described how the core of the TAMDAR DSS employs multi-attribute utility functions to value meteorological data. It also presented the data collection optimization scheme, the data visualization tools available and the user interface. This DSS tool employs a number of techniques and technologies including geographical information systems, simulation, and optimization models. This chapter described how the TAMDAR DSS is a unique fusion of these technologies and presents a novel approach to spatial decision analysis. The validity of the TAMDAR DSS will be demonstrated by a number of experiments and the accompanying analysis in the next chapter.

5 PERFORMANCE ANALYSIS OF THE TAMDAR DSS

This chapter analyzes the system performance of the TAMDAR DSS by assessing the accuracy and the effectiveness of the model. It also identifies a long term development strategy to improve the performance. The prime objective is to verify that the TAMDAR DSS produces results that are expected of a first generation, theoretical model. The first section of the chapter focuses on validation. The next part develops a road map for implementation and the remaining sections summarize the observations and results obtained during the design and test phases.

5.1 Test and Validation

One of the most difficult problems facing a decision support system designer is that of trying to determine whether a decision model is an accurate representation of the actual system being studied, i.e., whether the model is valid. This is particularly important and complex when a model is in early development and feasibility testing such as the case of the TAMDAR DSS. This analysis employs well established validation steps which are currently used in simulation modeling. Naylor and Finger (1967) first proposed this methodology when they identified a three-step approach for validating a simulation model. Law and Kelton (1991) augmented this approach by giving specific recommendations and examples of how to carry out each step. The approach is summarized in Figure 22.

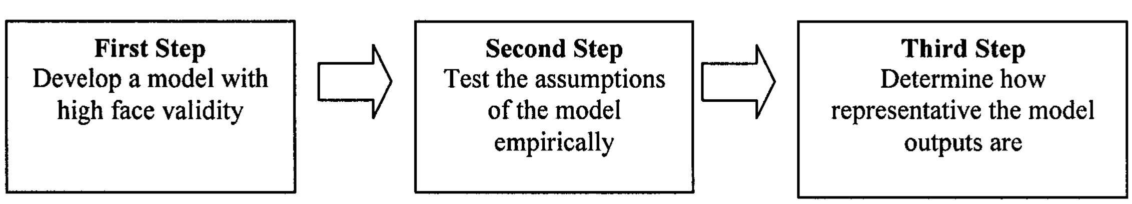

Figure 22 Three-step approach to model validation.

The primary objective for the first step is to develop a model with high face validity that ensures the credibility of the model for the people who are knowledgeable about the system under study. To achieve this, the system developers should understand the perspective of the stakeholders and evaluate the relevant subject-matter information. The goal of the second step is to test quantitatively the assumptions made during the initial stages of model development. For example, a testable assumption of the TAMDAR DSS is whether the data pattern simulator produces accurate predictions of data patterns.

The final step of the validation process involves comprehensive testing of a model's validity that is establishing that the model output data closely resemble the output data that would be expected from the actual system. If an actual system similar to the modeled one exists, then a simulation model of the existing system is developed and its output data are compared to those from the existing system itself. If the two sets of data compare favorably, then the model of the existing system is considered valid. In the case of the TAMDAR DSS, the actual system does not exist and complete testing is not possible. As a result, this research employs scenarios, which simulate the real operational environments in order to validate the system.

5.1.1 First Step: Face Validity

Face validation of DSS ensures that the designers and the potential users agree on the formulation of the problem and the general approach to solve it. It also tests whether the developed model is credible and contains all the relevant elements of the decision problem (Borenstein 1998). As a part of the face validation, the TAMDAR DSS concept was presented to a group of eighteen experts on June 12, 2002 during a semi-annual MDCRS meeting at NOAA National Weather Service Headquarters in Silver Spring, Maryland. Composition of participants were as follows:

- 7 NWS Meteorologists
- 1 NWS Contractor
- 3 NASA Aviation Experts
- 2 Airline Executives
- 3 Experts from Academia
- 1 Manager from ARINC

- 1 Expert from Forecast System Laboratory

Since these participants were knowledgeable in aircraft weather data applications, therefore, this meeting presented a valuable opportunity for evaluating the face validity of TAMDAR DSS. During the presentation, attendees were informed about the TAMDAR DSS concept, user-interface, data valuation approach, and optimization methods. After the presentation, participants provided comments on the system and their views are summarized below:

- The forecasters' priority rating attribute provides a powerful scheme and it can also have sub elements, which can be derived using a set of significant weather scenarios such as convective activity, low visibility, and icing.
- The TAMDAR DSS concept has potential to help reduce the costs.
- There are possible difficulties in composing the forecaster expert group since there are many conflicting data collection priorities among forecasters.
- Spatial and temporal coverage aspects of the data set are important and these attributes are relevant.
- The TAMDAR DSS provides a good communication medium in which different data requirements of different forecaster communities can be integrated into a single data acquisition strategy.
- One airline executive who works in the weather forecast office of a major airline, stated that TAMDAR DSS provides an effective and feasible approach to control the data acquisition and it can be applied to the current MDCRS system.

As a result of this meeting, participants generally agreed that the model was a feasible approach given that the required long term operational resources are provided. As a next step for face validation, a survey was submitted to a number of weather forecasting experts and 7 responses were received. The following criteria was employed in choosing the experts who participated in the survey:

- Having extensive professional experience and subject-matter knowledge in the area of aircraft-based meteorological data.
- Affiliation with a major organization, which is active in the area of aircraft-based meteorological data collection systems.

- Active participation in national and international meetings on aircraft-based meteorological data.

Six meteorologists and one MDCRS information systems expert participated in this survey. The three of the participants are highly regarded meteorologists, from the World Meteorological Organization, located in the United Kingdom, and the rest of the participants work in different organizations of National Oceanic and Atmospheric Administration (NOAA) in the USA. The selected experts are well-known professionals in the area of aircraft-based meteorological data collection. The survey questions focused on soliciting expert feedback on the effectiveness of the following elements:

- The multi-attribute utility approach in valuing the TAMDAR data
- The proposed utility attributes
- The developed optimization model for selecting the best flight segments
- Data Visualization Options
- Overall value of the System as a tool

The results of expert survey are tabulated in Table 12. Survey participants evaluated different aspects of the TAMDAR DSS by giving a score between 1 and 5. In this scoring system 1 corresponds to an ineffective system aspect while 5 represents a highly effective aspect. Results of the survey indicated that 6 experts gave 3 or higher rates for the effectiveness of the multi-attribute utility approach. Similarly, the effectiveness of the optimization model received scores of 3 or higher from 6 experts. The majority of the scores varied between 3 and 4, which indicates that the overall effectiveness of the system was found to be satisfactory.

One expert who gave 1 for almost all elements of the TAMDAR DSS concept, believes that it is impossible to break meteorological situations down into their components, therefore, expert systems and DSS will always fail in meteorological decision situations. His thoughts, although not shared by the other survey participants, represent the attitudes of some of the meteorologists towards decision support systems.

This survey also captured additional participant comments. Generally, these comments related more to overall system issues than to the operation of the model. For example, a major concern, expressed by several participants involved an operational concern about the possible difficulties in acquiring financial support for the TAMDAR system from the government. A secondary concern involved whether the concept of the system was cost effective. In summary, the experts agreed that the proposed model presents a reasonable approach to model and optimize TAMDAR data acquisition.

Table 12 Results of expert surveys.

	NUMBER OF PARTICIPANTS					
RATES→	**1**	**2**	**3**	**4**	**5**	**Average**
Effectiveness of the multi-attribute utility approach	1		1	5		3.43
Attributes						
Spatial Coverage Attribute	1			4	1	3.66
Temporal Coverage Attribute	1		1	4		3.33
Altitude Attribute	1		3	2		2.85
Priority Rating Attribute	1		2	4		3.42
Optimization Approach						
Effectiveness of the Optimization Model		1	3	2	1	3.42
Effectiveness of the Visualization Options						
Text-based			1	3	1	4
2D Map			1	4		3.80
3D Map	1	2		2		2.60
Overall Assessment						
User Friendliness	2		1		2	3
Sufficiency of features			1	3		3.75
Overall System Effectiveness	1		2	4		3.42
Total	**9**	**3**	**16**	**37**	**9**	

5.1.2 Second Step: Testing the Assumptions of the Model

Testing model assumptions constitutes the second step of the validation process. This section employs two groups of tests: sensitivity analysis and the validation of the data pattern simulator.

5.1.2.1 Sensitivity Analysis

Law and Kelton (1991) recommend the use of sensitivity analysis (SA) at the second stage of validation. The primary objective of SA is to examine uncertainties in the input variables and model parameters to determine how they influence outputs. As a result, SA focuses on the optimization module of the TAMDAR DSS, which processes two inputs: data volumes and utility scores of the flight segments.

Figure 23 and Figure 24 show the results of the sensitivity analysis conducted for a hypothetical situation where 50 flights are studied. This analysis was conducted based on an average day scenario and does not involve any large scale significant weather activity. As a first step, half of the flight segments whose data volume and utility score values are to be changed were selected randomly. This creates a typical asymmetry, which is expected to produce an observed measurable effect on model outputs. The first SA experiment was conducted by changing the data volume values of these selected aircraft. At the second SA experiment, the utility scores of the selected flight segments were altered and the variations in model output were recorded. In this analysis input values are changed one at a time.

Figure 23 indicates the model output is insensitive to change in utility scores between ±5%. Beyond this interval, an increase in utility variation produces an approximately linear variation in output. Figure 24 indicates the model is also insensitive to changes in data volume between approximately ± 5%. For data volume changes between 10-15%, the model output changed by approximately 2% for every 1% change in the data volume input. A 14% change in output means that the status of 14 of 100 flight segments change due to a change in the input signal.

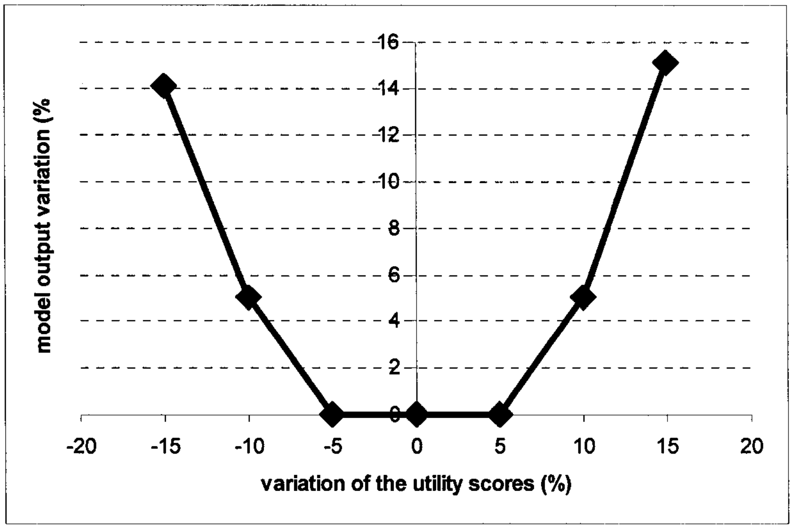

Figure 23 Variation of the model output with the utility scores.

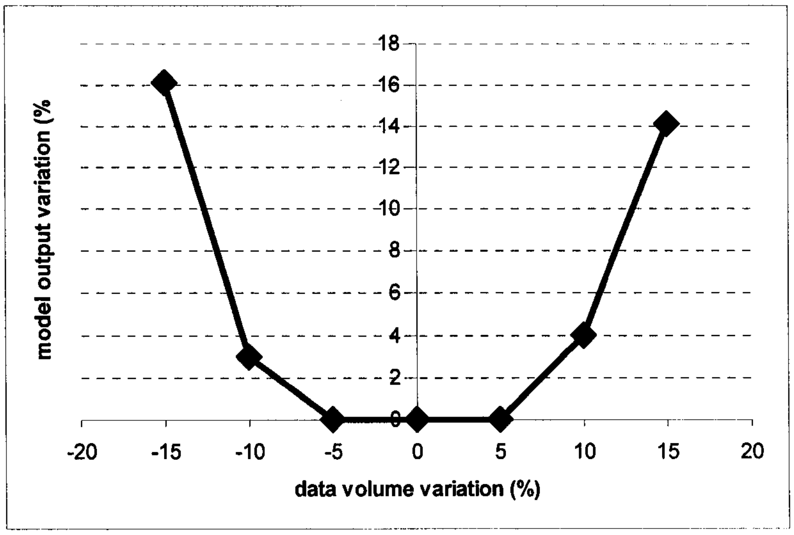

Figure 24 Variation of the model output with the estimated data volume.

The findings of SA increase the confidence in the model and its predictions by providing an understanding of how the model response varies with changes in the inputs. The tests indicate that the TAMDAR DSS optimized solution is appropriately sensitive to the input parameters. The variation of the model output is minimal for changes that are less than 10%. Therefore, the input variations ranging between –10% and 10% do not cause dramatic changes in the model output signaling that the system can tolerate reasonable amount of error levels in the inputs. If the input parameters change by more than 10% the TAMDAR DSS will output a new solution that is easily distinguished from the first.

One other major issue in the validity of the TAMDAR DSS involves the data pattern simulator since the success of the model as a whole relies on the accuracy of the simulator. The next section analyzes whether the data pattern simulator satisfies the requirements of the TAMDAR DSS.

5.1.3.2 Validation of the Data Pattern Simulator

A starting point in validating the data pattern simulator involves understanding the underlying uncertainties encountered in modeling flight patterns. Table 13 shows four possible major sources of uncertainty: weather conditions, safety-related decisions, air-traffic, and mechanical failures. Each of these has various direct impacts on different elements of flights and as a result they affect the accuracy of the data pattern simulator.

To assess the performance of the simulator, this section employs two measures: *total data volume error* (TDVE) and *model output error* (MOE). TDVE is defined as the difference (in percentage) between the actual and expected number of data points gathered from TAMDAR sensors while MOE represents the percentage change in the status of the flight segments due to system errors. These measures are chosen because they form a feasible performance measurement framework and cover all of the important aspects of data pattern variation.

The measures were selected based on the impact of the data pattern simulator on the final composition of the sensor list. In the sensitivity analysis stage, which was described in Figure 23 and Figure 24, a number of experiments were conducted using different levels of errors and measuring the impact on the output. The performance goals, in this section, are based on the consistency with the results of the sensitivity analysis. As shown in Figure 23 and Figure 24, ±5% change in data volume does not impact the output of the system. Consequently, this level was chosen as a performance goal for the data pattern simulator.

Table 13 Sources of uncertainty in the data pattern simulator.

Source of Uncertainty	Typical Direct Impact
Weather conditions	En route deviations Departure delays Flight cancellations Airport Closures
Security-related issues	Airport Closures Departure delays
Air Traffic	Arrival delays Departure Delays En route delays Unpredictable altitude and route deviations
Mechanical failures (unscheduled maintenance, equipment failures)	Departure Delays

In order to calculate MOE, sensor status lists that would result from simulated and actual flight data patterns are compared. MOE or the difference between the two sensor provides an estimate of the model performance in terms of its success in composing sensor status list correctly. For example a 3% (or MOE = 3%) error means that sensor statuses in three flight segments out of 100 are incorrectly determined.

Figure 25 shows the actual flight patterns, obtained from FAA radar records, for ten real flights. These flights were used in the analysis of the data pattern simulator's performance and Table 14 contains the output of the data pattern simulator for the same set of flights. By comparing the two sets of data patterns, we can draw a conclusion about the validity of the data pattern simulator.

For the origin and destination airports in Figure 25, the TAMDAR DSS data pattern simulator develops a simulated pattern. This result is shown in Figure 26. It represents a synthetic data pattern that simulates the coverage of the actual flights. As a second step, the TAMDAR DSS optimization module is run once with the actual data pattern (Figure 25) and then with the simulated data pattern (Figure 26). Finally, the status lists of selected flight segments (the output of TAMDAR DSS) are compared between the two runs. The results are tabulated in Table 14 and Table 15.

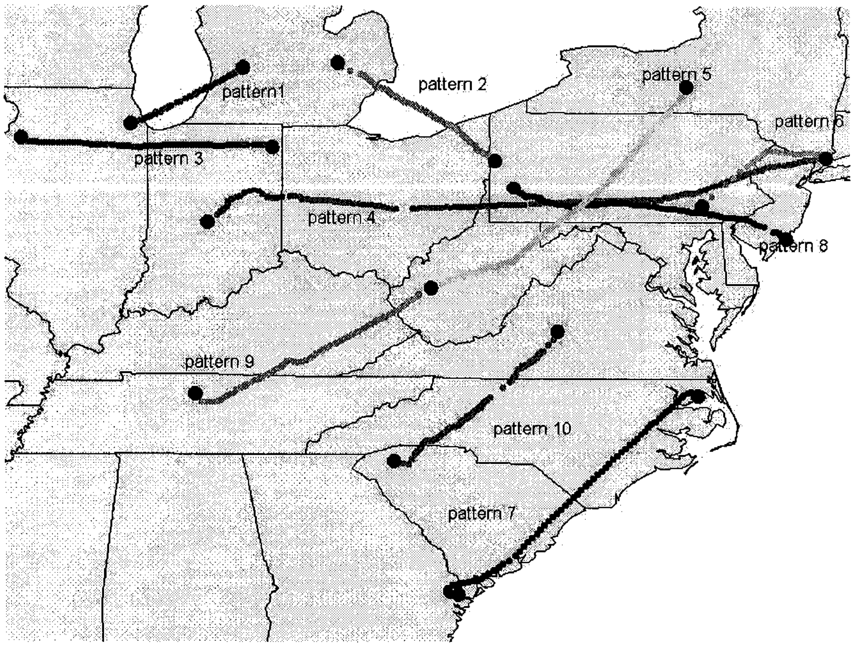

Figure 25 Real flight patterns obtained from FAA's radar records.

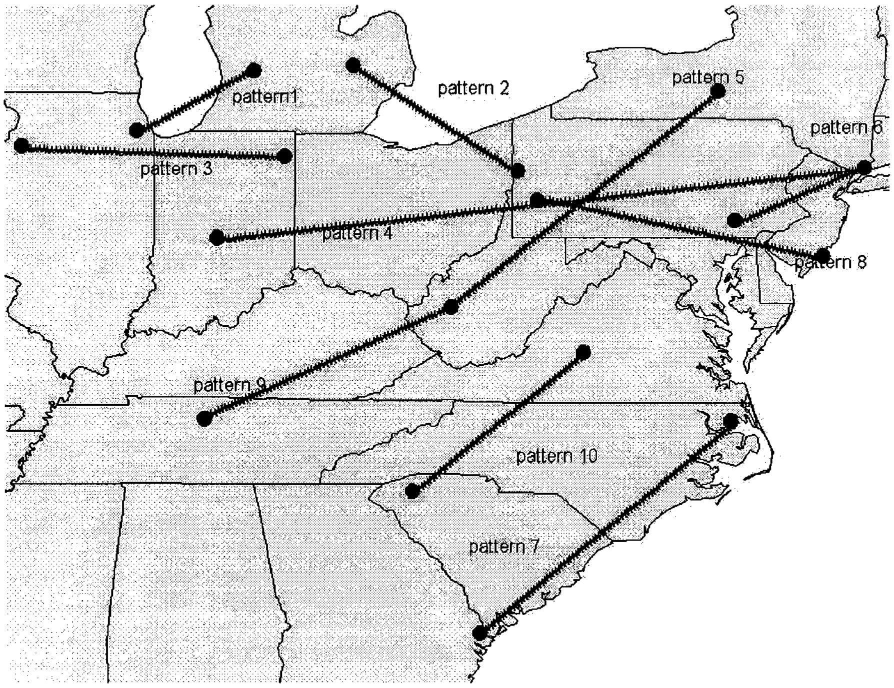

Figure 26 Distribution of the synthetic data patterns.

Table 14 Results of the Data Pattern Simulator Validation Experiment

	Ascent Phase		En route Phase		Descent Phase	
Flight no	Data Volume of the simulated data pattern	Data Volume of the actual data pattern	Data Volume of the simulated data pattern	Data Volume of the actual data pattern	Data Volume of the simulated data pattern	Data Volume of the actual data pattern
1	9	8	15	17	10	8
2	22	27	32	28	12	8
3	12	15	40	46	10	5
4	18	22	96	96	38	35
5	18	21	80	82	18	15
6	8	7	25	26	6	3
7	18	22	32	34	18	15
8	6	4	48	52	14	16
9	17	19	40	34	10	11
10	5	2	68	72	5	3
Total	133	147	476	487	131	119

Table 14 shows the comparison of the data volumes of the actual and simulated data patterns for each flight segment. Each line contains the data volume obtained during a flight and its phases. For example, although the simulator predicted that 25 data points would be collected during the en route phase of flight 6, the actual data pattern volume was 26. Similarly, for the same flight, the simulator identified six data points for descent phase while the actual volume is three. Table 14 shows how the level of data pattern simulator error varies within each flight and its segments.

The summary of the data pattern validation experiment is shown in Table 15. According to the results, data volume estimation error is 1.72 %. As a result of the errors in the data pattern estimation, only one flight segment status is determined incorrectly. In other words, the TAMDAR DSS activated the sensor in one flight segment where the sensor should have been off. Table 16 shows the final status of the sensor after optimization. The flight segment, which is miscalculated, is also shown in the table. This error level is deemed acceptable since it corresponds to 3.33% error in the model, which meets the performance goals.

As a result of the validation experiment, it is concluded that the performance of the data pattern simulator module is satisfactory. The next section examines the validation of the model as a whole, which focuses on the analysis of the model output validity.

Table 15 Summary of the Data Pattern Validation Experiment.

Summary of the Results	
Number of flight segments whose statuses are miscalculated due to errors in the simulator	1
Total Data Volume of the Simulated Data Pattern	740
Total Data Volume of the Actual Data Pattern	753
Data Volume Estimation Error	%1.72

Table 16 Sensor status list (0 meaning sensor is off, 1 meaning sensor is on).

Flight no. (Data Pattern)	**Ascent**	**En route**	**Descent**
1	1	0	1
2	1	1	1
3	1	1	1
4	1	1	0
5	1	0	0
6	**1***	0	1
7	1	1	1
8	1	1	0
9	0	1	1
10	1	1	1

5.1.3 Third Step: Measuring the Accuracy of the Model Output

Validation of the model output examines whether the system selects the best data collection scheme. To answer this question, this step evaluates whether or not implementation of the model output results in unacceptable information losses. If it is demonstrated that the eliminated data points would not cause a significant impact on the subsequent weather forecasts, the model performance is validated. As a baseline for unacceptable losses, the model output was tested against an international weather data collection standard: E-AMDAR (European AMDAR). This approach ensures that TAMDAR DSS does not cause elimination of any data required by the E-AMDAR baseline.

To conduct this validation, the TAMDAR DSS was run for 10 different flight configurations. Different numbers of flight were selected for each experiment in order to observe the behavior of the system under different loads. The result of this validation process is summarized in Table 17. The model achieved a data volume reduction of approximately 40% and still met the distribution criteria specified by E-AMDAR.

Table 17 Results of the model validation against E-AMDAR criteria.

Experiment no.	Number of Flights	Data Volume Reduction achieved (%)	Data Volume	Did the output data meet E-AMDAR criteria?
1	20	38%	2812	Yes
2	30	38%	5623	Yes
3	40	39%	6211	Yes
4	50	40%	7840	Yes
5	60	39%	9065	Yes
6	70	40%	10310	Yes
7	80	39%	10310	Yes
8	90	40%	11268	Yes
9	100	40%	16822	Yes
10	110	40%	18203	Yes

The analysis of this section supports the conclusion that the TAMDAR DSS provides adequate coverage to correctly assess the overall weather situation. The success of test and validation efforts does not suffice for final investment decisions unless they are accompanied by relevant financial measures. Therefore, the next section addresses this issue by explaining the economic benefits of the TAMDAR DSS in terms of objective monetary measures.

5.2 Economic Benefits of the TAMDAR DSS

Decision makers need a positive business case in order to implement a system. One should prove that the use of the TAMDAR DSS would result in substantial economic benefits. An economic feasibility study, which was done by Kauffmann and Ozan (2001) envisions 1,500 TAMDAR-equipped aircraft. According to TAMDAR sensor specifications (ODS, 2002), TAMDAR data is generated at ten-second intervals during ascent, three-minute intervals while en route, and one-minute intervals during descent. A survey, which analyzes the regional airlines' and package carriers' flight characteristics (Kauffmann and Ozan, 2001), concluded that the average cruise altitude for TAMDAR-equipped aircraft will be 18,000 feet, and the average flight duration will be 1.2 hours while an average TAMDAR-equipped aircraft will fly 7 hours per day.

The statistical data given above can be used to calculate the annual TAMDAR data volume without any optimization as follows. It takes approximately 18 minutes to climb 18,000 feet since turboprops have an average climb rate of 1,000 FPM (Xavius Software, 2001). During the ascent phase, an aircraft generates 108 data points. Assuming that the descent phase is symmetrical with the ascent phase, it will take 18 minutes to complete, and generate 18 points. On average, en route phase lasts 36 minutes (36 min is subtracted from 72 min, which is the total average flight time), and produces 12 data points. Therefore, each aircraft would generate 138 data points per flight, 804 data points per day and 293,460 points per year. Consequently, 1500 TAMDAR-equipped aircraft would generate 440,190,000 data points per year. Estimated cost of transmitting a TAMDAR point is $0.024. Therefore, annual data transmission costs for the fleet would be $10,564,560.

If the TAMDAR DSS produces a 40% decrease in the data volume, $4,225,824 would be saved annually. Decision makers could target different levels of savings based on the budgetary limitations, the desired data volume, or other factors. In summary, it is shown in the business case above, that the TAMDAR DSS can provide substantial economic benefits to its users.

The next section discusses observations on the practical aspects of designing the TAMDAR DSS.

5.3 Observations

Different forecasting goals require different data characteristics. For example, the data needs of a climatologist, who focuses on long-term forecasts, and those of an aviation weather forecaster, who produces short - term forecasts, may differ dramatically. Aviation weather forecasters focus on short term targeted forecasts with high resolution while a climatologist prefers to look at the greater picture with longer periods of time at much larger spatial areas. The examples are numerous that the data acquisition goals of the various weather forecasting communities are conflicting. The TAMDAR DSS has the potential to address these diverse goals.

One of the biggest challenges in designing a decision support system for the optimization of TAMDAR data is to convince meteorologists that such a system is necessary and feasible. Most meteorologists are reluctant to eliminate any data from their models even if the necessity for optimization is demonstrated with sound cost analysis. Their tendency is to gather all possible data from all available sources and filter it on the ground. The risk of losing important data points plays a crucial role in their judgment. On the other hand, installation of new sensors requires substantial funding both in recurring and non recurring areas. An optimization scheme will assure the greatest return, decrease the amount of government spending and, in the long term, result in more sensors, better data coverage, and a more useful system.

The previous point illustrates a basic difference in the perspectives of meteorologists and decision analysts. Meteorologists tend to look at weather events in a holistic perspective on a case by case basis. According to this view, it is difficult to make generalizations in weather forecasting because of the complexity of the phenomena. On the other hand, decision analysts tend to divide the system into smaller pieces and study their interactions. When forecasters are asked to identify the factors that make particular meteorological data more valuable than an alternative data source they are reluctant to answer this question directly and contend that the answer depends on each specific case.

In summary, a challenge TAMDAR will face is that decision scientists and meteorologists perceive the optimization problem differently. Forecasters generally see the weather data as essential information that is broadly applicable and should not be generally filtered. They focus on gathering and using as much high quality data as they can in order to generate their forecasts. As a result, meteorologists are reluctant to develop strategies that reduce the costs of data gathering if that includes, a priori, a reduction in data quantity.

The next section summarizes the results of this chapter by analyzing the observations and findings.

5.4 Results

The TAMDAR DSS model provides a feasible approach for optimizing data acquisition from participating aircraft. The results of the validation processes demonstrate that the developed model can be used in real operational environments and can render important economic benefits for its users. It has also been shown through a number of test runs that the model meets performance goals.

The proposed model addressed the most important issues and demonstrated the advantages of using an optimization scheme to maximize the benefit of the TAMDAR system. It demonstrates that an efficient economic analysis tool for decision makers is feasible and the business case shows that the use of this tool can reduce costs significantly. This will allow decision makers to control their data collection process effectively and meet their budgetary requirements. In addition, the concept of operations allows the TAMDAR decision makers to interact with the different elements of the decision process and provides them complete flexibility and freedom for setting their own operational goals and evaluating alternatives to meet cost goals.

Although the TAMDAR DSS requires only minimal human intervention, decision makers can increase the level of human involvement if they think it is necessary. During major storms or other critical situations, the portion of manual control can be increased.

5.5 Summary

This chapter has studied the performance of the TAMDAR DSS in optimizing the aircraft-based data collection. The TAMDAR DSS concept is based on the argument that multi-attribute utility functions can be used to value meteorological data and hence optimize the data collection. The validity of this argument has been demonstrated by a number of experiments and the factual information. This chapter has also described how TAMDAR DSS would be utilized in actual operations.

6 CONCLUSIONS

This chapter summarizes the results and findings of this research. The first section restates the main findings and contributions of this research and provides a summation of the developed model. Second, advantages of the TAMDAR DSS are discussed. In the third section, potential application areas are identified and discussed. The fourth section focuses on the future work and identifies the specific areas that can be improved over time and the final section summarizes the research effort.

6.1 Research Summary

This research focused on the economic optimization of the Tropospheric Airborne Meteorological Data Reporting (TAMDAR), aircraft-based meteorological data collection system. The TAMDAR system requires a decision support system (DSS) for efficient selection of the most desirable data points to collect based on a limited budget. This poses a number of challenging design problems including weather uncertainty, integration of subject-matter knowledge that is qualitative in some cases, geo-spatial dimensional analysis, conflicting user goals, and computational complexity. This research developed a multicriteria spatial decision support system (MC-SDSS) for identifying the best data collection scheme.

The basic operation of the TAMDAR DSS can be summarized as follows. To generate the decision alternatives, the spatial and temporal distribution of TAMDAR data is predicted before optimization. The data pattern simulator module of the TAMDAR DSS performs this task and estimates the spatial and temporal positions of data clusters. These simulated data patterns are fed to the data utility estimator module. At this stage, utility scores and data volumes of data pattern segments are computed using multi-attribute utility functions. The output of the data utility estimator module is processed by the optimization module, which ranks the flight segments according to their utility scores and data volumes and selects the best combination considering the budgetary constraints. The output of the TAMDAR DSS is a list that includes the statuses of sensors for each flight segment.

In addition to the optimization features, the TAMDAR DSS provides extensive data visualization capabilities that can be used at every stage of the decision process. System users can analyze the spatial and temporal data coverage before and after the optimization. 2D and 3D GIS-based spatial and temporal data visualization features help decision makers to analyze the TAMDAR data coverage effectively.

From a general perspective, this work presents a practical design methodology that synthesizes multi-attribute utility theory, simulation and spatial decision analysis techniques to achieve the optimization of aircraft-based weather data collection systems. The developed model has wide application and can be adapted to other weather information and data gathering problems.

6.2 Evaluation of the Contributions

The TAMDAR DSS offer many advantages and the most important is that its ability to provide a tractable decision tool that deals with a complex decision situation. The developed system helps decision makers to study the decision problem in varying levels of detail without losing the general perspective. The tool simplifies the decision problem and allows its users to focus on the higher level goals without having to deal with the micromanagement of the data coverage. The TAMDAR DSS features extensive automated data capturing and processing functionalities that require minimal human involvement, therefore, it designates an efficient command and control system for the data gathering.

Another distinctive characteristic of the TAMDAR DSS is its extensive temporal-spatial analysis capabilities. The TAMDAR DSS processes both spatial and temporal data, therefore, it furthers the available methods of analyzing spatial-temporal decision situations. The TAMDAR DSS simulation module plays a central role in spatial-temporal analysis by generating the decision alternatives and it constitutes an original application case in the field of MC-SDSS. The approaches used in the data pattern simulator provide definite advantages for decision problems involving situations in which decision alternatives of a system should be predicted.

The TAMDAR DSS also features extensive state-of-the-art data visualization capabilities that simplify the spatial and temporal analysis of the data coverage. For example, by using either 2D or 3D data presentation interfaces, decision makers can easily identify the gaps in the data coverage. Data visualization components access the same GIS database, therefore, the transitions between different data presentation formats are seamless.

6.3 Application Potential in Other Fields

The primary application area of the TAMDAR DSS is decision problems involving other meteorological data acquisition systems such as satellites, surface sensors, and weather balloons. The TAMDAR DSS is the first multicriteria spatial decision support system that is designed for the economic analysis of meteorological data collection systems. There is a substantial need for the economic optimization of the weather information gathering and the approaches developed in this work can be adapted to such systems. The meteorological data acquisition investments and operational costs of such systems require substantial government funding and the TAMDAR DSS constitutes a new tool that facilitates the economic decisions involving such systems.

As a more general application domain, the TAMDAR DSS model can also be adapted to economic optimization problems encountered in information gathering systems. Information gathering systems (IGS) are defined as systems that collect data about a particular subject. A common problem encountered in IGS is the information valuation challenge. The information valuation methodology developed for the TAMDAR DSS present a versatile approach that can be easily applied to other IGS applications. Many problems that are related to information gathering, have spatial and temporal dimensions in the decision context, and information valuation is a central issue. Other potential application areas include financial information gathering in banking (Kuljis et al., 1998), Internet-based market data collection systems (Murphy 2001), and information brokering systems (Nick et al. 1998).

6.4 Future Work

There are several areas that are open to further development. An important one is improvement of the data interface layers. Since some important system components were not accessible (e.g. interface to the actual system to turn sensors on or off), it was not possible to perform a real operational test. It is normal to expect some difficulties in connecting different elements of the system and maintaining a smooth data flow between geographically dispersed units. For example, each airline has its own command center, which regulates its communication with aircraft and each airlines' aircraft may differ from each other in terms of communication protocols. Therefore, TAMDAR DSS may require additional data interfacing layers in order to communicate with different airline communication network. It is anticipated that most of these problems can be solved through the use of additional simple software that will act as a translator between different elements of the system. Although this task is relatively simple, it will require time and resources for implementation.

The data valuation approach developed in this research provides a powerful tool that can help decision makers who work with meteorological data acquisition systems. However it was not the intent of this work to develop detailed and accurate utility functions applicable to a range of forecast needs. Specific applications of the DSS should involve continued refinement of the utility functions by surveying a larger number of experts.

6.5 Summary

This research introduces novel modeling solutions in the area of economic optimization of weather data collection systems. From a general perspective, the application presents a unique case of a spatial decision support system. It has considerable potential to generate new research avenues by providing a unifying framework to address similar problems in different disciplines. This research has developed a synergistic solution to an original problem by fusing various techniques and technologies to solve a complex decision problem.

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APPENDIX A DESCRIPTION OF THE TAMDAR DSS USER INTERFACE

Figure 27 shows the main window of the TAMDAR DSS, which appears when the program is activated. Major functional divisions of the window are indicated by different letters in Figure 27.

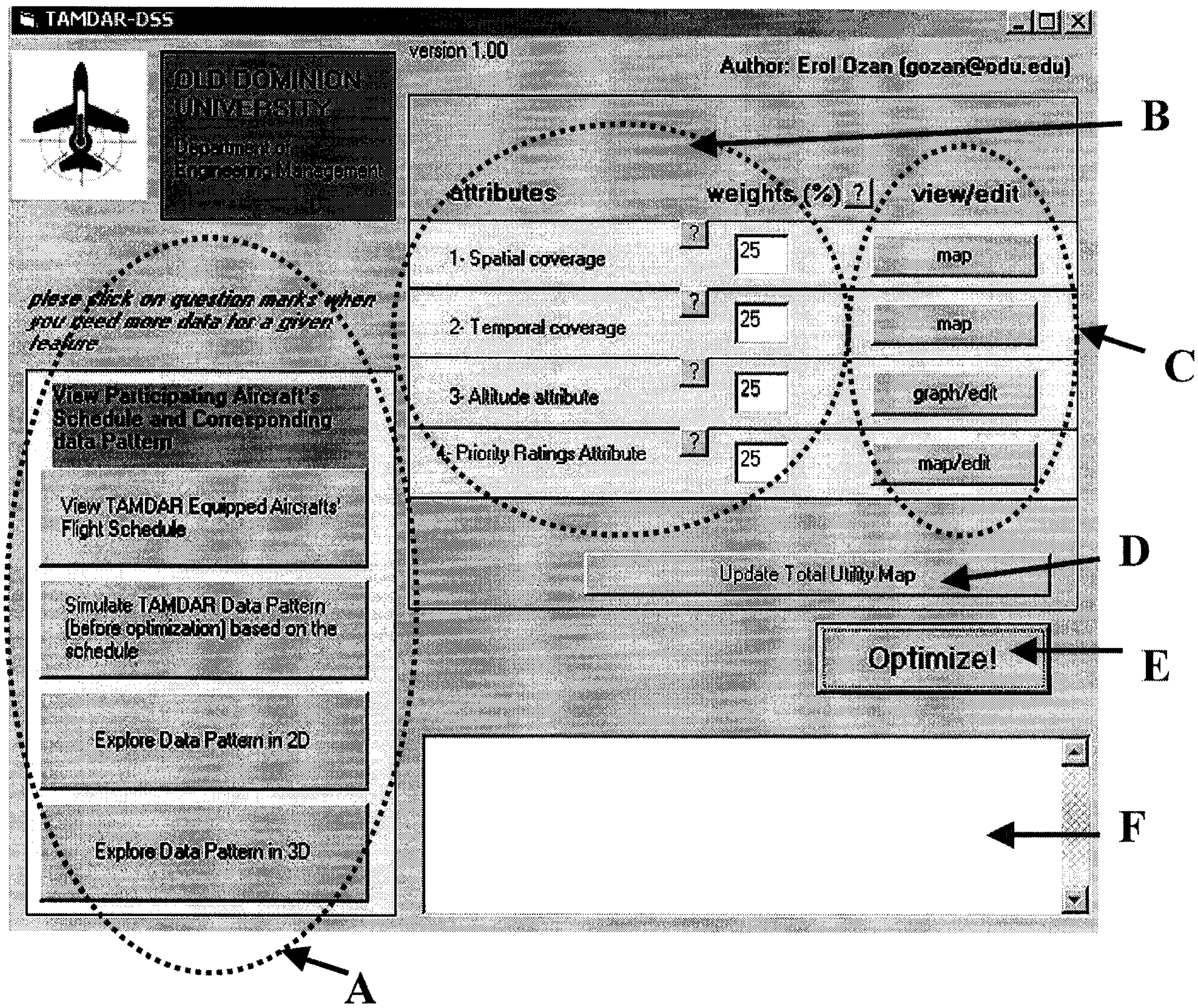

Figure 27 Main window of the TAMDAR DSS

The definitions of the control items are as follows:

- **A.** The control items in this region are for viewing TAMDAR-equipped aircraft flight schedules and the simulated TAMDAR data pattern, based on this schedule. The last two buttons are for visualizing the data pattern either in a 2D or 3D setting. For example, when the operator clicks on the button, which reads "explore data pattern in 2D", the 2D map, shown in

- Figure 28 pops up. Similarly, users view the data pattern in 3D as shown in Figure 29 and Figure 30.
- **B.** The control elements, indicated by "B" are used for modifying the weights of the utility attributes. Weight factors are entered into the designated boxes.
- **C.** Additional information or attribute modification functionality can be accessed by the buttons in this region.
- **D.** After modifying the utility weights, utility scores of each flight segment are computed by clicking on this button.
- **E.** The operator starts the optimization process by clicking on this button. The window shown in Figure 31 appears and the operator is given a final opportunity to adjust the data reduction goal.
- **F.** This region is for displaying text messages to the user. When users click on the small buttons, designated with question marks, an explanation of the features of the software is displayed in this text box.

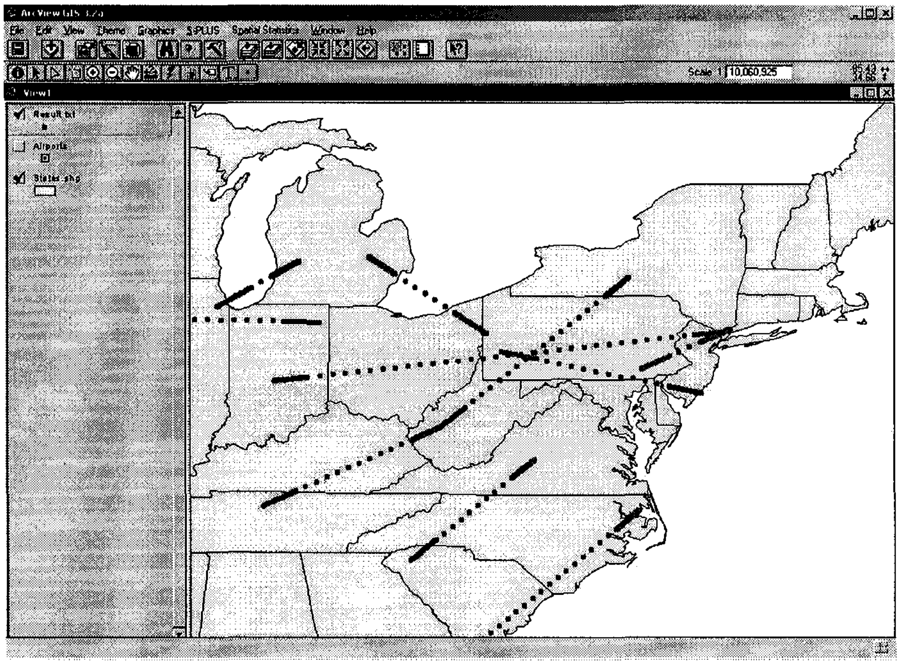

Figure 28 Simulated TAMDAR data pattern in 2D view mode.

A.1 Data Visualization

The TAMDAR DSS has extensive GIS data visualization capabilities. Figure A.2 shows the 2D map of a simulated TAMDAR data pattern, which is rendered by ArcView. A 3D visualization option is also available, as shown in Figure 29. Figure 30 shows a view taken from a different camera angle. The TAMDAR DSS features extensive 3D navigation functions, which include options such as zooming, panning, virtual fly over, camera roll, and virtual walk through.

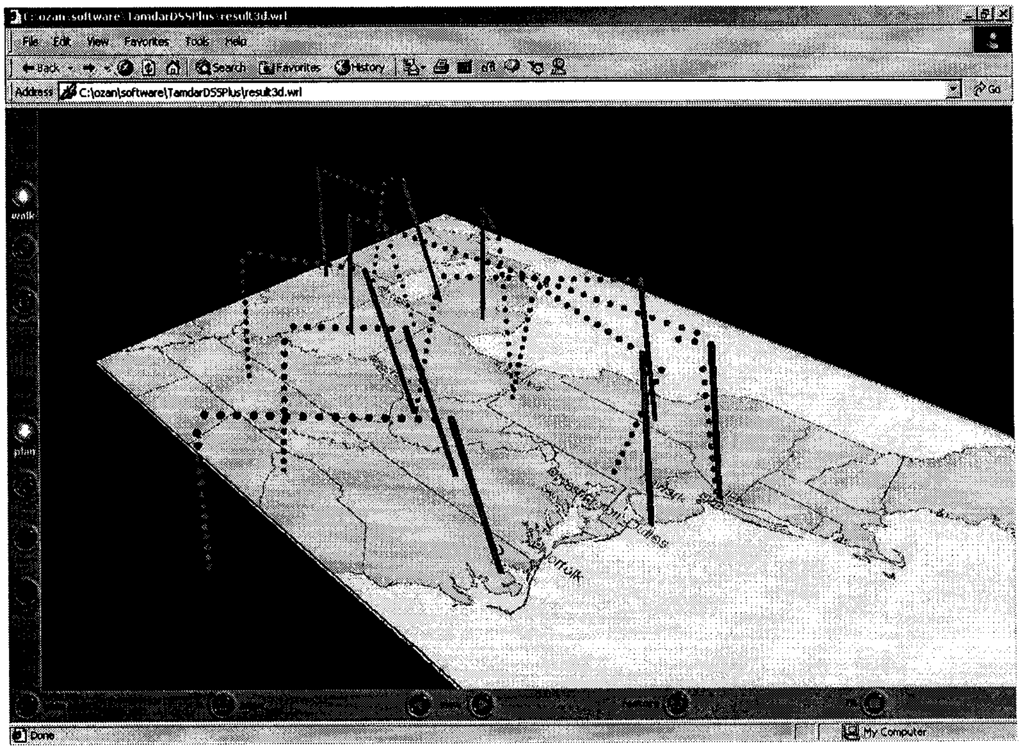

Figure 29 Simulated TAMDAR data pattern in 3D view mode.

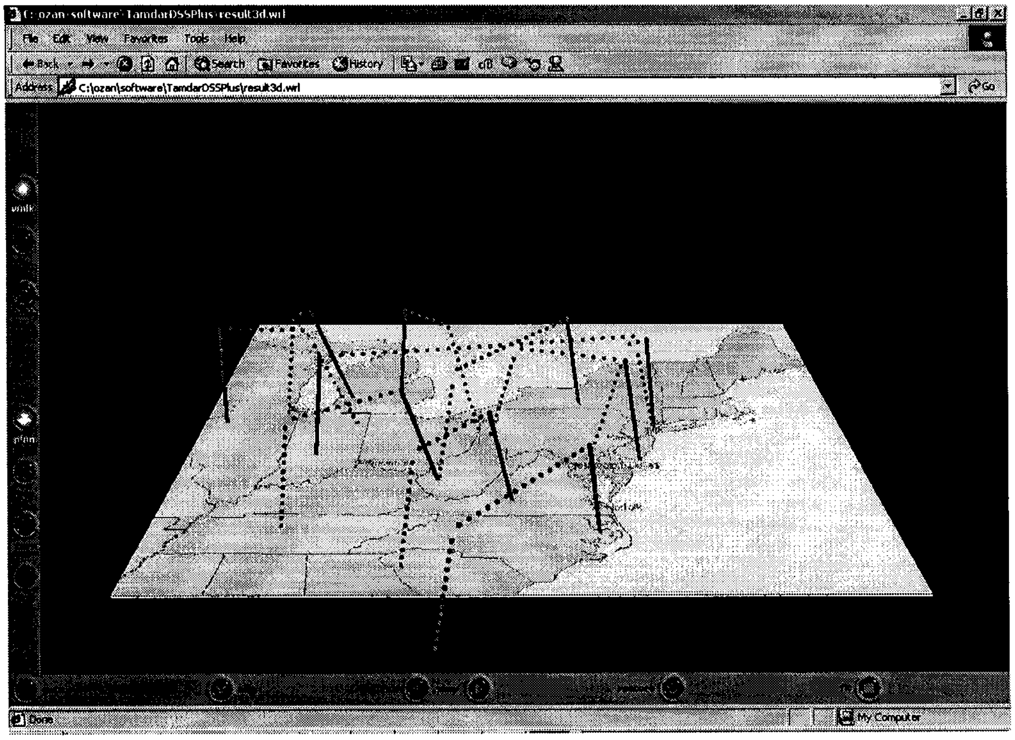

Figure 30 Simulated TAMDAR data pattern in 3D view mode (different angle)

A.2 Modifying Utility Attributes

The TAMDAR DSS operator chooses the utility weights based on the type of the impending weather and forecast goals of the meteorologists. Since this particular case depicts no significant weather activity, the operator chooses 25% weights for all attributes.

As a next step, the operator records the forecasters assessments into the system, if any new priority assessment is received. Forecasters assessments are entered by modifying the text file named "priority_regions.txt". In this file, each line corresponds to a priority region identified by polygon coordinates, altitude ranges, and the time of applicability. After completing this process, she clicks on the "update total utility map" in order to make the modifications effective.

A.3 Optimization

After completing above procedures, the TAMDAR DSS is ready for the optimization process, which can be invoked by clicking on the "optimize button" at the main window. As a result of this operation, the window, shown in Figure 31 appears and the operator can specify the data reduction rate target desired. The reduction rate is entered as a percentage. For example, if the operator enters 40 into the designated box, that means 40% of data points will be eliminated after the optimization. After completing the selection of the data volume rate, the operator clicks on the button that reads "run optimization", and the TAMDAR DSS completes the optimization. Results of the optimization are reported in the form of text files.

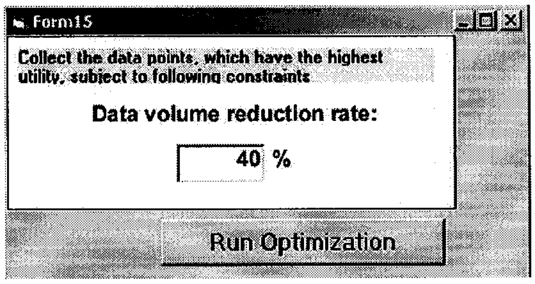

Figure 31 Specifying the data volume reduction rate.

A.4 Summary

Figure 32 summarizes the flow of the operations in the TAMDAR DSS. At the first step, the spatial and temporal distribution of TAMDAR data coverage is simulated. As a next step, the output of the simulator is processed by the utility estimator module. This module computes the utility scores of each flight pattern. The final step invokes the optimization and computes the output file, which contains the sensor status list.

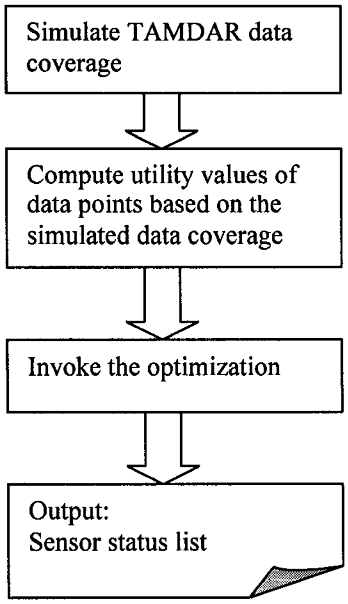

Figure 32 Flow of the TAMDAR DSS.

APPENDIX B TAMDAR DSS SOFTWARE CODES

This section includes the software codes of the TAMDAR DSS, which were written in Visual Basic and S-Plus programming language.

B.1 User Interface and Utility Estimator Software

This section presents the Visual Basic program that provides the user interface routines and utility estimation functionality of the TAMDAR DSS.

Form1

```
Private Sub Command1_Click()
        t= Shell("explorer optimizer.ssc", 1)
        t = DoEvents() 'process Windows events
End Sub

Private Sub Command10_Click()
        Text9 = "This attribute conveys information regarding the temporal distribution
        of the data. Data points, which are collected during time intervals with low data
        volume rates (e.g. between 2 am and 6 am) present higher utility values."
End Sub

Private Sub Command11_Click()
        Text9 = "Utility of TAMDAR data points is also related to the altitude of the
        data point. As a general principle, data points, collected at lower altitudes have
        higher utility."
End Sub

Private Sub Command12_Click()
        t = Shell("explorer result3d.wrl", 1)
        t = DoEvents() 'process Windows events
End Sub

Private Sub Command13_Click()
        t = Shell("explorer schedule.apr", 1)
        t = DoEvents() 'process Windows events
End Sub

Private Sub Command14_Click()
                Text9 = "Forecasters can enter their subjective evaluations for data
                valuation by editing this attribute layer."
End Sub

Private Sub Command15_Click()
```

```
        Text9 = "This section is for decision makers to enter the system constraints.
        They determine the maximum number of data points to be collected for a given
        time interval based on their budget. They can also enter the maximum allowable
        compromise for the total value of the data. Since some of the data points are
        eliminated during optimization, a decrese in data utility would be observed."
End Sub

Private Sub Command16_Click()
    t = Shell("notepad flights.txt", 1)
    t = DoEvents() 'process Windows events
End Sub

Private Sub Command17_Click()
        t = Shell("datapatternplus.exe", 1)
        t = DoEvents() 'process Windows events
End Sub

Private Sub Command18_Click()
        Form12.Show
End Sub

Private Sub Command2_Click()
        t = Shell("explorer spatial.apr", 1) 'activates arcview iamge
        t = DoEvents() 'process Windows events
End Sub

Private Sub Command3_Click()
        t = Shell("explorer temporal.apr", 1)
        t = DoEvents() 'process Windows events
End Sub

Private Sub Command4_Click()
        Form8.Show
End Sub

Private Sub Command5_Click()
        Dim priority_array(5, 10) As Double
        Dim priority_lat(5) As Double 'length of priority table

Dim lat_array()     ' Declare dynamic array.
Dim long_array()
Dim flight_no_array() As Integer
Dim flight_id_array() As String
Dim t_array()
Dim h_array()
Dim utility_s()
Dim utility_t()
```

```
Dim utility_a()
Dim utility_f()

'lat_pos , long_pos, flight_id, distance, h, t

ReDim lat_array(1)
ReDim long_array(1)
ReDim flight_no_array(1)
ReDim flight_id_array(1)
ReDim t_array(1)
ReDim h_array(1)
ReDim utility_s(1)
ReDim utility_t(1)
ReDim utility_a(1)
ReDim utility_f(1)

'-----------------define forecasters rating here-----------
segment_long = Array(-89, -87.3, -85.6, -83.9, -82.2, -80.5, -78.8, -77.1, -75.4, -73.7)
segment_lat = Array(36, 37.75, 39.5, 41.25, 43)
'--------------------------------------------------------
n = 1
'----------------Define File Names--------------------
inputfile = "result.txt"
outputfile = "output.txt"
forecasters_input_file = "priorityinput.txt"
forecasters_output_file = "priorityoutput.txt"
'---------------------------------------------------------

Open inputfile For Input As #1 ' Open file for input.
Open outputfile For Output As #2 ' Open file for output.
Open forecasters_input_file For Input As #3
'Open forecasters_output_file For Output As #4

'Capture forecasters input into array
X1 = 1
Do While ((Not (EOF(3))) And (X1 < 6))

        Input #3, priority_array(X1, 1), priority_array(X1, 2), priority_array(X1, 3),
        priority_array(X1, 4), priority_array(X1, 5), priority_array(X1, 6),
        priority_array(X1, 7), priority_array(X1, 8), priority_array(X1, 9),
        priority_array(X1, 10)
        'Print #4, priority_array(X1, 1), priority_array(X1, 2), priority_array(X1, 3),
        priority_array(X1, 4), priority_array(X1, 5), priority_array(X1, 6),
        priority_array(X1, 7), priority_array(X1, 8), priority_array(X1, 9),
        priority_array(X1, 10)
        X1 = X1 + 1
Loop
```

```
Print #2, "no", "f_no", "util_s", "util_t", "util_a", "util_f", "lat", "long", "t"
Input #1, flight_no, lat_pos, long_pos, flight_id, distance, h, t

Do While Not EOF(1) ' Loop until end of file.


        Input #1, flight_no, lat_pos, long_pos, flight_id, distance, h, t
        flight_no_array(n) = flight_no
        long_array(n) = long_pos
        lat_array(n) = lat_pos
        flight_id_array(n) = flight_id
        h_array(n) = h
        t_array(n) = t
        utility_s(n) = 0
        utility_t(n) = 0
        utility_a(n) = 0
        utility_f(n) = 0
        n = n + 1

        ReDim Preserve lat_array(n)
        ReDim Preserve long_array(n)
        ReDim Preserve flight_no_array(n)
        ReDim Preserve flight_id_array(n)
        ReDim Preserve t_array(n)
        ReDim Preserve h_array(n)
        ReDim Preserve utility_s(n)
        ReDim Preserve utility_t(n)
        ReDim Preserve utility_a(n)
        ReDim Preserve utility_f(n)

Loop
Close #1

sizeofresult = n - 1
resultdensity = 0

For k = 1 To sizeofresult
   density = 0
   timedensity = 0

   '--------------------------parameters-----------------------
   delta_spatial = 0.5 'the dimension of the square around each data point (in degrees)
   delta_temporal = 1  'length of time interval (hr)
   '--------------------------------------------------------------
```

```
'equations to define spatial neigborhood
latmax = lat_array(k) + delta_spatial
latmin = lat_array(k) - delta_spatial
longmax = long_array(k) + delta_spatial
longmin = long_array(k) - delta_spatial

'equations to define temporal neigborhood
delta_t_min = t_array(k) - delta_temporal
delta_t_max = t_array(k) + delta_temporal

lastflightno = 0
targetflightno = flight_no_array(k)

    For i = 1 To sizeofresult

        'logical expressions to identify spatial neighbours
        a = (lat_array(i) < latmax)
        B = (long_array(i) < longmax)
        C = (lat_array(i) > latmin)
        d = (long_array(i) > longmin)
        e = (flight_no_array(i) Eqv lastflightno)
        F = (flight_no_array(i) Eqv targetflightno)

        'Logical expressions for temporal utility
        G = (t_array(i) < delta_t_max)
        G2 = (t_array(i) > delta_t_min)

            If (a And B And C And d And (Not e) And (Not F)) Then
                density = density + 1
                lastflightno = flight_no_array(i)

            Else
            End If

            If (a And B And C And d And (Not e) And (Not F) And G And
G2) Then

                timedensity = timedensity + 1
                lastflightno = flight_no_array(i)

            Else
            End If

    Next i

'define spatial utility function here
utility_s(k) = 1 / (density + 1)
```

```
'define temporal utility function here
utility_t(k) = 1 / (timedensity + 1)

'define altitude utility function here
pntd = Form8.pointd
pnta = Form8.pointa
pntb = Form8.pointb
pntc = Form8.pointc

If (h_array(k) <= pntb) Then
utility_a(k) = 1
Else
utility_a(k) = pnta + ((pntd - pnta) * Exp((4 / pntc) * (pntb - h_array(k))))

End If

'define priority utility function here
priorityconditions = "prioritycond.txt"
Open priorityconditions For Input As #7 ' Open file for input.

'Input #7, xxx1, xxx2, xxx3, xxx4, xxx5, xxx6, xxxx7, xxx8

Do While Not EOF(7) ' Loop until end of file.

        Input #7, time_min, time_max, altitude_min, altitude_max, long_min, long_max,
lat_min, lat_max
        'logical expressions for checking priority regions
        expa = (lat_array(k) < lat_max)
        expb = (long_array(k) < long_max)
        expc = (lat_array(k) > lat_min)
        expd = (long_array(k) > long_min)
        expe = (h_array(k) > altitude_min)
        expf = (h_array(k) < altitude_max)
        expG = (t_array(k) < time_max)
        expG2 = (t_array(k) > time_min)

                If (expa And expb And expc And expd And expe And expf And expG
        And expG2) Then

                utility_f(k) = 1
                Else
                utility_f(k) = 0.125  ' default priority rate

                End If
Loop

Close #7
```

```
density = 0
timedensity = 0

'print results to output.txt file
Print #2, k, flight_no_array(k), utility_s(k), utility_t(k), utility_a(k), utility_f(k),
lat_array(k), long_array(k), t_array(k)
number_of_flights = flight_no_array(k)
Next k

Dim segment_utility() As Double
ReDim segment_utility(number_of_flights, 3)

Dim segment_data_volume() As Double
ReDim segment_data_volume(number_of_flights, 3)

'Weights of attributes
w1 = Text2 / 100 'spatial utility attribute
w2 = Text3 / 100 'temporal utility attribute
w3 = Text4 / 100 'altitude utility attribute
w4 = Text7 / 100 'forecasters ratings utility attribute

For counter2 = 1 To number_of_flights
segment_utility(counter2, 1) = 0
segment_utility(counter2, 2) = 0
segment_utility(counter2, 3) = 0

segment_data_volume(counter2, 1) = 0
segment_data_volume(counter2, 2) = 0
segment_data_volume(counter2, 3) = 0

Next counter2

For qq = 1 To k
indexi = flight_no_array(qq)
If flight_id_array(qq) = "a" Then
segment_utility(indexi, 1) = segment_utility(indexi, 1) + w1 * utility_s(qq) + w2 *
utility_t(qq) + w3 * utility_a(qq) + w4 * utility_f(qq)
segment_data_volume(indexi, 1) = segment_data_volume(indexi, 1) + 1
End If
Next qq

For qqq = 1 To k
indexi = flight_no_array(qqq)
If flight_id_array(qqq) = "e" Then
segment_utility(indexi, 2) = segment_utility(indexi, 2) + w1 * utility_s(qqq) + w2 *
utility_t(qqq) + w3 * utility_a(qqq) + w4 * utility_f(qqq)
```

```
segment_data_volume(indexi, 2) = segment_data_volume(indexi, 2) + 1
End If
Next qqq

For qqqq = 1 To k
indexi = flight_no_array(qqqq)
If flight_id_array(qqqq) = "d" Then
segment_utility(indexi, 3) = segment_utility(indexi, 3) + w1 * utility_s(qqqq) + w2 *
utility_t(qqqq) + w3 * utility_a(qqqq) + w4 * utility_f(qqqq)
segment_data_volume(indexi, 3) = segment_data_volume(indexi, 3) + 1
End If
Next qqqq
segment_utility_file = "segmentutility.txt"
utility_file = "utilityvector.txt"
Open segment_utility_file For Output As #5 ' Open file for output.
Open utility_file For Output As #6 ' This file simply includes utility values.
tt = 1
kk = 1

For counter3 = 1 To number_of_flights

Print #5, tt, counter3, segment_utility(counter3, 1), segment_data_volume(counter3, 1),
"a"
tt = tt + 1
Print #5, tt, counter3, segment_utility(counter3, 2), segment_data_volume(counter3, 2),
"e"
tt = tt + 1
Print #5, tt, counter3, segment_utility(counter3, 3), segment_data_volume(counter3, 3),
"d"
tt = tt + 1

Next counter3

Close #1
Close #2  'close file
Close #4
Close #5
Close #6
Close #3

t = Shell("notepad segmentutility.txt", 1)
t = DoEvents() 'process Windows events

End Sub

Private Sub Command6_Click()
Form2.Show
```

```
End Sub

Private Sub Command7_Click()
Form11.Show
End Sub

Private Sub Command8_Click()
Text9 = "Weight values represent the relative importance of each utility atribute.
Decision makers select different weight combinations for different weather and air-
traffic conditions."

End Sub

Private Sub Command9_Click()
Text9 = "This attribute conveys information regarding the spatial distribution of the
data. Data points, which are located in lower data point density areas have higher utility
values."
End Sub

Private Sub Form_Load()

Form8.pointd = 1
Form8.pointa = 0.25
Form8.pointb = 18000
Form8.pointc = 22000
End Sub
```

<u>Form2</u>

```
Private latpos As Double
Private longpos As Double
Private hh As Double
Private Sub Command1_Click()

t = Shell("explorer optimized.apr", 1)
    t = DoEvents() 'process Windows events
End Sub

Private Sub Command2_Click()
 t = Shell("notepad optimized.txt", 1)
    t = DoEvents() 'process Windows events
End Sub

Private Sub Command3_Click()

Dim SourceFile2, DestinationFile2

SourceFile2 = "optimized.txt"  ' Define source file name.
```

```
DestinationFile2 = "input3d.txt"    ' Define target file name.
FileCopy SourceFile2, DestinationFile2    ' Copy source to target.

 t = Shell("3dconvert.exe", 1)
 t = DoEvents() 'process Windows events

End Sub

Private Sub Command4_Click()
 t = Shell("notepad sensor.txt", 1)
      t = DoEvents() 'process Windows events
End Sub

Private Sub Form_Load()

Open "report.txt" For Input As #8

Input #8, dmmy1, dmy2, dmmy3
Input #8, dmmy4, before_optimization_volume, after_optimization_volume
Close #8
Text3 = after_optimization_volume
Text6 = before_optimization_volume
Text7 = before_optimization_volume - after_optimization_volume
Text2 = after_optimization_volume * Text5
Text1 = Text7 * Text5
Text8 = 100 - (100 * (after_optimization_volume / before_optimization_volume))

End Sub
```

<u>Form8</u>

```
Public pointa As Double
Public pointb As Double
Public pointc As Double
Public pointd As Double
Private Sub Command1_Click()
pointd = Text1
pointa = Text2
pointb = Text3
pointc = Text4
End Sub

Private Sub Form_Load()
Text1 = pointd
Text2 = pointa
Text3 = pointb
Text4 = pointc
End Sub
```

B.2 Optimization Module Software

The following software provides the optimization functionality for the TAMDAR DSS and written in S-Plus programming language.

```
optimizer<-function()

## input file: utilitytable
{
    g <-as.list(utilitytable)
    totalvolume <- sum(utilitytable$volume)  ## total volume of the data set before
                                              ##optimization
    percentageshift <- 0.95   ## enter here acceptable decrease (%) in data volume
                              ##(e.g. for 20% decrease enter 0.8)
    upvolume <- percentageshift * totalvolume ## upper limit of data volume
    sizen <- nrow(utilitytable)  ## reads the size of input file

    a <- Set(1:sizen)
    i <- Element(set = a)
    x <- IntegerVariable(index=i, type=binary)
    listdata <- list(1:sizen,g$utility)
    u <- Parameter (listdata,index=i)
    listdata2 <- list(1:sizen,g$volume)
    u2 <- Parameter (listdata2,index=i)
    x[i] ~ 0
    0 <= Sum((x[i]*u2[i]),i) <= upvolume    ## system constraint
    f <- Objective(type = maximize)
    f ~ Sum((u[i]*x[i]),i)                  ## objective function
}

s1 <- System(model=optimizer)        ## build a system
solve(s1,f)$variables$x$current
solution <- current(s1,x)
solution
objec <- current(s1,f)
objec
yield <- 100 * (objec / sum(utilitytable$utility))
yield
```

B.3 Polygon Test Software

The algorith explained in this section is a standard approach developed by Bourke (1998). In this algorithm, N represents the number of polygon vertices (x_i,y_i) where i ranges from 0 to N-1. The last vertex (x_N,y_N) is assumed to be the same as the first vertex (x_0,y_0), that is, the polygon is closed. To determine whether a point (x_p,y_p) is inside the polygon we consider a horizontal ray emanating from the point (x_p,y_p) and to the right. If the number of times this ray intersects the line segments making up the polygon is even then the point is outside the polygon. On the other hand, if the number of intersections is odd then the point (x_p,y_p) lies inside the polygon. Figure 33 illustrates the concept described above.

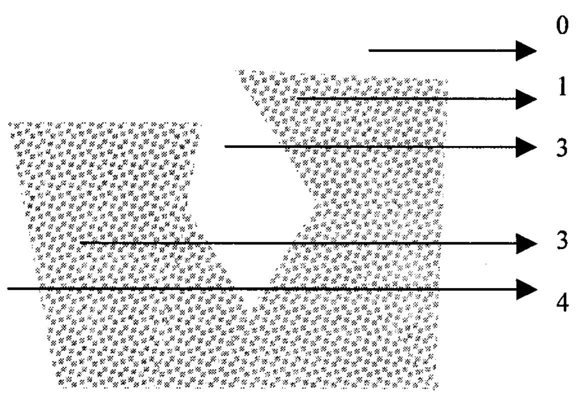

Figure 33 Horizontal rays used in polygon test.

For the purposes of this discussion 0 will be considered even. The test for even or odd will be based on modulus 2, that is, if the number of intersections modulus 2 is 0 then the number is even, if it is 1 then it is odd.

The difficulties occur when an edge or vertex of the polygon lies on the ray from (x_p,y_p). Figure 34 shows such possible cases.

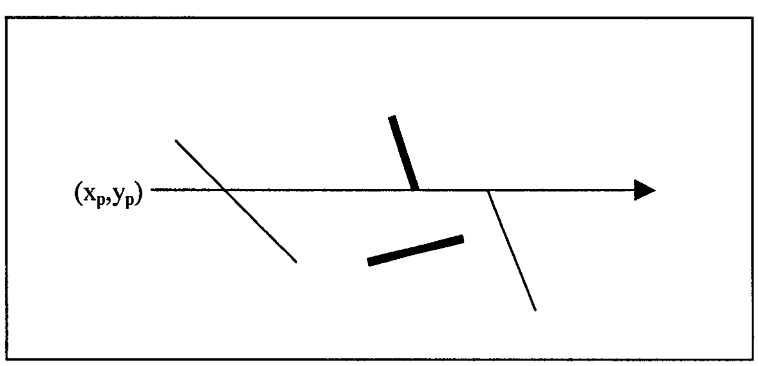

Figure 34 Possible difficult cases with polygons

The thick lines above are not considered as valid intersections, the thin lines represent valid intersections. This algorithm ignores the edges lying along and also the ones ending on the ray. This ensures that the endpoints are only counted once.

Note that this algorithm also works for polygons with holes as illustrated in Figure 35.

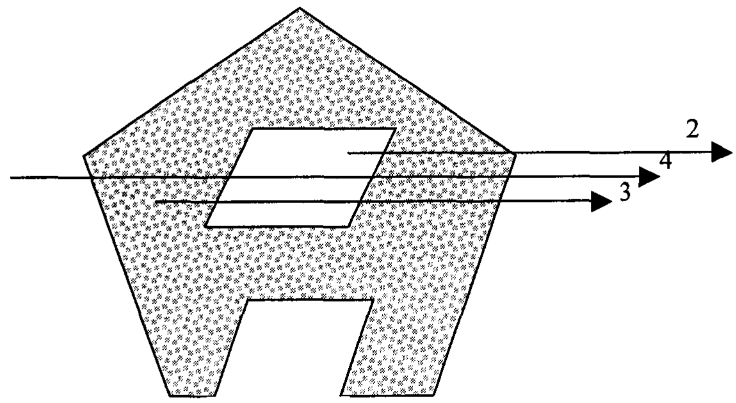

Figure 35 Polygons with holes.

The following function, written by Bourke (1998) returns INSIDE or OUTSIDE indicating the status of a point P with respect to a polygon with N points (Bourke, 1998).

```
#define MIN(x,y) (x < y ? x : y)
#define MAX(x,y) (x > y ? x : y)
#define INSIDE 0
#define OUTSIDE 1

typedef struct {
   double x,y;
} Point;

int InsidePolygon(Point *polygon,int N,Point p)
{
  int counter = 0;
  int i;
  double xinters;
  Point p1,p2;

  p1 = polygon[0];
  for (i=1;i<=N;i++) {
    p2 = polygon[i % N];
    if (p.y > MIN(p1.y,p2.y)) {
      if (p.y <= MAX(p1.y,p2.y)) {
        if (p.x <= MAX(p1.x,p2.x)) {
```

```
          if (p1.y != p2.y) {
            xinters = (p.y-p1.y)*(p2.x-p1.x)/(p2.y-p1.y)+p1.x;
            if (p1.x == p2.x || p.x <= xinters)
              counter++;
          }
        }
      }
    }
    p1 = p2;
  }

  if (counter % 2 == 0)
    return(OUTSIDE);
  else
    return(INSIDE);
}
```

VITA

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