Southwest Region University Transportation Center

Evaluating the Feasibility of Reliever and Floating Hub Concepts when a Primary Airline Hub Experiences Excessive Delays

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Center for Transportation Research
University of Texas at Austin
3208 Red River, Suite 200
Austin, Texas 78705-2650

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16. Abstract

This study intends to evaluate strategies to reassign and optimize airport and airline schedules when experiencing a disruptive disturbance at a major hub airport and still maintain a reasonable service. One such option is to temporarily use a nearby airport to act as a connecting hub, which can help reduce delays caused by a major hub's closure. This airport would be known as a reliever or alternate hub. Another option would be over-flying of the hub and swapping larger aircraft onto other routings throughout the system enabling passengers to connect through alternative hubs. Such a scheme is referred to as a "floating hub" concept.

A network-flow approach is used for the schedule allocation and to quantify the costs of the various operating strategies. Operating decisions such as flight cancellation and aircraft rotation options are optimized using a Generic Algorithm approach. Costs for potential weather delays, additional fuel consumption, infrastructure investment and passenger-delay costs are then compared for all scenarios to evaluate the feasibility of the proposed strategies.

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EVALUATING THE FEASIBILITY OF RELIEVER AND FLOATING HUB CONCEPTS WHEN A PRIMARY AIRLINE HUB EXPERIENCES EXCESSIVE DELAYS

Evert Meyer
Ph.D. Candidate, Department of Civil Engineering,
University of Stellenbosch, South Africa

Colin Rice
Masters Candidate, Department of Civil Engineering,
The University of Texas at Austin

Dr. Patrick Jaillet
Professor, management Science and Information Systems Department,
The University of Texas at Austin

Dr. Michael McNerney
Director of the Aviation Research Center,
The University of Texas at Austin

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Southwest Region University Transportation Center
Center for Transportation Research
The University of Texas at Austin
Austin, TX 78712

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EXECUTIVE SUMMARY

As a result of deregulation, the major national carriers have altered their route structure to consolidate as many flights as possible to major hub airports, where efficiencies of scale are gained in the transfer of passengers. However, a single schedule disturbance from a thunderstorm or other weather-related event at the hub can reek havoc on the operating plan and schedule of the airline. Airlines traditionally react to these disturbances by canceling or delaying flights, or by rebuilding the schedule on the fly. This study looks at the feasibility, cost, and optimum schedule for using another nearby airport as the alternate hub to transfer passengers during the disturbance at the major hub.

WEATHER

Weather is the single most important parameter affecting aircraft flight operations. As a result of IFR separation requirements, many major hub airports have capacity constraints during poor weather conditions. Thunderstorms and winter storms often cause significant delays at major hubs. These delays are typically dealt with by imposing ground holds, diversions, or flight cancellations -- all of which can affect operations with the national air transportation system.

RELIEVER-HUB CONCEPT

Conceptually, instead of delaying, diverting, or canceling flights when the major hub is constrained owing to inclement weather or to technical failures, all or a portion of the affected bank of an airlines' aircraft could be sent to an alternate hub. At the alternate hub passengers would transfer to the maximum extent possible and all but one or two aircraft would proceed to their second destination. In this way, the airline minimizes passenger, aircrew, and aircraft disruption. However, there is a significant cost in providing the infrastructure and ground services needed for this irregular surge in operations.

LOCATION OF POTENTIAL RELIEVER HUBS

The researchers evaluated the potential location of reliever hubs for a case study of Dallas-Fort Worth International Airport. Using evaluation criteria of flying time differential, weather pattern differential, passenger delay cost, the need for an inter-hub shuttle, existing airfield capacity and infrastructure required, we developed a cost model that could identify the best available reliever hub. For the test case of DFW airport, Austin Bergstrom International Airport was selected as the best alternate hub, primarily on the basis of least cost of infrastructure needed. However, this cost model can not discriminate among potential airports based upon passenger delay costs. Austin, having the greatest passenger traffic to DFW than the other alternate hubs considered, would also rank first for this reason as well.

INFRASTRUCTURE INVESTMENT COSTS

The comparative infrastructure investment costs among the potential reliever hubs for DFW airport were calculated. Austin Bergstrom International Airport ranked as the least cost to make the needed improvement of additional gates and other terminal space. A detailed estimate was then prepared for Austin for a test case in which 4 to 30 new gates were added.

LINEAR PROGRAMMING MODEL

A linear programming model was developed for identifying the best airport for an alternate hub. The model, tested for the DFW case, selected Austin.

OPERATING AND PASSENGER COSTS

Airline direct and indirect operating costs were studied with respect to operating a reliever hub. The direct costs were estimated using data available from the airlines and from public sources. The indirect costs were then defined and estimated. Passenger delay costs were estimated, along with and the effect of passenger goodwill associated with getting passengers to their destinations in the shortest time.

OPTIMIZING THE DISRUPTION SCHEDULE

A generic algorithm was developed to solve the problem of minimizing direct operating costs while minimizing passenger delay. The model solves the disruption airline fleet scheduling problem using a space-time network. A test case was evaluated using up to 200 flights and 13 cities served by American Airlines from DFW airport. The test case solution used a genetic algorithm for multi-criteria optimization. The output of the model is a series of potential choices relating to the use or non-use of the alternate hub for various flights. These choices are then evaluated according to the number of passenger minutes of delay versus operating costs.

CONCLUSIONS

Based on the test cases, using an alternate or reliever hub is definitely an effective way of reducing airline schedule disturbances. Austin Bergstrom International, which will be operational in spring 1999, will be an ideal choice for a reliever hub for DFW airport.

Developing a reliever hub system is an effective way of reducing airline schedule disturbances caused by inclement weather. The infrastructure investment required would be recovered quickly through the significant reductions in airline and passenger delays. For a test case of Austin Bergstrom International Airport as a reliever hub for American or Delta Airlines at DFW airport, it is estimated that the investment costs would be recovered in 2-3 years based upon savings in direct costs. The savings in passenger delay alone, depending on the value placed by the airline, could justify the use of alternate hubs.

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ABSTRACT

The U.S. air transportation system is dominated by a network of large hub airports. When airline schedule disruptions occur -- as a result of by meteorological or technical disturbances -- the entire national air transportation system can be substantially delayed. This study evaluated the feasibility of using an alternate or reliever hub to connect transfer passengers who otherwise would have flights delayed or canceled as a result of disturbances at the hub airport. The study developed criteria for selecting an alternate hub and evaluated the feasibility of using an alternate hub for the Dallas-Fort Worth International Airport. This study also developed a generic algorithm for optimizing an alternate schedule of flights into and out of the alternate hub to minimize direct operating costs and passenger delay. Based upon a case study that used the Austin Bergstrom International Airport as an alternate hub for Dallas-Fort Worth International Airport, the research concluded that it would be feasible and profitable to construct the necessary infrastructure to operate the alternate hub in Austin.

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1.0 INTRODUCTION

A single incident affecting the schedule of an airline or an airport requires a complex reassignment problem associated with enormous cost, and can have far-reaching effects, influencing the nationwide air-traffic system. Such disturbances may be caused by technical aircraft failures, adverse meteorological conditions and airport/runway closure. Flights to/from the airline's feeder cities are usually canceled, delayed, or diverted. For airlines, this is extremely inefficient. Traditionally, airlines have dealt with such occurrences in a reactive way, using rescheduling software to recover from a weather induced delay to resume their normal operating schedule as soon as possible. Such a strategy leaves many passengers stranded at their points of origin or at the connecting hub airport until they can be accommodated on later flights.

This study intends to evaluate other strategies to reassign and optimize airport and airline schedules when experiencing a disruptive disturbance at a major hub airport and still maintain a reasonable service. One such option is to temporarily use a nearby airport to act as a connecting hub, which can help reduce delays caused by the major hub's closure. This airport would be known as a reliever or alternate hub. Another option would be over-flying of the hub and swapping larger aircraft onto other routings throughout the system enabling passengers to connect through alternative hubs. Such a scheme is referred to as a "floating hub" concept.

A network-flow approach is used for the schedule allocation and to quantify the costs of the various operating strategies. Operating decisions such as flight cancellation and aircraft rotation options are optimized using a Genetic Algorithm approach. Costs for potential weather delays, additional fuel consumption, infrastructure investment and passenger-delay costs are then compared for all scenarios to evaluate the feasibility of the proposed strategies.

2.0 WEATHER AND AVIATION

Weather is the single-most important parameter affecting flight operation. Weather dictates the route a pilot must follow, heading and airspeed, and takeoff/ landing direction. By far, weather is the greatest hazard to aviation. Adverse weather can endanger an aircraft's safety and generally should be avoided. Since takeoff and landing are the most critical parts of flying, severe weather occurring near an airport can cause mishaps and fatalities. Although fog and light rain are the most common weather occurrences, the most hazardous weather events to aviation are thunderstorms and winter storms.

In good visibility near airports, pilots operate under VFR (visual flight rules). VFR is used when visibility is greater than three miles. Pilots are responsible for enforcing proper separation, which is 500 feet below clouds, 1000 feet above clouds, 2000 feet horizontally from clouds, and one nautical mile from all other traffic. If the above minimums cannot be maintained, then a pilot must operate under IFR (instrument flight rules). Under IFR, pilots depend on their instruments and air traffic control for navigation. Air traffic controllers are responsible for enforcing adequate aircraft separation between IFR aircraft.

2.1 WEATHER AND AIRPORT CAPACITY

As a result of IFR separation rules, airport capacity under IFR can be significantly lower than airport VFR capacity. An airport's IFR capacity is typically about 50% lower than its VFR capacity, due to the separation requirements. Under VFR, with 1.5 nautical mile spacing, a single runway can handle a total of at least 60 arriving or departing aircraft per hour. Under IFR, arrivals and departures must be sequentially spaced 3 nautical miles, or approximately two minutes apart.

With a 50-50 mix of alternating arriving and departing aircraft, a single runway system is unaffected by operation under IFR. If a departure immediately follows an arrival and is followed by another arrival and subsequent departure, 2 minute sequential separations are maintained. However, a closely spaced parallel runway system is severely affected by inclement weather. Since air traffic controllers become responsible for traffic separation under IFR, they must rely on radar to enforce adequate spacing. Current radar procedures cannot ensure proper lateral separation when parallel runways are spaced less than 4000 feet apart. As a result, closely spaced parallel runways are known as "dependent parallels" and are considered as a single runway system under IFR. Dependent parallels together can handle a maximum of 30 arrivals and 30 departures per hour. Under VFR, both runways together can handle at least 60 arrivals and 60 departures per hour.

"Independent parallels" are parallel runways spaced more than 4300 feet apart. Simultaneous instrument approaches and departures can be conducted. Therefore, independent parallels are affected less by operation under IFR; each runway is able to handle approximately 60 aircraft per hour, or a total of 30 arrivals and 30 departures. Two independent parallel runways can handle 120 aircraft per hour. IFR with dependent parallels reduces airport capacity by 50% or more. This causes serious delay problems at congested airports.

2.2 THUNDERSTORMS AND AVIATION

Thunderstorms impose the greatest number of hazards to aviation. They can cause severe turbulence, reduced surface visibility, damaging hail, and ice on the airframe. There are two basic types of thunderstorms: frontal thunderstorms and air-mass thunderstorms. Frontal thunderstorms are also known as squall lines and are usually associated with the passage of strong cold fronts. Air mass thunderstorms are formed by convection on a hot day, as hot surface air is forced upward. Frontal thunderstorms are self-renewing and can become very violent, lasting for several hours. Air mass thunderstorms are equally severe, but generally dissipate within an hour or two.

The decision whether or not to fly through rough weather is ultimately left up to the pilot. Technically, airports seldom ever close during a thunderstorm. The aircraft's radar and air traffic controllers are only able to advise pilots of severe weather. Generally, thunderstorms should be avoided under all circumstances. Landings or takeoffs should never be conducted under or near a thunderstorm [Turner, 71-73]. Passenger jet aircraft are more susceptible to wind-shear accidents because they are more stable and slower to change airspeed than general aviation aircraft. Their engines take longer to "spool-up" to full power and due to the increased weight, the lift surface of heavy jets require more time to overcome the effects of windshear. In Table 2-1, the National Transportation Safety Board has identified 18 air carrier accidents since 1970 which involved windshear as a cause or factor.

2.3 WINTER STORMS AND AVIATION

During winter, snow and ice adversely affect aviation. Ice buildup on the wings distorts the air foil and reduces lift. According to NASA, 1/16 inch of ice accumulated on a wing can reduce lift by 20% [Turner, 116]. Therefore, when snowfall or sleet are occurring at an airport, parked aircraft must be de-iced before takeoff to avoid excessive aircraft takeoff distances. During peak periods at hub airports, one hundred or more aircraft may require de-icing at approximately the same time. If this de-icing demand cannot be met, serious delays will result. During blizzards

TABLE 2-1 ACCIDENTS WITH WINDSHEAR AS A FACTOR OR CAUSE

Date	Location	Airline	Aircraft	Fatalities
July 27, 1970	Okinawa, Japan	Flying Tigers	DC-8	4
May 18, 1972	Ft. Lauderdale, FL	Eastern	DC-9	0
December 12, 1972	JFK Airport, NY	TWA	B-707	0
July 23, 1973	St. Louis, MO	Ozark	FH-227	38
October 28, 1973	Greensboro, NC	Piedmont	B-737	0
November 27, 1973	Chattanooga, TN	Delta	DC-9	0
December 17, 1973	Boston, MA	Iberia	DC-10	0
January 30, 1974	Pago Pago	Pan Am	B-707	96
June 24, 1975	JFK Airport, NY	Eastern	B-727	112
August 7, 1975	Denver, CO	Continental	B-727	0
November 12, 1975	Raleigh, NC	Eastern	B-727	0
April 27, 1976	St. Thomas, USVI	American	B-727	37
June 23, 1976	Philadelphia, PA	Allegheny	DC-9	0
June 3, 1977	Tucson, AZ	Continental	B-727	0
July 9, 1982	New Orleans, LA	Pan Am	B-727	153
May 31, 1984	Denver, CO	United	B-727	0
June 13, 1984	Detroit, MI	USAir	DC-9	0
August 2, 1985	Dallas/Ft. Worth	Delta	L1011	135

heavy snowfall can accumulate at airports, and must be removed from all pavement surfaces for safety. Depending on the duration and snowfall intensity, this can be a lengthy process. Additionally, blowing snow also causes visibility problems.

2.4 HOW DELAY AFFECTS AN AIRLINE FINANCIALLY

In order to assess the financial effects of delay on an airline, each aircraft is assigned a cost depending on its task during the delay. Aircraft continuously incur costs, primarily due to depreciation of capital. If a delay results, the aircraft is not earning any revenue for the airline. Most airlines pay their pilots only when their aircraft is away from the boarding gate and when the engines are running. Therefore, ground delays and delays in the air are more costly than gate delays.

Airline operating costs are displayed in Table 2-2, in 1997 dollars. These figures show the average of airline fleet operating costs, and include fuel, depreciation, maintenance, and crew costs. Lost passenger time and schedule disruption are not considered. These figures are used by the FAA in Airport Capacity Enhancement Plans.

TABLE 2-2 AVERAGE OF AIRCRAFT OPERATING COSTS

Delay Type	Cost Per Minute	Cost Per Hour
Ground Delay	$19.33	$1160
Airborne Delay	$32.74	$1964
Gate Delay	$13.79	$827
Overall Delay	$22.28	$1336

2.5 WEATHER AND AIRLINE SCHEDULE DISTURBANCES

Traffic at airline connecting hubs usually operates in four or more distinct daily peaks, lasting an hour or less apiece. During these peaks, the airport briefly operates near its physical runway capacity. However, the airport's terminal and runways are underutilized for the majority of the day. If inclement weather reduces runway capacity or closes the airport during a flight bank, serious delay results for the airline and its passengers.

If airport arrival capacity is reduced because of inclement weather, flights are usually delayed in the air and forced to circle. If they run low on fuel before the weather clears or if the weather is too dangerous to attempt a landing, the flights must be diverted to another location. The passengers on the diverted flights must wait for the weather at the hub to clear. Whenever a flight is diverted, a delay of two hours or more usually results. If the original connecting flight was able to depart the airport near its scheduled time, the passenger may have missed his connection; he may have to wait for the next flight to his final destination, causing even more delay.

If inclement weather affects a departing flight bank at large hub airports, extreme departure delays with queues of 40 or more can result. Bad weather at a connecting hub creates ripples or a cascading effect throughout an airline's entire route system. A flight delayed an hour at American Airlines' DFW hub is an hour late arriving at the next spoke city. Subsequently, this flight would depart from the spoke city, heading to another hub still an hour late. Each passenger served by this aircraft, for the rest of the day, would be an hour late. If an aircraft is routed Dallas-Austin-Chicago, an hour delay departing Dallas causes this flight to arrive in Chicago also an hour late. Passengers on this flight who connect in Chicago may miss their connection, even though the weather in Austin and Chicago are good.

When an entire bank is delayed because of bad weather at a connecting hub, American tries to avoid mixing of flight complexes. American attempts to maintain its complex integrity at all costs, using "company arrival control" or CAC. If flight bank integrity is maintained, delayed passengers are able to easily make their connections when they do arrive at the hub. Even though the later flights are able to use the hub without being delayed by weather, they must be delayed to keep the flight banks separated. American's fleet dispatch would delay the later flights before they depart the spoke cities. If a flight complex at Dallas is being delayed and if the next flight complex operates on schedule, when it arrived in Dallas there would not be any available gate positions for its aircraft. Additionally, if traffic backs up at Dallas because of weather, the Air Route Traffic Control Centers (ARTCC) may restrict new arrivals into the Dallas airspace until the backlog of planes is cleared. For example, if Dallas is overburdened, ARTCC may also hold Dallas-bound flights on the ground at the spoke cities.

2.6 A TYPICAL BAD WEATHER DAY FOR AMERICAN AIRLINES

May 19, 1997 was a "typical bad weather day" for American Airlines at DFW. Appendix B contains statistics on flight complex performance at each of American's hubs on this date. On-time percentages are shown with average delay during each phase of flight operation. Thunderstorms were reported within the vicinity of the airport during one of the evening flight banks around 6:00-6:30 PM. Flights during the 6:30 flight bank departed from the gate an average of only 29 minutes behind schedule while the average wait for takeoff was 76 minutes. As a result, each of these flights arrived at their spoke city by an average of 103 minutes late. For the following flight bank, at 8:05 PM, each flight departed from the gate an average of 141 minutes behind. No takeoff delays were reported, as the weather had cleared. Many of these flights made time up in the air, and arrived at their final destination an average of 109 minutes late. Flights in the final flight bank, at 9:35 PM departed from the gate an average of 81 minutes late, with no takeoff delay. They arrived at their final destinations an average of 67 minutes late. As demonstrated by these statistics, a single thunderstorm event around 6:00 PM disrupted American's schedule for the rest of the evening.

After the thunderstorm occurred at DFW on May 19, a total of 131 evening flights were delayed an average of 97 minutes. Twenty-nine flights were diverted and thirteen were canceled.

With an hour of delay averaging $1,350 per aircraft, weather delay costs for American at DFW on this day alone exceeded $286,000 not including flight cancellations and passenger-delay costs. According to the National Climatic Data Center (NCDC), an average of 72 severe weather occurrences are reported annually within the vicinity of the DFW Airport. Since American has few flights from DFW between 11 PM and 6 AM, 51 of these storms are estimated to occur during normal operating hours. Multiplying the average number of storms by the delay cost incurred by the typical storm of May 19, 1997, weather delays are estimated to cost American at least $15 million annually, in direct operating costs alone.

2.7 PASSENGER-DELAY COSTS

To measure the effects of weather delay on passengers, it is necessary to convert passenger delay times into monetary costs. This can be accomplished by assigning a cost to each passenger who experiences delay. Passenger-delay costs can be simply computed by multiplying the number of passengers-hours of delay by the average hourly income of an airline passenger. Since most air travelers are usually well-to-do business executives, an average wage of approximately $20.75 per hour was used. In 1993, American Airlines carried an average of 89 people per flight from DFW. With an estimated 6,630 annual flights being delayed at DFW by weather for an average of 90 minutes, delay costs for passengers on these flights alone when the weather disturbance occurs only are estimated to exceed $18.4 million annually. Since one delayed flight can easily affect two later flight-loads of passengers, these passenger delay costs can easily be tripled.

3.0 THE "RELIEVER-HUB" CONCEPT

Conceptually, instead of delaying, diverting or canceling flights when DFW is weather-affected, all of American's inbound flights to DFW could be sent to one or two nearby locations, called "reliever hubs". If all incoming American flights were temporarily diverted to one or two locations only, many connections could still be made at minimal cost. Passengers making those connections would be inconvenienced far less and American would reduce systemwide delays. Although airline hubs are typically several hundred million dollar investments, utilizing a nearby airport occasionally may not require much additional infrastructure.

Pilots are required by the FAA when filing a flight plan to designate alternate airports in case the destination airport is closed. In the case of Dallas/Ft. Worth when planes are unable to land, American pilots divert to many nearby locations, including Austin, San Antonio, Waco, and Abilene. Usually, no extra gates are available at the alternate airport for a diverted flight. Passengers are unable to deplane as the aircraft sits on any available apron. The passengers are forced to wait for the weather to clear at Dallas. If American Airlines would divert all or part of its inbound DFW flights to one or two specific locations, the delay savings may make construction of a makeshift terminal worthwhile. Passengers would be able to connect to their final destination while using the amenities provided in the terminal. Flight delays and passenger frustration would be reduced. Passengers whose destination or point of origin is Dallas would be delayed at the reliever hubs until the weather cleared. They would be ferried to/from Dallas as soon as weather becomes safe enough for flying.

3.1 LOCATING THE IDEAL RELIEVER-HUB SET

Implementing a set of reliever-hubs is predicted to alleviate delays caused by weather. However, a the best location for reliever-hubs must be carefully chosen to minimize all associated costs. When flights are sent to a reliever hubs, some flights will be longer, some will be shorter. The reliever-hub combination which minimizes flight distances must be carefully chosen. Reliever hubs must also be located in cities with good weather. If a reliever hub is weather-affected when the primary hub is also weather-affected, then the effectiveness of reliever-hub system is lessened. Additionally, reliever hubs must have sufficient room for terminal and runway expansion. If an airport is land-locked by the surrounding community, it may be expensive or impossible to erect infrastructure to handle the extra demand.

Costs derived for potential weather delays, additional fuel consumption, traffic congestion, and infrastructure investment will be used in a mixed integer programming model to find the ideal hub locations. The model will find the least-cost scenarios for reliever hub implementation. Passenger delay costs for using reliever hubs will be compared against the "do-nothing" scenario. After a model has been calibrated for choosing reliever hubs for the representative airline, the results obtained can then be applied to a larger scale. Feasibility will be established if operating reliever hubs are less expensive than canceling or delaying flights.

3.2 DEVELOPMENT OF A REPRESENTATIVE AIRLINE

Dallas/Ft. Worth International Airport (DFW) was chosen as the initial weather-affected hub for several reasons. Soon, DFW will become the world's busiest airport, in terms of aircraft operations. DFW is projected to surpass Chicago/O'Hare International Airport by the year 2002. Geographically, DFW is centrally located between the common east-west origin/destination markets of United States. DFW is approximately three flying or less to Los Angeles, New York City, Miami, San Francisco, and Washington, DC. Additionally, DFW serves as a major connecting hub for two of the largest U.S. airlines, American and Delta.

Next, the nation's largest airports and American's largest markets were chosen to be served by our representative airline. Although American Airlines serves 88 cities non-stop from DFW, only 30 cities were chosen for the representative airline to avoid complexity, as large networks are extremely difficult to model.

TABLE 3-1 MARKETS SELECTED FOR SERVICE

City	Airport Code Code	City	Airport Code Code
Seattle, WA	SEA	Houston, TX	IAH
San Francisco, CA	SFO	Tampa, FL	TPA
Los Angeles, CA	LAX	Boston, MA	BOS
New York, NY	LGA	Kansas City, MO	MCI
Washington, DC	DCA	Corpus Christi, TX	CRP
Miami, FL	MIA	Charlotte, NC	CLT
Austin, TX	AUS	Cincinnati, OH	CVG
Tulsa, OK	TUL	Denver, CO	DEN
El Paso, TX	ELP	Detroit, MI	DTW
New Orleans, LA	MSY	Las Vegas, NV	LAS
Chicago, IL	ORD	Orlando, FL	MCO
St. Louis, MO	STL	Minneapolis, MN	MSP
San Antonio, TX	SAT	Philadelphia, PA	PHL
Phoenix, AZ	PHX	Pittsburgh. PA	PIT
Atlanta, GA	ATL	Salt Lake City, UT	SLC

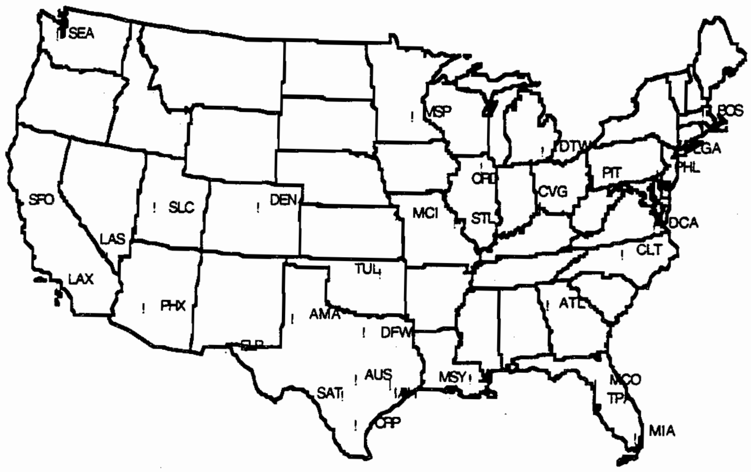


Figure 3-1 Thirty cities chosen for geographic hub location analysis

3.3 SELECTION OF POTENTIAL RELIEVER-HUBS

Six possible reliever hubs were also chosen for the network. The potential reliever hub airports chosen were the closest airports to the weather-affected hub, capable of handling conventional jet airliners. The reliever hub airports and cities represent various sizes. Most of the airports are uncongested; however, one potential hub currently serves as a connecting hub for Continental Airlines. Possible reliever hubs are shown in Table 3-2.

TABLE 3-2 POTENTIAL RELIEVER HUBS SELECTED FOR STUDY

Potential Hub City	Airport	Airport Code	Distance from DFW (mi)
Austin, TX	Bergstrom Intl Airport	AUS	183
Houston, TX	Houston Intercontinental	IAH	224
Tulsa, OK	Tulsa Intl Airport	TUL	237
Corpus Christi, TX	Corpus Christi Intl Airport	CRP	354
Amarillo, TX	Amarillo Intl Airport	AMA	313
Waco, TX	Waco Regional Airport	ACT	93

Varying passenger demands would have little or no effect on choosing the reliever hub location. Most flights would still operate as scheduled into the reliever hubs, instead of the weather-affected hub. Therefore, origin and destination passengers for the representative airline are assumed to be equal in all markets, for simplicity. On any given flight to a hub, four passengers are bound for each of the 29 other cities, and the hub city. On a flight from a hub, four passengers are present from each of the 29 other cities, and the hub. Each flight will consist of 120 passengers on 140-seat MD-80 aircraft, giving the representative airline a load factor of 86%.

Figure 3-2 Potential reliever hubs selected

4.0 FACTORS INFLUENCING LOCATION OF RELIEVER HUBS

Determining the best location for a reliever hub can be a complex task. Instead of flying to the normal hub, all flights would operate through the reliever hubs until the weather clears. Locating reliever hubs too far from the original hub would be increase flight distances and operating costs. Also, to avoid being affected by the same weather, the reliever hubs must be an adequate distance away from the original hub. Additionally, the reliever hubs must have sufficient runway and terminal capacity to handle the extra volume of air traffic. In the following sections, the factors affecting selection of reliever-hubs are discussed and quantified.

4.1 GEOGRAPHICAL LOCATION OF RELIEVER HUB

The selection of the geographical location of the reliever hub can be optimized by evaluating additional flight distances, resulting from reliever hub usage. Distance from the weather-affected hub must be minimized to avoid excessive operating cost. As long as the reliever hub location is a reasonable distance from the main hub, the difference in flight operating costs for a single reliever hub will be insignificant. Some flights will be longer, while some flights will be shorter. Locating a reliever hub to the north of DFW will reduce operating costs for flights to the north; a south location will reduce costs for flights to the south, but will increase costs for northbound flights.

The additional operating costs were calculated by converting the extra air mileage needed to reach the reliever hub into flight times. All thirty flights are presumed to arrive and depart during every flight bank at Dallas/Ft. Worth. Flight *i* travels from city *A* to Dallas/Ft. Worth, then departs Dallas/Ft. Worth and travels to city *B*. If bad weather is forecasted to hit DFW, then the representative airline diverts all of its flights to the selected reliever hubs until the weather clears.

For this study, distances for individual flight segments were evaluated only. City-pair distances were not evaluated. Air mileage from all cities to each possible reliever hub was tabulated in Table 4-1. Table 4-2 shows the air mileage difference to operate each flight into each reliever hub, in comparison with DFW. For example, a flight from Seattle to Austin travels 103 more miles than a flight from Seattle to DFW. A flight from Seattle to Tulsa travels 102 less miles than a flight from Seattle to DFW.

As noted before, each potential hub provides distinct geographical advantages and disadvantages. Using Houston as a hub would provide savings for all cities located to the south and/or east of Dallas. Houston is significantly closer to Miami, New Orleans, Tampa, Corpus Christi, and Orlando. Austin, San Antonio, and Atlanta are slightly to closer Houston than to Dallas, and would provide a small savings. On the other hand, Seattle, San Francisco, Los Angeles, Chicago, and Denver are significantly farther from Houston than Dallas. For a potential reliever hub city where the airline already has service, the original flight from that city to the hub is not operated. These savings are deducted from the total flight operating cost for a hub. For example, since the representative airline already has service from Austin, a flight is not needed to ferry passengers to a hub when Austin is used as the reliever hub. A flight from Dallas to Austin is approximately 183 miles. If Austin is temporarily being used a reliever hub, this flight is not necessary. The airline saves 183 air miles in aircraft operating costs for not running this flight, as shown in Table 4-2. Passengers whose final destination is Austin will not need a connecting flight.

Originating passengers in DFW will not be able to depart until the weather clears. When DFW becomes usable, the airline will return to DFW for its hub operation. Passengers whose final destination is DFW will be stranded at the reliever hub. Although DFW passengers would still be inconvenienced, the systemwide delay caused by the weather disturbance would be minimized. Previously, without a reliever hub, all passengers traveling through DFW during inclement weather would be delayed. Using a reliever hub would enable most flights to remain close to their original schedule, while only delaying the passengers whose origin or destination is the primary hub.

Table 4-3 shows the additional flight time necessary, based on the mileage difference in Table 4-2. Since estimates of airline delay are calculated in minutes, and since airline fleet operating costs estimates are based on time, additional flight time needed for use of a reliever hub was evaluated. Additional flight time estimates were based on average in-flight speed of 450 miles per hour. A flight from Seattle to Dallas normally takes approximately 221 minutes. Flying to Houston would add nearly 29 minutes to the same flight. These additional flight times are based on the assumption that the airline notifies pilots of reliever hub usage far in advance. When notified of a projected hub closure, the pilot would change his course as early in the flight as possible, and fly directly to the reliever hub.

According to the airline operating costs shown in Table 2-4, the average in-flight aircraft operating cost is approximately $33 per minute. Table 4-4 shows the operating cost differential for each flight. All 30 flights usually operate into Dallas for a cost of $103,866. A flight from Seattle to Austin would cost $415 more than for the same flight into Dallas. Flying from Seattle to Amarillo would cost approximately $1230 less than flying to Dallas. If all flights were sent to Corpus Christi, the airline would lose $18,497 dollars per flight bank. Sending all flights to Corpus Christi results in a 18% net increase in operating cost. Sending all flights to Tulsa results in a net savings of nearly 5%. As a hub, Tulsa saves the airline money, over Dallas, because of its geographical location.

TABLE 4-1 AIR MILEAGE FROM CITY-TO-HUB

Flight	City	DFW	AUS	IAH	TUL	IAH	AMA	ACT
1	SEA	1660	1763	1874	1558	1905	1355	1715
2	SFO	1460	1500	1610	1419	1578	1160	1486
3	LAX	1235	1238	1379	1283	1310	954	1240
4	LGA	1395	1523	1421	1238	1618	1567	1440
5	DCA	1216	1339	1235	1071	1431	1376	1260
6	MIA	1120	1107	964	1168	1071	1430	1100
7	AUS	183	0	150	420	174	412	101
8	TUL	237	420	429	0	588	335	320
9	ELP	553	526	668	674	602	417	539
10	MSY	447	446	305	538	465	759	430
11	ORD	801	971	922	587	1130	879	880
12	STL	550	717	667	351	861	673	627
13	SAT	246	70	191	483	125	435	165
14	PHX	868	868	1009	935	947	555	871
15	ATL	731	812	689	674	876	992	759
16	IAH	224	143	0	429	201	518	159
17	TPA	828	930	787	965	915	1234	917
18	BOS	1561	1695	1597	1394	1795	1719	1620
19	MCI	459	643	643	224	810	779	548
20	CRP	354	174	201	588	0	621	265
21	CLT	936	1032	1043	843	1232	1174	974
22	CVG	811	955	879	646	1071	976	886
23	DEN	643	769	863	543	929	443	707
24	DTW	986	1145	1075	790	1275	1130	1058
25	LAS	1056	1085	1222	1075	1182	758	1074
26	MCO	983	995	853	1004	988	1285	977
27	MSP	852	1035	1034	616	1203	802	941
28	PHL	1302	1427	1324	1151	1521	1486	1356
29	PIT	1067	1207	1117	899	1318	1223	1129
30	SLC	988	1078	1194	925	1217	677	1036

TABLE 4-2 MILEAGE DIFFERENCE OVER DFW

Flight	City	AUS	IAH	TUL	CRP	AMA	ACT
1	SEA	103	214	-102	245	-305	55
2	SFO	40	150	-41	118	-300	26
3	LAX	3	144	48	75	-281	5
4	LGA	128	26	-157	223	172	45
5	DCA	123	19	-145	215	160	44
6	MIA	-13	-156	48	-49	310	-20
7	AUS	-183	-33	237	-9	229	-82
8	TUL	183	192	-237	351	98	83
9	ELP	-27	115	121	49	-136	-14
10	MSY	-1	-142	91	18	312	-17
11	ORD	170	121	-214	329	78	79
12	STL	167	117	-199	311	123	77
13	SAT	-176	-55	237	-121	189	-81
14	PHX	0	141	67	79	-313	3
15	ATL	81	-42	-57	145	261	28
16	IAH	-81	-224	205	-23	294	-65
17	TPA	102	-41	137	87	406	89
18	BOS	134	36	-167	234	158	59
19	MCI	184	184	-235	351	320	89
20	CRP	-180	-153	234	-354	267	-89
21	CLT	96	107	-93	296	238	38
22	CVG	144	68	-165	260	165	75
23	DEN	126	220	-100	286	-200	64
24	DTW	159	89	-196	289	144	72
25	LAS	29	166	19	126	-298	18
26	MCO	12	-130	21	5	302	-6
27	MSP	183	182	-236	351	-50	89
28	PHL	125	22	-151	219	184	54
29	PIT	140	50	-168	251	156	62
30	SLC	90	206	-63	229	-311	48

TABLE 4-3 ADDITIONAL FLIGHT TIME REQUIRED IN MINUTES

Flight	City	Time to DFW	AUS	IAH	TUL	CRP	AMA	ACT
1	SEA	221.33	13.73	28.53	-13.60	32.67	-40.67	7.33
2	SFO	194.67	5.33	20.00	-5.47	15.73	-40.00	3.47
3	LAX	164.67	0.40	19.20	6.40	10.00	-37.47	0.67
4	LGA	186.00	17.07	3.47	-20.93	29.73	22.93	6.00
5	DCA	162.13	16.40	2.53	-19.33	28.67	21.33	5.87
6	MIA	149.33	-1.73	-20.80	6.40	-6.53	41.33	-2.67
7	AUS	24.40	-24.40	-4.40	31.60	-1.20	30.53	-10.93
8	TUL	31.60	24.40	25.60	-31.60	46.80	13.07	11.07
9	ELP	73.73	-3.60	15.33	16.13	6.53	-18.13	-1.87
10	MSY	59.60	-0.13	-18.93	12.13	2.40	41.60	-2.27
11	ORD	106.80	22.67	16.13	-28.53	43.87	10.40	10.53
12	STL	73.33	22.27	15.60	-26.53	41.47	16.40	10.27
13	SAT	32.80	-23.47	-7.33	31.60	-16.13	25.20	-10.80
14	PHX	115.73	0.00	18.80	8.93	10.53	-41.73	0.40
15	ATL	97.47	10.80	-5.60	-7.60	19.33	34.80	3.73
16	IAH	29.87	-10.80	-29.87	27.33	-3.07	39.20	-8.67
17	TPA	110.40	13.60	-5.47	18.27	11.60	54.13	11.87
18	BOS	208.13	17.87	4.80	-22.27	31.20	21.07	7.87
19	MCI	61.20	24.53	24.53	-31.33	46.80	42.67	11.87
20	CRP	47.20	-24.00	-20.40	31.20	-47.20	35.60	-11.87
21	CLT	124.80	12.80	14.27	-12.40	39.47	31.73	5.07
22	CVG	108.13	19.20	9.07	-22.00	34.67	22.00	10.00
23	DEN	85.73	16.80	29.33	-13.33	38.13	-26.67	8.53
24	DTW	131.47	21.20	11.87	-26.13	38.53	19.20	9.60
25	LAS	140.80	3.87	22.13	2.53	16.80	-39.73	2.40
26	MCO	131.07	1.60	-17.33	2.80	0.67	40.27	-0.80
27	MSP	113.60	24.40	24.27	-31.47	46.80	-6.67	11.87
28	PHL	173.60	16.67	2.93	-20.13	29.20	24.53	7.20
29	PIT	142.27	18.67	6.67	-22.40	33.47	20.80	8.27
30	SLC	131.73	12.00	27.47	-8.40	30.53	-41.47	6.40
Total		3433.60	100.93	81.73	-17.20	303.20	272.27	41.87

TABLE 4-4 ADDITIONAL OPERATING COST PER FLIGHT

	City	AUS	IAH	TUL	CRP	AMA	ACT
1	SEA	415.43	863.13	-411.40	988.17	-1230.17	221.83
2	SFO	161.33	605.00	-165.37	475.93	-1210.00	104.87
3	LAX	12.10	580.80	193.60	302.50	-1133.37	20.17
4	LGA	516.27	104.87	-633.23	899.43	693.73	181.50
5	DCA	496.10	76.63	-584.83	867.17	645.33	177.47
6	MIA	-52.43	-629.20	193.60	-197.63	1250.33	-80.67
7	AUS	-738.10	-133.10	955.90	-36.30	923.63	-330.73
8	TUL	738.10	774.40	-955.90	1415.70	395.27	334.77
9	ELP	-108.90	463.83	488.03	197.63	-548.53	-56.47
10	MSY	-4.03	-572.73	367.03	72.60	1258.40	-68.57
11	ORD	685.67	488.03	-863.13	1326.97	314.60	318.63
12	STL	673.57	471.90	-802.63	1254.37	496.10	310.57
13	SAT	-709.87	-221.83	955.90	-488.03	762.30	-326.70
14	PHX	0.00	568.70	270.23	318.63	-1262.43	12.10
15	ATL	326.70	-169.40	-229.90	584.83	1052.70	112.93
16	IAH	-326.70	-903.47	826.83	-92.77	1185.80	-262.17
17	TPA	411.40	-165.37	552.57	350.90	1637.53	358.97
18	BOS	540.47	145.20	-673.57	943.80	637.27	237.97
19	MCI	742.13	742.13	-947.83	1415.70	1290.67	358.97
20	CRP	-726.00	-617.10	943.80	-1427.80	1076.90	-358.97
21	CLT	387.20	431.57	-375.10	1193.87	959.93	153.27
22	CVG	580.80	274.27	-665.50	1048.67	665.50	302.50
23	DEN	508.20	887.33	-403.33	1153.53	-806.67	258.13
24	DTW	641.30	358.97	-790.53	1165.63	580.80	290.40
25	LAS	116.97	669.53	76.63	508.20	-1201.93	72.60
26	MCO	48.40	-524.33	84.70	20.17	1218.07	-24.20
27	MSP	738.10	734.07	-951.87	1415.70	-201.67	358.97
28	PHL	504.17	88.73	-609.03	883.30	742.13	217.80
29	PIT	564.67	201.67	-677.60	1012.37	629.20	250.07
30	SLC	363.00	830.87	-254.10	923.63	-1254.37	193.60
Total		7506	6425	-5086	18497	9567	3340
% difference over DFW		7.23	6.19	-4.90	17.81	9.21	3.22

Tulsa is closer than Dallas for most of the airline's cities. Additionally, it may be feasible to select a few hubs, and send certain flights to certain hubs. Selecting two hubs, while providing a shuttle between the two, may also produce a practical solution. For example, it may be more efficient to send all western flights to a hub located to the west of Dallas, while sending eastern flights to a hub located to the east of Dallas. Passengers whose connecting flight departs from the other hub would be accommodated with a shuttle at regular intervals.

4.2 USING AN INTER-HUB SHUTTLE

If more than one hub is selected, a shuttle would have to be used, to ensure that all passengers make their connection. For example, Houston and Tulsa are selected as reliever hubs. A passenger is traveling from Seattle to Miami. If DFW is closed, his Seattle flight is routed through Tulsa, while his Miami flight departs from Houston. In order to reach his final destination when the reliever hubs are in-use, the passenger must travel from Seattle to Tulsa, Tulsa to Houston, then Houston to Miami. All passengers in Tulsa whose connecting flight actually departs from Houston must be transferred. Assuming that all origin and destination demands between all points are equal, each flight will carry 120 passengers, with 4 bound for each of the 29 other cities plus the hub.

If 15 flights are sent to Tulsa and Houston apiece, 60 passengers on each flight will have to be transferred to the other hub. To ferry 900 passengers, seven 140-seat shuttles would need to be provided between each hub. Houston and Tulsa are 429 miles apart. The average airline block time between Houston and Tulsa is 1.4 hours. With an average airborne operating cost of $33 per minute, each shuttle would cost the airline $2,800. Fourteen shuttles would cost approximately $39,200.

4.3 PASSENGER DELAY COSTS

If DFW becomes closed, all flights can simply be diverted to the reliever hubs. This would avoid delay to the passengers on these flights and prevent cascading delays. If the reliever hubs are used, the later flight banks can operate into DFW as scheduled instead of being delayed by an earlier flight bank. As discussed earlier, a single thunderstorm can negatively affect an airline's schedule for the remainder of the day. A thunderstorm occurring at DFW can delay a flight bank for two hours or more delaying all subsequent flight banks.

Additionally, one flight delay can easily affect three other flights. Flights delayed by weather are late arriving at their next destination and late arriving at all subsequent destinations. If each aircraft picks up two more loads of passengers after leaving Dallas, those passengers are all late. For this study, 116 passengers on each aircraft are assumed to be delayed for 90 minutes. Using the passenger-delay cost of $20.75 per hour, discussed in section 3-3, costs approach $234,700 per flight bank or $11.9 million annually, with 51 thunderstorm occurrences. Due to the cascading effect, these costs can easily be doubled, reaching at least $23.9 million annually.

4.4 WEATHER AT POTENTIAL RELIEVER HUB

Another important factor in determining the location of a reliever hub is the weather. If a reliever hub is located too close to the original hub, there is a greater chance that the reliever hub will also be affected by the same weather. In order for the reliever hub to be effective, it must have better weather than the closed hub. Although it is not possible to completely eliminate the possibility of having a reliever hub weather-affected, it is possible to choose a hub with the least probability of having similar weather.

Weather data for each possible reliever hub was obtained from Global Daily Summary, Temperature and Precipitation, 1977-1991, on CDRom from the National Climatic Data Center. Siginificant weather events at each location are reported every three hours. An example of the weather data for Austin is shown in Table 4-5.

The significant weather occurrences were evaluated for each city over a standard ten-year period from January 1, 1982 to December 31, 1991. Weather events affecting air carriers were grouped into the above categories. Fog consists of weather reports E, F, and G. Thunderstorms consist of codes A, Q, T, and Y. Icestorms consist of codes B, C, J, P, and Z. As shown by the above chart, Corpus Christi and Houston have the highest number of fog occurrences, as they are closest to the coast. Tulsa has the highest report of winter storms, as it is located the farthest north. Houston has the highest number of thunderstorms. Table 4-6 shows the number of weather reports affecting aviation for each potential hub.

TABLE 4-5 WEATHER OBSERVATIONS FOR AUSTIN, JANUARY 1982

	Time							
Date	0:00	3:00	6:00	9:00	12:00	15:00	18:00	21:00
820101	O	O	O	O	O	O	O	L
820102	L	L	L	F	F	O	F	F
820103	L	L	F	O	O	O	O	H
820104	H	O	O	O	O	O	O	O
820105	O	O	O	O	O	O	O	O
820106	O	O	-	-	-	O	O	F
820107	F	O	O	O	O	O	O	O
820108	O	O	O	O	O	O	O	O
820109	O	O	O	O	O	O	-	-
820110	O	O	O	O	O	O	O	O
820111	O	O	O	O	O	O	-	-
820112	P	S	Z	F	F	F	O	O
820113	O	O	O	S	S	O	O	O
820114	O	O	O	O	O	O	O	O
820115	O	O	O	O	O	O	O	O
820116	O	-	O	O	O	O	O	O
820117	O	O	O	O	O	O	O	O
820118	O	O	F	F	O	O	O	O
820119	O	O	F	F	H	O	F	F
820120	F	L	R	R	R	R	F	F

Observation codes for Table 4-5 are:

- = no report available
A = hail
B = blowing snow
C = snow crystals
D = dust/sand
E = rime fog
F = fog
G = ground fog
H = haze
I = diamond dust
K = drifting snow
L = drizzle
M = mist
O = no significant weather
P = ice pellets
Q = squall
R = rain
S = snow
T = thunderstorm
U = lightning
V = virga
W = showers
X = distant precip
Y = funnel clouds
Z= freezing precip

TABLE 4-6 WEATHER OBSERVATION TOTAL BY TYPE 1982 - 1991

	Fog	Thunderstorms	Snow/Ice	Total
Amarillo	1263	850	1085	3198
Austin	1944	647	71	2662
Corpus Christi	2727	364	68	3159
Dallas/Ft. Worth	1680	720	194	2594
Houston	3148	972	68	4188
Tulsa	1715	743	515	2973
Waco	2089	777	158	3024

In locating a reliever hub, the weather conditions at the reliever hub occurring when the existing hub is closed are the most relevant. The reliever hub will only be used when the primary hub is weather-affected. As a result, the number of simultaneous weather occurrences need to be minimized. A reliever hub does not need to be at a location which is often simultaneously affected by inclement weather. The following probabilities were defined to evaluate the weather data:

$P(A,w)$ = probability of weather type w at DFW

$P(B,w)$ = probability of weather type w at reliever hub

$P(B/A)$ = probability of inclement weather type w at reliever if weather type w occurs at DFW

$P(B/A) = P(A \cap B)/P(A)$

Table 4-7 shows $(A \cap B)$ or the number of same-type simultaneous weather reports at both locations. For example, 38 thunderstorms were reported in Amarillo while thunderstorms were concurrently reported at DFW. The last column shows the total simultaneous weather occurrences for all types. For example, in Austin, 810 events of fog, storms, and snow were reported while DFW was also affected by either fog, storms, or snow.

TABLE 4-7 NUMBER OF SIMULTANEOUS WEATHER OCCURRENCES BY TYPE, $(A \cap B)$

Location	Fog	Storms	Snow/Ice	All
Amarillo	162	38	49	389
Austin	570	112	35	810
Corpus Christi	529	15	17	673
Houston	585	70	22	813
Tulsa	258	34	41	475
Waco	885	226	89	1276

Although Amarillo receives much more snow than Dallas, few events are simultaneous because of the distance between the two cities. Waco, which is closest to DFW, has the highest number of simultaneous weather occurrences. Table 4-7 was converted into probabilities by dividing each value by the number of occurrences for the corresponding weather type at DFW.

According to Table 4-8, when the DFW weather is bad, the weather in Waco is also usually bad. Dallas and Waco are located only 100 miles apart. When there is snow in Dallas, there is a 46% chance that snow is also present in Waco. To increase effectiveness of the reliever hub, the simultaneous bad weather occurrences must be minimized. Although Amarillo appears to have the lowest probability of simultaneous inclement weather, there is still a 15% chance that Dallas and Amarillo will both be affected concurrently.

TABLE 4-8 PROBABILITY OF SIMULTANEOUS WEATHER OCCURRENCE BY TYPE, $P(B/A)$

	Fog	Storms	Snow/Ice	All
Amarillo	0.096	0.053	0.253	0.150
Austin	0.339	0.156	0.180	0.312
Corpus Christi	0.315	0.021	0.088	0.259
Houston	0.348	0.097	0.113	0.313
Tulsa	0.154	0.047	0.211	0.183
Waco	0.527	0.314	0.459	0.492

Without reliever hubs, a single flight bank delayed 90 minutes would cost the representative airline approximately $60,750 in operating costs. If a reliever hub is used whenever DFW is unavailable, the airline would save that amount as flights would not be delayed. If two reliever hubs are selected for use and one of them is closed, all flights can simply be routed through the other reliever hub. Flight banks will be delayed only when all alternate hubs are closed. Costs incurred by the probability of a single reliever hub closure are shown in Table 4-9. Average weather delay cost (risk factor) for a specific reliever hub is simply the probability of a simultaneous hub closure multiplied by the cost of an average 90 minute delay per flight. For dual reliever hubs, the probability of a weather-causing closure of the both reliever hubs in addition to the primary hub is negligible. The potential costs of a hub closure in a single reliever-hub system are subtracted from the benefits of not having any flights delayed:

TABLE 4-9 WEATHER-DELAY COSTS FOR SINGLE RELIEVER-HUB SCENARIO

City	Probability of Simultaneous Closure	Anticipated Weather Delay Cost, per bank	Net Savings
Amarillo	0.150	$9,113	$51,637
Austin	0.312	$18,954	$41,796
Corpus Christi	0.259	$15,734	$45,016
Houston	0.313	$19,015	$41,735
Tulsa	0.183	$11,117	$49,633
Waco	0.492	$29,889	$30,861

4.5 TRAFFIC CONGESTION AT POTENTIAL RELIEVER HUB

The reliever-hub airport must be placed at a location which has minimal traffic delays to enhance its effectiveness. Locating a reliever-hub at a heavily congested airport would be a poor choice. To quantify air traffic delays and congestion, air traffic delays should be measured by airports in average minutes per operation. This figure can then be converted to annual delay hours by simply multiplying by the total number of aircraft operations. Physical delay costs can be calculated by multiplying delay hours by average aircraft operating costs.

Delay per aircraft at each reliever-hub airport can be modeled by using a Markov queuing model. Airport capacity for each individual reliever hub was investigated. Capacity was evaluated according the FAA runway capacity diagrams in Advisory Circular AC 150-5060-5. Assuming that the reliever hub airport would be operating under VFR, airport capacity was assigned to the variable μ, mean service rate, in aircraft per hour. Arrival rate λ was assigned the peak hour traffic demand, plus the traffic generated by the reliever hub. Peak hour traffic estimates for each airport were generated by taking 15% of the average total daily traffic. Efficiency is measured as ρ; W_q is defined by Little's Law as the average wait time, and can be calculated by using the following equation:

$$W_q = \frac{\rho}{\mu(1-\rho)} \tag{4-1}$$

$$\textbf{where } \rho = \frac{\lambda}{\mu}$$

TABLE 4-10 shows the anticipated average delay per aircraft, if an airport is used as a reliever hub. Since flight banks usually occur during peak hours, it is important not to exceed or approach ultimate airport operational capacity. The delay curve becomes asymptotical as demand approaches capacity. The additional traffic generated by the airport's use as a reliever hub must be added to the airport's current peak traffic volume. This ensures that the airport does not exceed its capacity under the worse-case scenario. The estimated delays produced by the queuing model do not include taxi delays; therefore, delays computed may be slightly underestimated.

Houston Intercontinental Airport (IAH) is severely congested during its peak period. Under normal conditions, it is estimated to handle 137 operations during its daily peak. Its capacity is approximately 164 aircraft per hour. Delays would begin to become unacceptable (>4 min) as the airport reaches 150 operations per hour. Sending more than 26 extra aircraft to Houston during its peak hour could cause the airport to overload. Without any additional runways, Houston can be used only if delays remain acceptable. Therefore, a maximum of 13 aircraft can be sent to Houston, to keep the peak hour total from exceeding 150 operations per hour. If Tulsa International Airport (TUL) was used as a reliever hub for our representative airline, it would begin to approach capacity during peak, also. With 30 additional aircraft, delays at Tulsa would become borderline acceptable. Delays would drastically increase with the addition of a few more flights.

TABLE 4-10 RELIEVER-HUB CAPACITY ANALYSIS

Airport	Annual Traffic (Thousands)	Avg Volume	Peak Volume	Avg+ Hub	Peak+ Hub	IFR Capacity*	VFR Capacity*	Average Delay, W_q (Minutes)
Amarillo Intl	89	14	37	44	67	57	85	2.6
Austin/ Bergstrom	203	31	83	61	113	113	149	1.3
Corpus Christi Intl	139	21	57	51	87	57	130	0.9
Houston Intl	334	51	137	81	167	113	164	***
Tulsa Intl	198	30	81	60	111	108	125	3.9
Waco Rgnl	49	7	20	37	50	57	82	1.2
*ultimate capacity, based fleet mix index of traffic using hub								

Congestion costs can be computed by multiplying the average delays at each airport by the average airline operating costs and are shown in Table 4-11.

TABLE 4-11 RELIEVER HUB CONGESTION COSTS

Airport	Average Delay (min)	Cost per Flight
Amarillo Intl	2.6	$57.80
Austin/Bergstrom	1.3	$28.90
Corpus Christi Intl	0.9	$20.89
Houston Intl*	4.0	$88.92
Tulsa Intl	3.9	$87.14
Waco Rgnl	1.2	$26.68
*average delay with 13 flight max.		

4.6 INFRASTRUCTURE INVESTMENT COSTS

In today's world of cost-consciousness, most airports have little unused space as construction is usually demand-driven. As with most transportation facilities, planning for future expansion does not begin until congestion exists. In order to use an airport as a reliever hub, extra gates must be added. Extra gates will require extra terminal space.

Many airports can add gates by simply adding on to an existing terminal building. Each boarding gate requires a departure lounge. Approximately 10-15 ft^2 of space per person must be provided to seat passengers awaiting departure [Horonjeff 456]. Table 4-12 shows recent terminal expansion/construction projects and their costs. These costs and the infrastructure costs discussed in the remainder of this chapter are construction prices which often do not include the cost of design, project management, or cost of financing.

TABLE 4-12 RECENT TERMINAL CONSTRUCTION PROJECTS

Airport	Size Ft2 (thousands)	Cost (millions)	Number of Gates	Cost per Ft2	Cost/Gate (millions)	Ft2/Gate (thousands)
Savannah	275	68	10	247.3	6.8	28
Greater Pittsburgh	1205	205	75	170.1	2.7	16
Colorado Springs	270	38	15	140.7	2.5	18
Lambert/ St.Louis	235	75	10	319.1	7.5	24
Tampa	235	110	15	468.1	7.3	16
McAllen	115	27	4	234.8	6.8	29
Austin/ Bergstrom	450	90	20	200.0	4.5	23
Average				254.3	5.5	217

4.6.1 Austin/Bergstrom International Airport: A Special Case-Study

At the time of this study, Austin/Bergstrom International Airport was still under construction. Because of its proximity and because the results of this study may have an influence on the airport's final terminal layout, Austin/Bergstrom was chosen as a special case-study. On opening day in 1999, the terminal at Bergstrom will have 19 gates and house 450,000 square feet of space, without any changes to the present design. The present design is estimated to cost approximately $100 million and is shown in Figure 4-1.

Currently, American Airlines has indicated a need for only 4 gates in the terminal at Bergstrom. Seven gates can be added by extending the westernmost terminal pier by 450 feet. This would add 40,500 ft^2 to the terminal, at a cost of $9.5 million. An 800' by 600' section of apron would also need to be constructed, costing $4 million. Seven boarding bridges at a cost of $250,000 apiece would add $1.75 million. Summing these costs, adding seven gates to give American a total of eleven at Bergstrom would cost approximately $15.3 million. This expansion is shown in Figure 4-2.

To add more gates at Bergstrom, a southward-pointing satellite would have to be constructed at the western end of the terminal. Combined with the west-wing, discussed in the last paragraph, a total of 96,675 ft^2 would be added to the present terminal design. This terminal addition would cost $22.6 million. Nearly 1.1 million square feet of apron space would also need to be constructed, at a cost of $9.1 million. Seventeen boarding bridges would cost $4.25 million. Summing these costs, adding 17 gates to give American a total of 21 would cost $36.0 million. This expansion is shown in Figure 4-3.

In order to add a large number of gates at Bergstrom (30 or more), it would be feasible to build a remote terminal, located 1,000 feet to the south of the main terminal. The best design for the remote terminal would be a linear terminal, 1625 feet long and 100 feet wide, parallel to the main terminal. The apron for the terminal would have to be 3,125 feet long and 1,000 feet wide. A moving walkway would have to be constructed underground to link the remote terminal with the main terminal. Tunneling costs for a moving walkway would be close to $5000 per linear foot. Costs for a two-lane moving walkway approach $5500 per linear foot. As a result, adding a remote terminal, with 30 gates, and moving walkway would have a total cost upwards of $82.0 million. This expansion is shown in Figure 4-4.

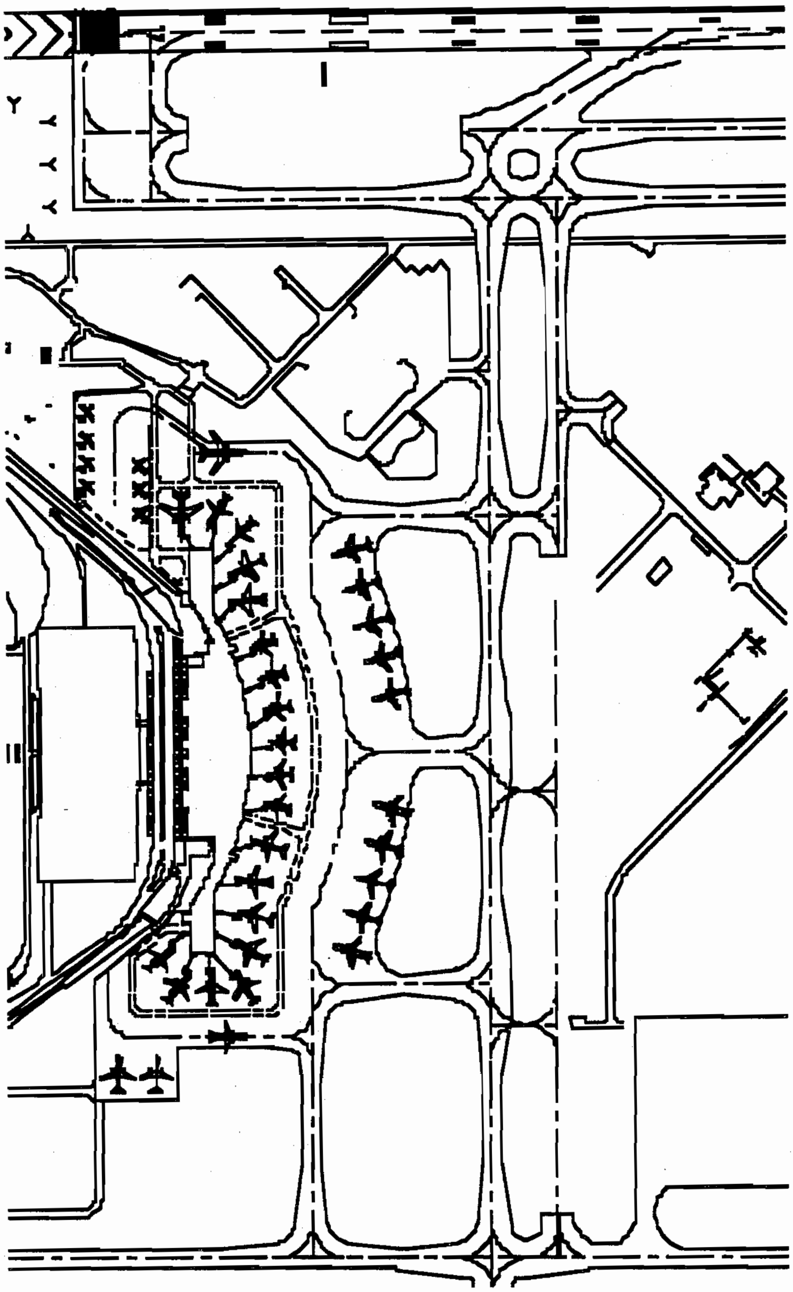


Figure 4-1 Current terminal layout design for Austin/Bergstrom International Airport

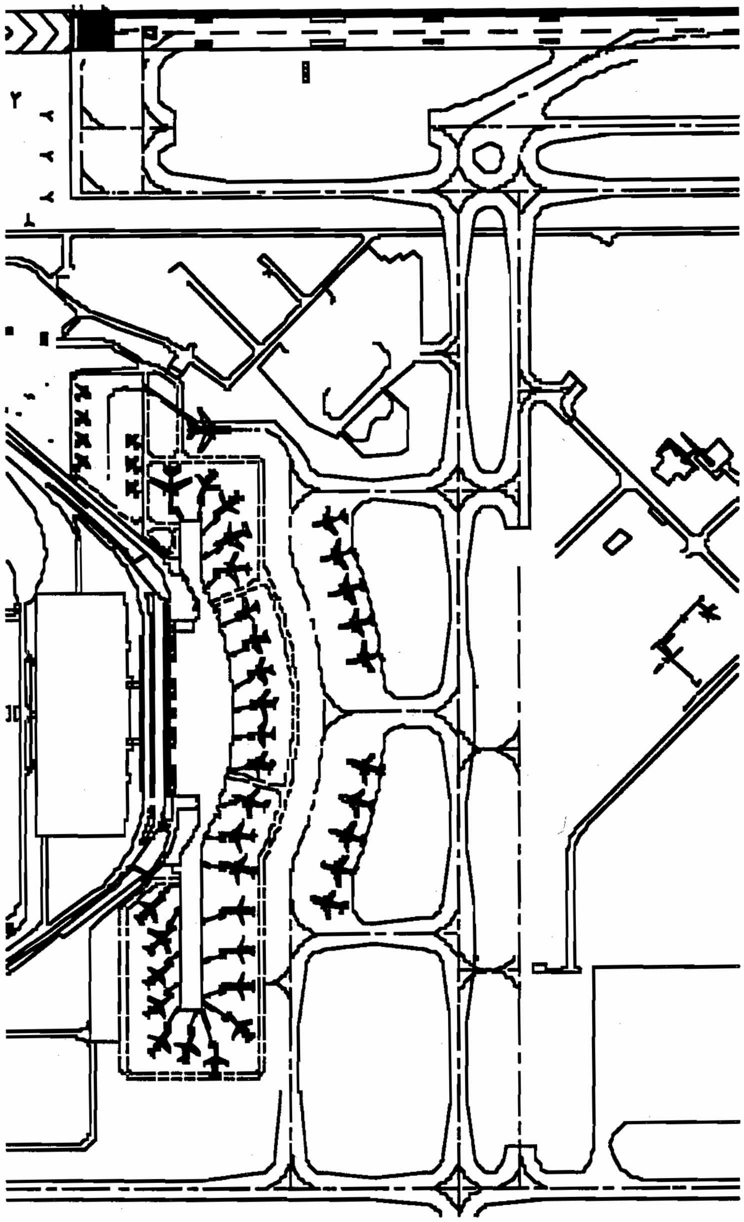


Figure 4-2 Case 1 terminal expansion for Austin/Bergstrom International Airport

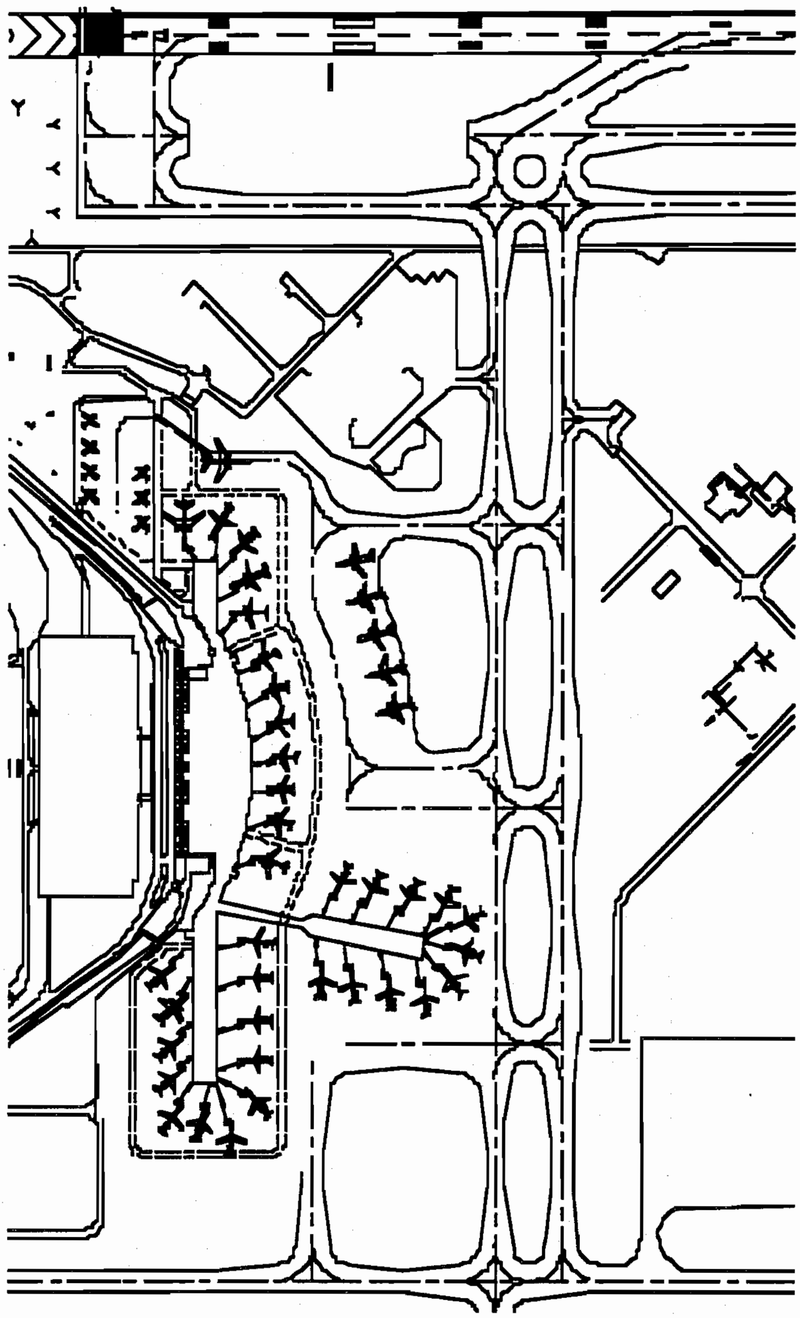


Figure 4-3 Case 2 terminal expansion for Austin/Bergstrom International Airport

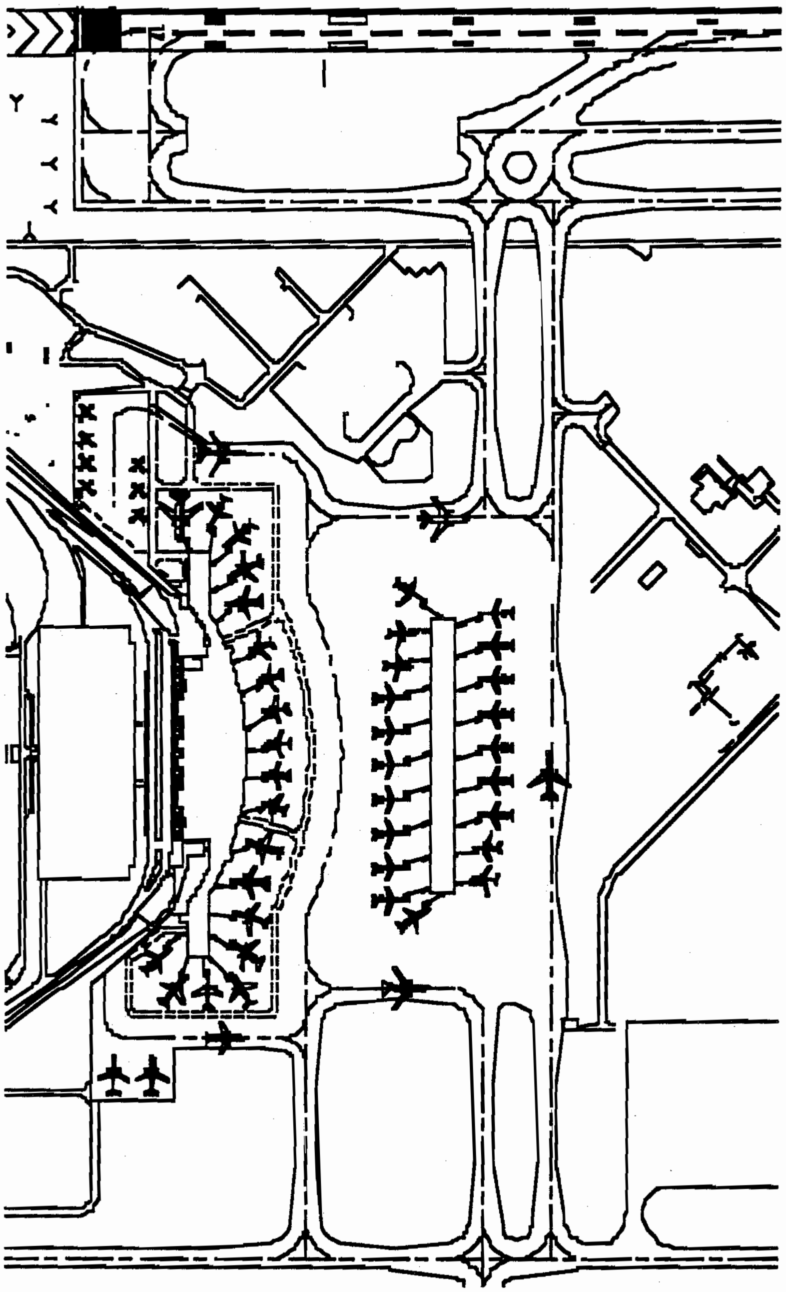


Figure 4-4 Remote terminal case for Austin/Bergstrom International Airport

4.6.2 Analysis of Airport Infrastructure Costs

Based on the present design for a 4 gate terminal expansion at Austin-Bergstrom, adding terminal space costs an estimated $234 per square foot, or approximately $1.6 million per gate, including the boarding bridge. New terminal construction at other airports, as shown in Table 4-13, has averaged $254 per square foot, or $1.8 million per gate. Extra terminal space also requires extra parking apron space. Airports generally provide an average of 1.6 acres or 70,000 ft^2 of apron space per aircraft, while airport pavement costs are typically $75 per yd^2. Airport layout plans for all airports researched in this study are shown in Appendix C.

All of the potential reliever hub airports selected for this study would require construction of additional landside infrastructure in order to handle extra aircraft. Waco and Corpus Christi would require erection of a completely new terminal and extended runways. According to the FAA Airport Design Computer Program, a 9,000 foot runway would be sufficient for aircraft traveling a stage length of 3,000 miles or less. Waco would need to extend its primary runway, Runway 1-19 from 6,597 feet by 2,400 feet, to achieve a 9,000 foot length. Corpus Christi would need to extend its primary runway, Runway 13-31 from 7,508 feet by 1,500 feet to achieve 9,000 feet. Along with a 75 foot parallel taxiway, these extensions would cost each airport approximately $4.5 million and $2.8 million, respectively. At Amarillo, twelve to fifteen gates can be added to the existing terminal easily, if the fixed-base operator (FBO) is relocated. That would require construction of a 600 foot by 600 foot apron elsewhere on the airport, which would cost approximately $3 million.

Adding terminal space at all other reliever hub airports would not pose any problems. Construction costs at individual airports will be variable, since the number of flights sent to a specific hub will be determined later by the location model. For this study, two gates will be provided for every three aircraft using a reliever hub. Ideally, a gates should be constructed to accommodate all aircraft using the hub. However, since the reliever hub will be used infrequently, this ratio was chosen to reduce total investment costs. Additional aircraft and passengers can be accommodated in remote parking spots. A summary of the derivation infrastructure investment cost estimates can be found in Appendix D. In most cases, reliever hub construction would eliminate costs associated with weather delay immediately, if passenger-delays are included. If an airline invested in a reliever hub system, it would receive a return on its investment during the first year, with passenger delay reduction. However, for this study, all infrastructure costs were converted to annual capital recovery costs, so that they could be combined with annual operating costs. Airlines usually like to receive a return on their investment quickly, within five years or less. For this reason, an inflation rate of 3% was used, for the investments over a five year period. Fixed infrastructure costs are shown in Table 4-13.

TABLE 4-13 FIXED INFRASTRUCTURE INVESTMENT COSTS

Airport	Total Cost	Annual Cost
Amarillo Intl	$3 million	$655,000
Austin/Bergstrom	-0-	-0-
Corpus Christi Intl	$2.8 million	$611,520
Houston Intercontinental	-0-	-0-
Tulsa Intl	-0-	-0-
Waco Regional	$4.5 million	$983,000

4.6.3 Personnel/Operational Costs

Sufficient ground crew personnel would also be needed at the reliever hub. If the primary hub is predicted to be closed, then the ground crew personnel can simply be ferried from the primary hub to the reliever hubs. American Airlines employs approximately 320 baggage handlers at Dallas/Ft. Worth. With 58 gates and shifts, this results in 2.8 people per aircraft.

American's fleet consists primarily of narrowbody MD-80 aircraft, which can generally back up under their own power. Additional push-back carts needed to back-up the few 757s and widebody aircraft probably would not be needed. The existing push-back equipment at the reliever hub airport could be used. For aircraft which are not given a boarding gate, the rear stairs could be used for boarding and de-boarding. However, extra baggage carts would be needed, to transfer bags for all connecting passengers. At DFW, American Airlines owns uses approximately seven bag carts and one tractor to pull the carts for every gate. This equipment would be required at the selected reliever hubs, to ensure prompt baggage transfer. According to American Airlines, each bag cart costs $2,500, while a gas tractor costs $17,000. If seven bag carts and a tractor are provided at the reliever hubs for each aircraft, $34,500 worth of baggage equipment would be needed.

A fixed-base operator (FBO) is a company located at an airport who provides services to aircraft using the airport. An FBO provides most services requested by pilots, for a nominal charge. An FBO offers fuel, maintenance, food, and even locates ground transportation and hotel accommodations. At smaller airports, FBOs provide airliners with meals and fuel. At hub airports, airline maintain their own "fuel farms". In the case of a reliever hub, an FBO would happily provide fuel for an airline, with a contracted price. This cost would probably be similar to an airline fueling its aircraft at the primary hub, using its own fueling facilities. According to Signature Flight Support at Robert Mueller Municipal Airport in Austin, Texas, 30 planes could be refueled in an hour with no problem, as long as they are given advance notice. Signature has a sufficient number of workers on-call to handle this extra demand.

Table 4-14 shows the variable infrastructure investment costs. For example, if 10 aircraft are designated to be sent to Waco, two gates will be added for every three aircraft using Waco. Building a seven gate terminal, an apron of sufficient size, and purchasing baggage carts would cost a total of $1.8 million per aircraft. For ten aircraft, this cost would approach $18 million.

TABLE 4-14 REQUIRED INFRASTRUCTURE INVESTMENT COSTS, PER AIRCRAFT

Airport	Terminal+Bridge Cost	Apron Cost	Total Cost	Annual Cost
Amarillo Intl	$1.1 million	$581,000	$1.7 million	$365,142
Austin/Bergstrom	$1.1 million	$303,000	$1.4 million	$304,427
Corpus Christi Intl	$1.2 million	$581,000	$1.8 million	$396,549
Houston Intercontinental	$1.2 million	$581,000	$1.8 million	$396,549
Tulsa Intl	$1.1 million	$581,000	$1.7 million	$365,142
Waco Rgnl	$1.2 million	$581,000	$1.8 million	$396,549

5.0 GEOGRAPHIC LOCATION OF RELIEVER HUB

Evaluating a reliever-hub combination which provides the best results can be a difficult task. Distance, weather, capacity, and infrastructure costs all play a major role in locating a set of reliever hubs. With six possible hubs, limiting the number of hubs that can be chosen to a maximum of two still creates 21 possible combinations. Furthermore, if multiple hubs are chosen, careful selection must ensure that a flight will be operated through the closest hub. Tabulating the distance and cost for each individual flight and all possible hub combinations, coupled with weather, traffic, and infrastructure costs would be extremely time consuming. Using a computer to evaluate the best alternative provides much faster results.

5.1 DEVELOPING A LOCATION MODEL

Finding the optimum location and number of reliever hubs was done by developing a simple mathematical programming model to minimize all costs resulting from reliever hub usage. Given an objective function and a set of limitations, a computer can find the best alternative by adjusting the model's parameters. The mixed integer programming model used is shown below:
Objective Function:

$$\textbf{Minimize } Z = \sum_{j=1}^{h}((a_j + b_j + c_j) f_j + 2t\sum_{i=1}^{n} d_{ij} x_{ij}) + \sum_{j=1}^{h} e_j y_j \qquad (5\text{-}1)$$

where:

x_{ij}, y_j, s $\in \{0,1\}$, o_j are integers

Z = annual operating cost of reliever-hub set

a_j = potential weather delay cost per flight at hub j, per year

b_j = potential traffic delay cost per flight at hub j, per year

c_j = infrastructure investment cost per flight at hub j

d_{ij} = additional operating cost of flight (i,j)

e_j = fixed infrastructure investment cost at hub j

f_j = number flights operated from hub j

h = total number of possible reliever hubs

H = desired maximum number of reliever hubs

n = number of cities served

t = avg # of flight banks operating through reliever hubs, per year

x_{ij} = 1 if flight operates from city i to hub j

0 if otherwise

y_j = 1 if hub j is constructed

0 if otherwise

subject to the following constraints:

1. a maximum of H hubs can be chosen

$$\sum_{j=1}^{h} y_j \leq H \tag{5-2}$$

2. all cities must be served only once

$$\sum_{j=1}^{h} x_{ij} = 1, \text{ for i=1...n} \tag{5-3}$$

3. hub must be built if used

$$\sum_{i=1}^{n} x_{ij} \leq n y_j, \text{ for j=1...h} \tag{5-4}$$

and

$$\sum_{i=1}^{n} x_{ij} = o_j, \text{ for j=1...h} \tag{5-5}$$

Costs for the model were developed in Chapter 4. Each flight is assigned a specific operating cost differential, d_{ij}, developed in section 4.1. Two types of infrastructure investment costs are used in the model: fixed costs and variable costs. Fixed costs represent facilities which must be constructed to use the airport as a reliever hub, regardless of demand. Variable costs are needed to size the hub according to demand. Fixed infrastructure investment costs for runway extensions were also discussed in section 4.6. Since the implementation of any reliever hub will minimize passenger delay, savings are uniform for all possible reliever hub selections and are subtracted from each solution. Costs used in the model are shown below in Table 5-1:

TABLE 5-1 ANNUAL COSTS PER AIRCRAFT ASSOCIATED WITH RELIEVER-HUB USAGE

	Weather-Delay Per Aircraft	Traffic Delay Per Aircraft	Infrastructure Per Aircraft	Total Cost Per Aircraft
Amarillo	$15,492	$2,948	$365,142	$383,582
Austin/Bergstrom	$32,222	$1,474	$304,427	$309,123
Corpus Christi	$26,748	$1,065	$396,549	$451,110
Houston	$32,326	$4,535	$396,549	$433,410
Tulsa	$18,899	$4,444	$365,142	$388,485
Waco	$50,811	$1,361	$396,549	$448,721

Additionally, each potential hub has its own weather delay cost, traffic delay cost, and infrastructure investment cost. Due to runway capacity constraints, the number of aircraft sent to Houston will be limited to a maximum of 13, in all trials. Table 5-1 shows the costs to accommodate an aircraft at each hub, assuming that flights will be sent to the reliever hubs 51 times annually. For example, if 10 aircraft are designated to be sent to Waco, an infrastructure investment of nearly $4.5 million per year, for five years would be required. Fixed costs in the model are for infrastructure which must be constructed to use the airport as a hub, regardless of the number of flights. For example, the runway at Waco must be extended if five flights are sent to Waco or if all 30 flights are sent. Fixed costs were shown in Table 4-13.

The purpose of the objective function is to tabulate all costs associated with reliever hub usage. If a flight from city one to hub two is operated, then $x_{12} = 1$; if not $x_{12} = 0$. If hub one is selected, then the solution for the model returns $y_1 = 1$; if not $y_1 = 0$. In the objective function, d_{ij} is multiplied with x_{ij}. Therefore, a cost for a flight from city i to hub j is tabulated only if x_{ij} is non-zero. Clearly, the easiest way to minimize the objective function would be by operating the fewest number of flights. However, the constraints require that all cities must be served only once; therefore, exactly 30 flights must operate.

If all 30 flights operate, it is still possible to minimize the solution by sending each flight to the closest hub. For example, flights from Los Angeles would be sent to Amarillo, flights from San Antonio would be sent to Austin, flights from New Orleans would be sent to Houston, and flights from the East Coast would be sent to Tulsa, etc. This configuration would be impractical, as it would be extremely difficult to transport passengers to their final destination efficiently, with four separate reliever hubs. This possibility can be eliminated by ensuring that hub infrastructure must be built if any flights are sent and by limiting the maximum number of hubs that can be selected.

This algorithm finds the best alternative by minimizing all costs, while ensuring that all of the constraint conditions are met. The model will output the optimal number of reliever hubs needed, the best location for the reliever hubs, number of flights operated through each, and estimated annual savings or cost to the airline, as compared with not using reliever hubs to alleviate weather delays.

Variable d_{ij} contains the additional cost of operating flight(i,j) to from city *i* to hub *j*, instead of from city *i* to the weather-affected hub. This number is doubled, as flights must fly to and from the reliever hubs during their usage. Variable *t* is the expected number of flight banks operated through the reliever hubs annually, or the frequency of thunderstorm occurrences. According to the statistics from the DFW weather observation station, 51 occurrences of turbulent weather occur within the vicinity of the airport annually during normal operating hours. Assuming that no pilot would desire to use the airport during a storm, a weather reliever-hub system would be used 51 times annually.

5.2 SOLVING THE MODEL

The model developed for this study was solved using Solver in Microsoft Excel, with the aid of a mathematical programming add-in developed by Dr. Paul Jensen, head of the Operations Research Group at the University of Texas. The model contains a matrix of 192 variables and 43 constraints. Potential flights (x_{ij}) from 30 cities to all 6 hubs must be evaluated, resulting in 180 variables. Dummy variables showing whether or not a hub is used (y_j) and hub size variables (f_j) create 12 additional variables. Once the data is entered, solving takes approximately 3.5 minutes on a 486DX4-100 PC with Windows '95.

Initially, the model was run with flight operating costs only, to show the effect of geography and to find a generalized solution. Allowing a maximum of three, the best reliever hub locations are: Houston (IAH), Amarillo (AMA), and Tulsa (TUL). Each city is served by the closest hub. This solution is shown in Figure 5-1. Without the shuttle, this solution would "save" the airline $2.2 million annually in operating costs alone. However to avoid stranding passengers, a shuttle must be provided. Using this solution, all flights from the west coast would be sent to Amarillo. The only connecting flights immediately available at Amarillo would be flights returning to the west coast. Virtually all passengers arriving in Amarillo would need to be ferried to another hub to reach their final destination. this would create a demand for a large number of shuttles. A solution with less hubs would be more feasible.

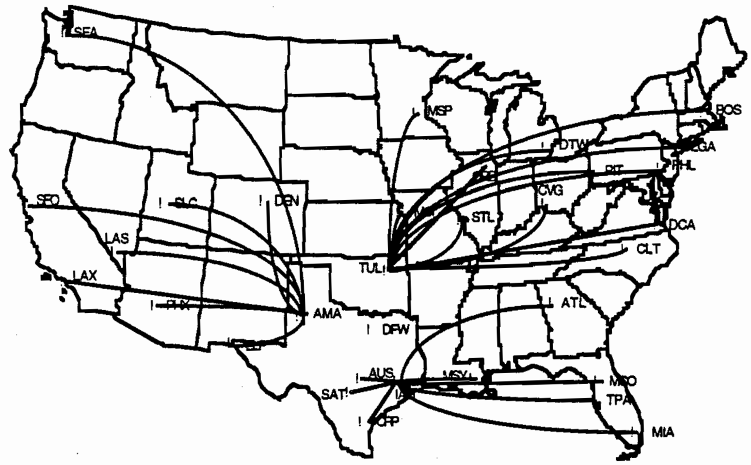


Figure 5-1 Best solution for Triple Reliever Hubs, considering distance only

Restricting the solution to two hubs produces somewhat improved results. Also, due to runway capacity limitations, a maximum of 13 flights can be sent to Houston. The model was adjusted to ensure this restriction. After running the model, Tulsa and Houston were selected as hubs; All northern cities connect through Tulsa, while all southern cities connect through Houston. Twenty-one flights would be sent through Tulsa, 9 would be sent through Houston. Figure 5-2 shows the new route network. With two hubs, a shuttle system must be provided. At Tulsa, an average of 36 passengers on every arriving flight will have to transfer to Houston. Since 21 flights will use Tulsa, 756 passengers will have to be ferried. This will require 6 shuttles. In Houston, an average of 84 passengers per arriving flight will need to transfer to Tulsa. Since 9 flights will use Houston, 756 passengers will have to be ferried, requiring 6 shuttles. A total of 12 shuttles will have to be provided, at a cost of $32,300 per flight bank, or $1.6 million annually. Without a shuttle, this route system would save the airline $1.4 million annually. However, the shuttle must be implemented to avoid stranding passengers, resulting in a net cost of $200,000 annually compared with normal operations through Dallas.

Considering infrastructure costs, the most effective solution would be locating a reliever hub at Austin. The infrastructure costs have the largest impact, and Austin would have the lowest infrastructure investment. The current terminal design at the new Austin airport has lower than average construction costs. Also, Austin has sufficient runway capacity, coupled with a low traffic demand. Few airports are able to handle simultaneous instrument approaches. In all but the most turbulent weather, Austin-Bergstrom's runway capacity would be unaffected.

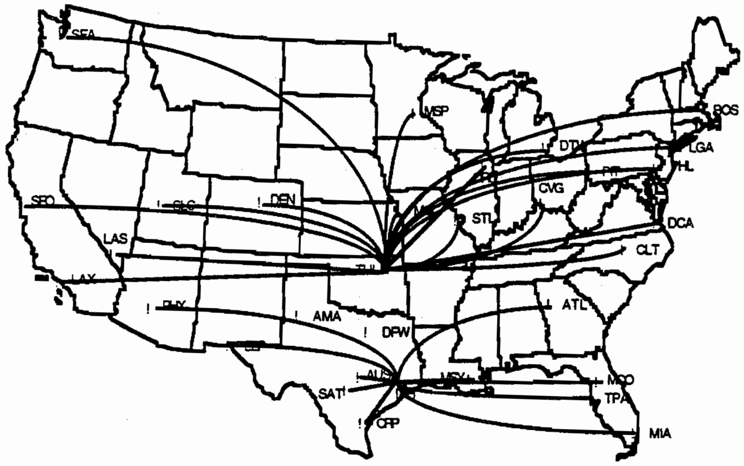


Figure 5-2 Best solution for Dual Reliever Hubs, considering distance only

The best solution considering operating costs only would be locating the reliever hub at Tulsa. Tulsa is more centrally located to all of the representative airline's destinations. This solution reduces overall operating costs by minimizing distances between each city and the hub. The majority of the airline's cities are located north of Tulsa. Tulsa is more centrally located than any other hub. This solution, shown in Figure 5-3, saves the airline approximately $519,000 annually while no shuttle is necessary.

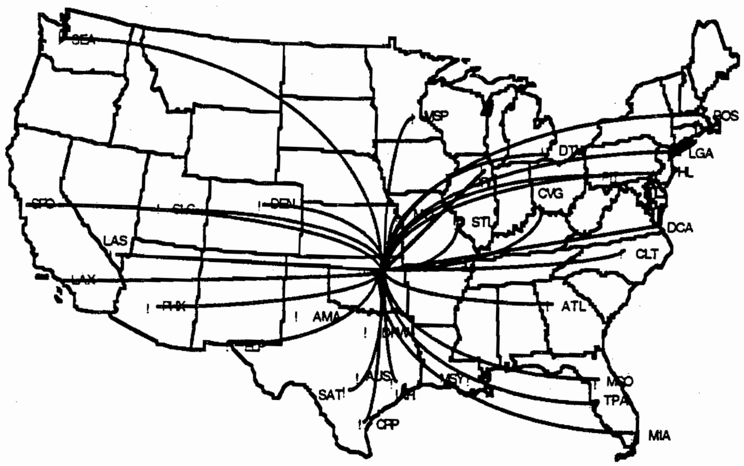


Figure 5-3 Best solution for Single Reliever Hub, considering distance only

Based on operating costs, weather delay costs, and infrastructure costs, sending all 30 flights to Austin would cost the representative airline approximately $9.7 million annually. For passenger delay, using a conservative estimate of $23.9 million in annual savings would bring the total savings for reliever hub usage to $14.2 million anually. Using Austin as the only reliever hub is shown in Figure 5-4.

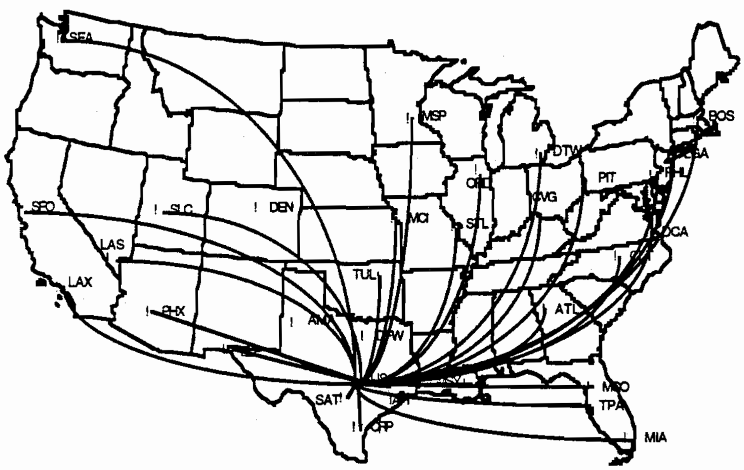


Figure 5-4 Best overall solution for single reliever hub

If a dual hub system is required, according to the model, the best solution would be sending 16 planes to Austin and 14 to Tulsa. This solution is shown in Figure 5-5. This scenario would cost the airline $11.2 million per year, and is less desirable for several reasons. In Austin, 56 passengers on each flight would need to be transferred to Tulsa, and in Tulsa, 64 passengers per flight would need to be ferried to Austin. As soon as a flight bank arrives at each of the hubs,

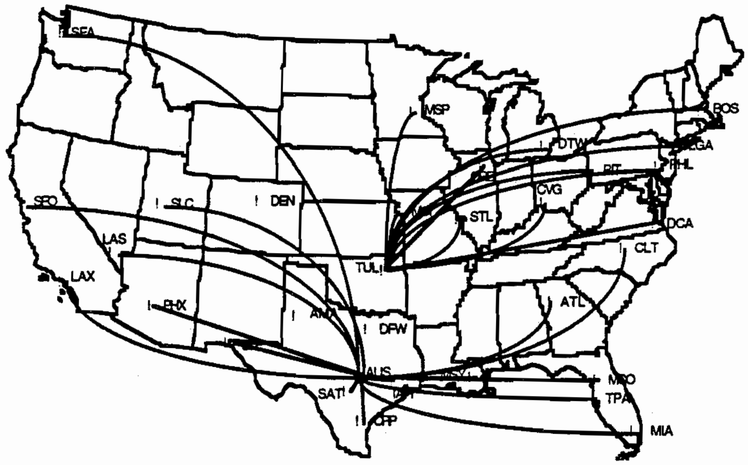


Figure 5-5 Best overall solution for Dual Reliever Hubs

passengers needing a transfer would embark on the shuttle. Average airline block time between Austin and Tulsa is approximately 1.4 hours. A total of two hours would be needed to give passengers sufficient time to be sorted, enplaned, and deplaned. To ensure all passengers reach their final destination, the flights banks themselves would be unable to depart from Austin and Tulsa until after the shuttle runs are complete, nearly two hours later. This would cause a two hour delay for all passengers. Therefore, the double connection required for the dual-hub scenario would penalize the airline heavily. Passenger delay costs would not be reduced.

5.4 ANALYSIS OF RESULTS

Although flying to Austin/Bergstrom would increase flight operating costs by 7% over Dallas/Ft. Worth, the lower infrastructure investment costs compensate for the difference. Infrastructure costs at Tulsa are $388,000 per aircraft, per year, while costs at Austin are $309,000 per aircraft, per year. The cost differential results from a lower per unit square foot cost for the terminals and a more efficient use of apron space at Austin. Even though Tulsa's weather is more statistically desirable than Austin's, the difference in weather cannot undermine the strength of the infrastructure costs. Based on the weather data, Tulsa is less likely to be simultaneously affected with Dallas by adverse weather. If Tulsa is used as a reliever hub, weather delays are projected to be \$567,000 annually. At Austin, weather delays will be approximately \$967,000 annually.

5.5 LIMITATIONS OF SOLUTION

The solution achieved by this study is subject to limitations. Weather observations provided by the NCDC are only available in three hour intervals. If a thunderstorm occurs at anytime during a three-hour interval, then a thunderstorm is recorded for the entire interval. It is difficult to determine exactly when and the duration for which the thunderstorm affected the airport. Holding the average delay d of 90 minutes per aircraft during a thunderstorm constant, 17 storms per year would have to occur to make using a reliever hub feasible. If 17 or more storms occur annually, the savings in passenger delay would make investment in a reliever hub rewarding for the representative airline. This solution was achieved by solving Equation 5-1:

$$15012n + 119608n - 9.3\text{ million} + 5216nd \geq 0 \tag{5-1}$$

In Equation 5-1, the first term shows annual additional operating cost to send all flights to Austin, per storm n. The second term shows the annual delay savings in airline operating costs if a reliever hub is implemented. The third term represents the annual infrastructure investment required to use Austin as a reliever hub. The fourth term represents the annual passenger delay savings based on the frequency and duration of reliever hub usage. Equating this expression to zero enables the solution to show the break-even point for reliever hub investment. If Equation 5-1 is greater than zero, then building a reliever hub is practical.

Additionally, it is difficult to ascertain how much physical delay a single thunderstorm causes. Many variables affect delays caused by thunderstorms. In the case of Dallas/Ft. Worth, thunderstorms have been known to close one side of the airport, while the other side is completely dry. Based on Equation 5-1, the product of thunderstorm delays and thunderstorm frequency must exceed 1,458 minutes annually per affected aircraft for the Austin reliever-hub to be beneficial. For example, if an average thunderstorm causes 60 minutes of delay, then 25 storms or more occurring would make using Austin as a reliever-hub feasible.

Holding infrastructure costs constant, the relationship between the amount of delay and reliever hub feasibility for Austin is shown in Equation 5-2:

$$nd \geq 1458\text{ min/acft-yr} \tag{5-2}$$

where:

n = number of annual thunderstorms

d = average duration of delay induced by each storm

Equation 5-2 shows the minimum amount of annual weather delay necessary per flight to establish reliever hub feasibility for Austin. Equation 5-2 is a logarithmic function and is graphed in Figure 5-6. The feasible region is located above the function.

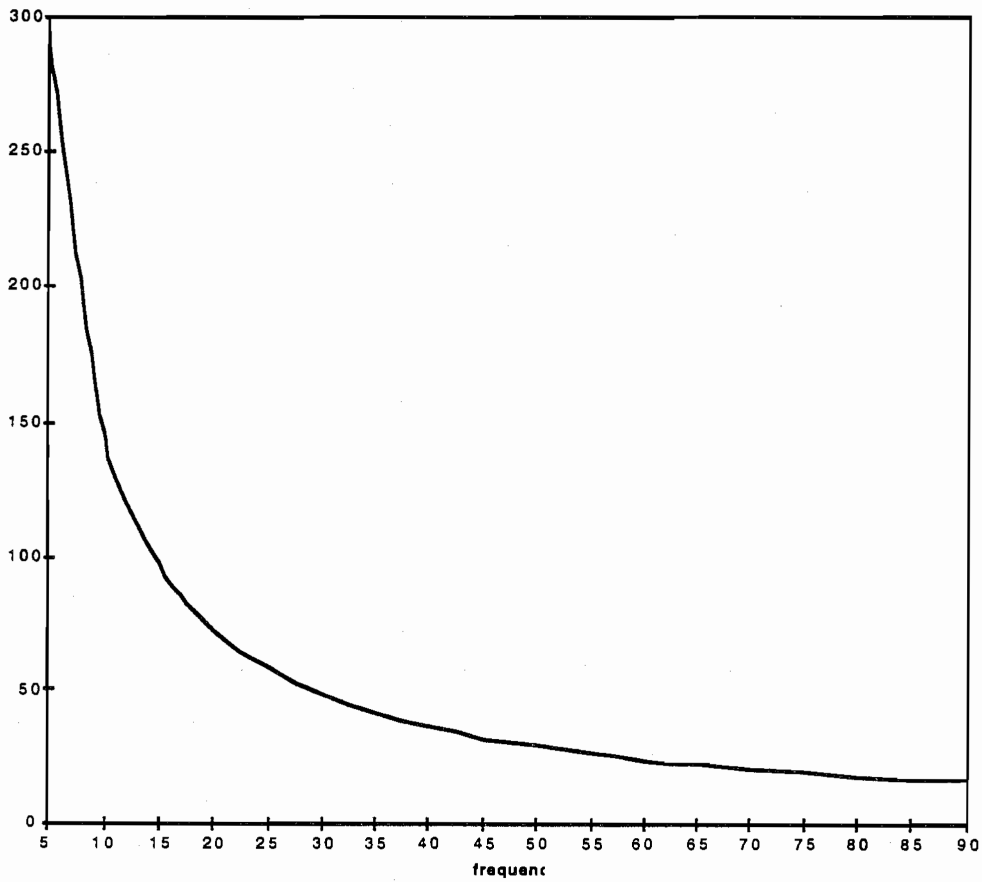


Figure 5-6 Thunderstorm frequency vs. average resulting delay to establish reliever hub feasibility for Austin

6.0 OPERATIONAL FEASIBILITY OF THE ALTERNATE-HUB CONCEPT

Since most larger domestic carriers use a hub and spoke system, disturbances at the hubs have the largest effect on operations and may propagate through the whole network requiring extensive re-allocation of aircraft and cancellations. Since such incidents have a very large economic impact, and cause considerable inconvenience to passengers, the problem has attracted serious attention from the airlines, for whom even a few small changes may save millions of dollars annually. When a schedule disturbance occurs, especially at a hub airport, any well optimized and closely functioning schedule becomes ineffectual. Rapid reassignment to minimize the resultant cascade of effects to other flights in the schedule is required.

Traditionally, airlines recover from these situations by applying proven heuristic or rule-of-thumb assignment strategies, normally through experienced schedulers aided by software to balance air crew assignment restrictions and aircraft availability. According to American, if more than 15 flights in a bank are diverted to other airports, the rest are canceled. Cancellations at a hub are more likely during the morning hours as mishaps occurring early would adversely affect the rest of the day's schedule. American tries to avoid canceling evening flights so that passengers are less likely to become stranded overnight at a hub. [Waring, 1997] On a typical day, American Airlines cancels 20-40 flights (about 1%) of its 2500 scheduled flights. According to the FAA, another 6% of American's daily flights are delayed more than 15 minutes.

The larger airlines make use of computer based re-scheduling procedures to recover from a perturbation, and try to recover in such a way as to limit the impact on their system-wide schedules whilst minimizing some measure of delay. Simultaneous application of other algorithms ensure correct crew and aircraft re-assignment. Currently, the possible actions available to schedulers when recovering from a schedule perturbation is generally limited to flight swapping, whilst accepting some level of delay, and/or cancellation.

When a large hub such as Dallas/Ft. Worth or Chicago is severely curtailed by bad weather, thousands of passengers are left stranded as flights are canceled or delayed. Since storms or adverse weather conditions can sometimes be predicted ahead of time, it seems reasonable that an airline given an alternate hub or operation strategy could adapt its schedule to preempt large anticipated delays and cancellations. Of course, various issues such as cost-effectiveness and practical operational constraints must be considered.

In order to determine the operational benefits of the Alternative hub concept, a model is needed that would behave similarly to an airline operation covering a representative market spread. To effect this purpose in this study, an airline scheduling computer model was developed and various operating strategies were evaluated for a single airline system over a 24 hour period. This proved to be a daunting task in it self, a problem that has demanded considerable attention from the airlines and researchers alike.

The main parameters of importance when assessing an operational model are of course net revenue, i.e. passenger revenue - direct operating cost, and some measure of passenger service. When faced with multi-criteria evaluations, question arises how to compare more than one dissimilar parameters, and if they can and should be combined into a common unit, typically some monetary or utility value. The exact definition of the actual evaluative parameters used in this study will be discussed in greater depth under the Model section in this report.

The two important operational aspects that need to be considered when evaluating the alternative hub-concept are fleet re-assignment and passenger routing. Although as we will later see, these two aspects are highly inter-dependent, it would serve well at this stage to analyze the properties of each.

6.1 FLEET ASSIGNMENT PROBLEM

The fleet assignment problem as associated with air carriers appears simple in concept - match aircraft to flight legs so that seats are filled with paying passengers. An airline seat is perhaps the most perishable commodity in the world and every airliner that takes of with an empty seat represents a revenue opportunity that is lost forever. Nearly all the direct operating costs attributable to an airline are incurred merely by flying the aircraft on a given sector and the marginal cost of filling each additional seat in an aircraft is negligible - perhaps a few pounds of fuel and the cost of in-flight meals and beverages. In order to minimize the cost of offering a given service, an airline has a limited set of options, some of which may be short term escapable costs, and others which are fixed in the long term.

6.2 AIRLINE COST DETERMINANTS

The normal practice of airline revenue analysis is to broadly divide all costs into Direct and Indirect operating costs. The aim is to identify and separate those costs and revenues not directly associated with the actual operation of an airline's flight services. ICAO and most airlines have adopted this practice.(Doganis, 1991) Under this structure the following items are included under each.

6.2.1 Direct Operating Costs

- Flight Operations
- Flight crew and salaries
- Fuel and Oil
- Airport and route charges
- Aircraft Insurance
- Rental/lease of flight equipment/crews
- Maintenance and Overhaul
- Engineering labor costs
- Spare parts consumed
- Depreciation and amortization
- Flight equipment

6.2.2 Indirect Operating Costs

- Station and ground expenses
- Ground staff
- Buildings, equipment, transport
- Handling fees paid to others
- Ground equipment and property
- Passenger services
- Cabin crew salaries and expenses
- Other passenger service costs
- Passenger insurance
- Ticketing, sales and promotion
- General and administration

6.2.3 Escapable Short Term Costs

The broad division into direct and indirect costs is especially useful when dealing with aircraft and route evaluation. The indirect costs of a particular network or operation can be assumed to remain constant, no matter if a particular route is being flown or not, or the type of aircraft operated on it. Direct operating costs on the other hand are directly attributable with the operation of an aircraft on a given route. These are therefore deemed to be "escapable costs", although the exact extent of ecapability does to a certain degree depend on the time frame involved. When a particular flight is canceled at the last minute, certain sunk costs such as crew and ground service may already have occurred and are therefore not escapable. Though, with a couple of hours of warning these costs may also be avoided. Direct operating costs can therefore be subdivided into variable direct operating costs, which are activity related and are escapable in the short term, and indirect operating costs which are only escapable over a medium to longer term.

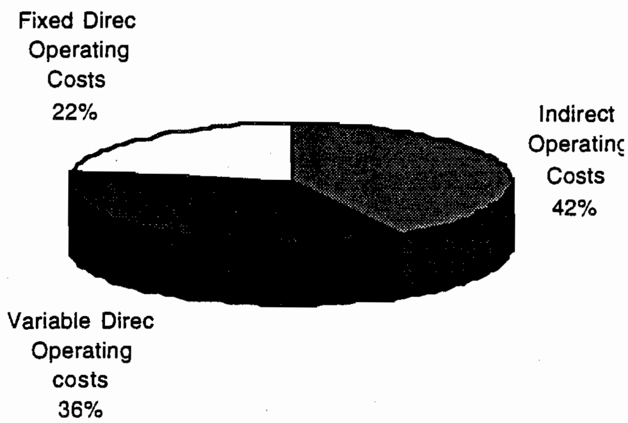


Figure 6-1 British Airways' cost in terms of escapability, 1988/89 (Doganis, 1991)

The major opportunity to scale the of cost of providing a service on a given route, happens when selecting the type of aircraft. Modem commercial aircraft are available in many sizes with varying capabilities such as payload, interior volume, speed and range. Although the per seat available cost of larger aircraft may be less, unless the extra capacity is converted to paying passengers, a smaller aircraft will nearly always have a lower trip cost. Right-sizing aircraft is therefore an important component to minimizing airline costs. Unfortunately, this task is a very complex one, involving many trade-offs, and bound by a multitude of restrictions.

6.3 AIRCRAFT TYPE AND CHARACTERISTICS

Many properties and technological aspects affect the direct operating costs of an aircraft. The most important from an economic viewpoint are likely to be size, speed and range at full payload. An aircraft's productivity may be a function of these characteristics, the relative importance of each depends on the type of mission it is used.

6.3.1 Aircraft Size

Aircraft size influences cost in two ways. A larger and heavier aircraft will require more fuel to fly a given sector at a similar speed than a smaller aircraft and incurs higher landing fees. The cost of ownership is also higher through increased financing costs and insurance. However, larger aircraft have certain economies of scale. Larger aircraft have proportionally lower drag and carry more payload per unit of weight. The general rule is that a larger aircraft has lower operating costs per unit of output, that is per ton-mile or seat-mile. However, their total trip cost is of course still higher, and unless the extra output is converted into revenue, the economic goal is to use the smallest, and cheapest aircraft on any given route that fulfills the demand.

6.3.2 Aircraft Speed

Since hourly productivity is the product of payload and speed, the greater an aircraft's cruising speed the greater will be it's output per hour. An aircraft flying at 500 miles/hour carrying a 100 passengers has a hourly output of 50,000 seat-miles. An aircraft with a similar payload capability, but flying at 600 miles/hour produces 60,000 seat-miles every hour. If their hourly operating costs where similar, say $2,000 /hour, the faster aircraft would have a unit cost of 3.33 cents per seat-mile compared to the slower aircraft's 4 cents per seat-mile.

With the exception of the Anglo-French Concorde, most modern jet aircraft operate in the high sub-sonic speed regime since supersonic flight imposes serious cost and environmental limitations. Therefore variations are not very large, typically in the order Mach 0.7 - Mach 0.85, which translates to about 150 miles per hour difference between the fastest passenger airliners such as the Boeing 747-400 and slower examples such as the Fokker 100. Over longer flight sectors this difference does indeed become important, which is reflected in the performance advantage normally associated with long-range aircraft.

TABLE 6-1 OPERATING COSTS FOR TYPICAL PASSENGER AIRLINERS PER BLOCK HOUR (COMPILED USING AIRLINE GUIDE 1991 DATA)

Aircraft	Seats	Crew Cost	Fuel Cost	Maintenance	Capital Costs	Total	Cruise Mach	Cent/ Seat-Mi.
DC 9-30	100	428	528	431	231	1618	0.78	2.51
B 737-200	107	428	527	313	362	1630	0.78	2.37
B 737-300	128	428	491	310	472	1701	0.78	2.07
MD 80	142	428	603	296	510	1837	0.78	2.01
A320-200	150	428	493	320	480	1721	0.81	1.72
B 727-200	150	557	848	640	274	2319	0.82	2.29
B 757-200	188	542	647	436	695	2320	0.79	1.89
B 767-200	204	637	988	655	904	3184	0.8	2.36
B 767-300	254	658	996	619	1190	3463	0.8	2.07
L-1011-200	260	729	1657	1191	590	4167	0.82	2.37
A300-B4	261	729	1249	642	588	3208	0.82	1.82
A300-600	267	658	1249	652	1424	3983	0.82	2.21
B 747-SP	300	1503	2459	1597	1109	6668	0.85	3.17
DC 10-10	271	729	1424	1541	519	4213	0.82	2.30
DC 10-30	271	729	1878	1368	970	4945	0.82	2.70
B 747-100	376	1503	2710	1545	668	6426	0.83	2.50
B 747-200	376	1503	2750	1586	1190	7029	0.84	2.70
B 747-400	416	1503	2735	1043	2384	7665	0.85	2.63

6.3.3 Range and Take-off Performance

Various aircraft are designed to cater for particular traffic densities and stage lengths. Each may have different take-off and range characteristics which in turn influence costs. An aircraft may require a particularly long runway when taking off with a large payload and sufficient fuel to cover a long stage. If the required runway length is not available at the originating airport, payload capacity is reduced. Structural and fuel capacity limitations may also determine take of weights, and therefore economic output.

The trade-of between these various properties for each aircraft are given in Payload/Range diagrams. (Ashford et al, 1991, pp. 86) These diagrams constitute a segmented function between the sum of available payload and fuel, and range. The diagram documents the maximum structural capacity of the airframe to carry the required load, the maximum take-off weight and maximum fuel capacity. As the required range increases, each of these limitations becomes the critical parameter to determine the useful payload.

6.4 AIRCRAFT SELECTION

The ideal aircraft would be a so-called "rubber aircraft", that could perfectly atretch itself to the exact required capacity and cost to accommodate all possible markets. Therefore, most large airlines try to emulate such an aircraft by operating a fleet of differently sized aircraft to cover all capacity and performance requirements. For example, an airline's fleet may comprise of aircraft varying from 50-seater regional jets such as the Embraer 145, 120-seat Boeing 737-200 and DC 9-30's, 220-seat Boeing 767's and Airbus A-300's right up to 400 seat Boeing 747-400's.

A recent marketing strategy of aircraft manufactures is to offer families of aircraft based on a similar configuration of varying capacity and cost. Examples are Boeing's 737-300, 737-400 and 737-500, the 757/767 family and the A319/320/321 and A330/340 offerings from Airbus. The philosophy behind operating these families of aircraft is to provide airlines with greater commonality in maintenance and spares, and offer cross-crew ratings. The latter allows a crew to fly different aircraft on a single type-rating providing better scheduling freedom without incurring the additional costs of keeping pilots rated on more than one type of aircraft. A pilot could for instance fly a trip using a 180-seat Boeing 757 in the morning and operate a 220-seat Boeing 767 that same afternoon.

Ideally such families of aircraft would permit sufficient operating flexibility to permit dynamic reassignment of the fleet to mach updated forecasts of demand. From an airline scheduling point-of-view, this gives rise to a kind of dispatch mode of operation where capacity is provided dynamically on demand. A limitation though, is that a scheduled air carrier is obliged to operate all published flights under normal circumstances, even though demand for a particular flight may be too low on a given day to might make that flight profitable.

6.4 AIRLINE SCHEDULING

Designing an airline network is an extremely complex task that requires assignment of the available resources (aircraft fleet size and composition, air crew, airport slots etc.) onto a route network in such a way as to optimize certain goals (e.g. minimize costs, maximize frequencies and level of service). Despite the complexity of the problem, airlines operate schedules which attempt to optimize aircraft and air crew utilization. These schedules are typically developed around hub-and-spoke operations allowing, greater penetration of markets at lower costs. As a result, daily schedules of airlines and airports are massively complex mechanisms that are extremely sensitive to disruption.

6.4.1 Passenger Demand Variability

The daily operations of an airline are geared around a skeleton schedule in which the same set of legs are assumed to fly daily using the same aircraft assignments. These schedules are to a certain extent determined by the various airport slot assignments assigned to each airline. Depending on peak variations, weekend and seasonal demand cycles, a typical domestic airline provides daily schedule and fleet assignment modifications to accommodate these variations in expected demand.

The stochastic nature of passenger demand contributes to a basic problem in airline scheduling - how to maintain consistently high load factors while still capturing the largest possible market share, especially during peak periods. Because variability of demand is high, typically standard deviations of the order 20-50% of the mean, even the best solutions give rise to average load factors in the order of 60 - 70%.

Demand is highly variable over a single day, since peaks in demand usually occur in earlier part of the morning and mid-late afternoon. Demand fluctuations also occur over time periods such as the week-day to week-end cycles or longer, reflecting the seasonal variation in demand.

6.4.2 Marketability

The scheduled times of arrival and departure are particularly important from a marketing point of view. Connections at major transfer points need to be minimized in order to provide adequate total travel times on a hubbed network. This gives rise to aircraft arriving and departing at major hubs in waves or banks, with periods of relative inactivity in between as is clearly depicted in Figure 6-2. Of course this is a recipe for all sorts of congestion delays and a finely tuned trade off is required to maintain profitability and acceptable passenger service levels.

Other factors to be considered are arrival and departure times that coincide with the beginning and end of the business day, hotel check-in and check-out times and land transport availability.

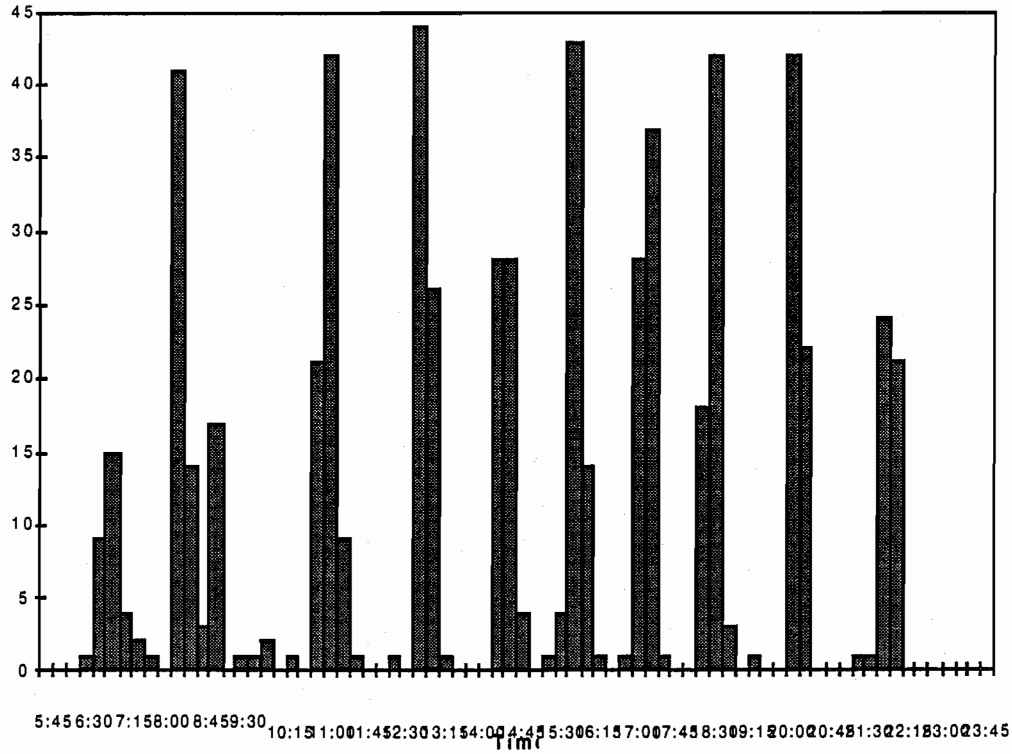


Figure 6-2 A histogram of arrivals and departures for American Airlines at Dallas-Ft. Worth International Airport showing the marked effect of flight banks

6.4.3 Aircraft Utilization

Since aircraft are very capital-intensive assets, attempts are made to maximize aircraft utilization rates. However, increased utilization impacts punctuality and aircraft serviceability. A schedule that makes use of a high aircraft utilization rate, while being economically attractive, has little leeway for schedule disturbances and unplanned aircraft maintenance.

Southwest Airlines is perhaps the best example of this type of operating philosophy. They are able to operate in this manner through the unique nature of their route structure and aircraft fleet. By only operating one type of aircraft, the Boeing 737, they are able to simplify maintenance and parts inventory requirements, thereby maintaining a high dispatch reliability. Furthermore their route structure consists of short-sector point-to-point service, avoiding large hubs and their associated delays where possible.

Currently airlines assign airplanes at schedule creation, typically 30-120 days in advance of service execution. A schedule must take into account restrictions on the departure and arrival times at various airports served. Curfews may exist limiting operations of noisy aircraft during evenings and early mornings. Long flights crossing time zones have limited time windows in which flights can be scheduled, since both take-off and landing times need to be synchronized to avoid curfews and highly congested hours.

6.4.5 Aircraft Availability

Depending on the type of aircraft, and age, availability will differ. Typically a Boeing 747 may be limited to 120 hours of continuous operation before 8 hours of maintenance is required. Including terminal and towing times, this may mean 12 hours downtime. Every three weeks a 24-hour maintenance break is required, and at three month intervals a major maintenance check is necessary taking 2 ½-5 days, depending on the aircraft's position in it's 20,000-hour maintenance cycle. Other aircraft are needed for training requirements, or standby in case of unscheduled maintenance on one or more assigned aircraft.

6.4.6 Load Factors

An obvious way to achieve good system economies is to maintain high load-factors, i.e. minimize those empty seats for which no revenue is gained. One way of achieving this is to fly a large fleet of smaller airplanes, although the economies of scale of operating larger aircraft are then lost. Lower capacity, although providing high load factors may cause unacceptable levels of passenger turnaway (spill) during peak periods, causing customer dissatisfaction and leaving the door open for competitors to gain a foothold in the market. Consequently, most large US carriers operate at system-wide load factors in the order of 65%, although flights during peak periods will approach the high 90%'s.

In another way to increase load factors, airlines attempt to rationalize their routes in such a way as to provide sufficient demand to consistently fill the larger aircraft in their fleets through hubbing. Passengers from smaller markets are all flown to a centralized hub and then transferred onto other aircraft to their final destination, thus allowing passengers having different final destinations to fill a single larger aircraft.

6.4.7 Frequency of Service

The frequency of service provided in a given market is extremely important to gain maximum ridership. In competitive environments, an airline providing a high frequency of service has been shown to attract a disproportionaly higher market share than it's capacity in relation to competitors in the same market. Again, a way of improving frequency of service would be to operate a larger fleet of small aircraft, but as seen earlier this has certain cost trade-offs. Hubbing provides a way of increasing frequency of service by rationalizing all flights out of a market without having to use smaller aircraft.

6.4.8 Crewing Constraints

Aircraft assignment may be constrained by crewing constraints. In setting up an airline schedule, crew along with aircraft can be considered limited resources and the efficiency of their deployment does significantly impact the cost structure of providing service. The task of crew scheduling generally follows the establishment of a flight schedule and aircraft allocation and involves mapping all flights on the schedule to a crew without violating various crewing restrictions. Crew Scheduling is a extremely challenging task, and many studies have been devoted to it, including Levine, 1996, who developed a hybrid genetic algorithm to solve it. For the sake of simplicity, we assume that the Crew Scheduling Problem to be solvable once fleet assignment has been made, and that by treating it as a separate problem, the airline cost structure is not fundamentally changed. This is not unreasonable since the hourly operating cost of all aircraft include a crew cost component, which is generally higher for larger aircraft or those with a three man cockpit configuration .

7.0 THE AIRLINE SCHEDULE MODEL

7.1 THE SPACE-TIME NETWORK REPRESENTATION

The fundamental mathematical structure that was chosen to build the fleet scheduling model is a space-time network. A network is a 2-dimensional set of nodes and links on which commodities flow, in this case passengers and aircraft. Nodes are generally used to represent intersection points or events. In the space-time network, a node may for example represent the arrival of a flight at a certain airport at a given time. This is significant since such an event has associated with it many different activities at various levels. Some passengers disembarking the flight have arrived at their final destination, others need to transfer onto a connecting one. After a short time period needed for cleaning end refueling, the arriving aircraft is freed to be re-assigned to a next flight.

Nodes in the network are connected by links according to the real or virtual connectivity that may exist between them. Such a link might for example be a representation of a flight connecting city A at 9.00 am (say node 1) with city B at 11.00 am (call it node 2). Two nodes may also represent the same geographic location in space, but at different time instances. A arc connecting two such nodes would then represent a period of holding over time at the same location.

The fundamental assumption is that two nodes are connected only if there is a physical way in which the commodity we are transporting (be it passengers or aircraft) can travel from the one to the other. Since reversal of time travel is deemed impossible, this has the result that undirected or bidirectional arcs (i.e. arcs that can be traversed in both directions) are not feasible.

In a model describing a complete airline system, this definition would result in two types of arcs: Flight links, representing a single hop of one aircraft with one take off and landing, and Ground arcs, representing aircraft and passenger waiting times on the ground.

For flows through the system to make sense, the commodities (i.e. passengers and aircraft) need to be pushed, or using a fluid dynamic analogy, pumped through the system at a constant time rate. This calls for the imposition of few mathematical restrictions to avoid physical impossibilities such as time travel or recirculation, where the same person or aircraft ends up existing in two places simultaneously. First, all the arcs are set to allow travel in one direction only. The commodities are introduced to the system through so-called source nodes and removed at corresponding sink nodes. Source and sink nodes are connected to relevant network nodes using dummy arcs, which "feed" passengers and aircraft into and out of the network without imposing a cost or a capacity restriction. To maintain conservation of flow, a commodity is removed at a sink node for every one introduced at a source.

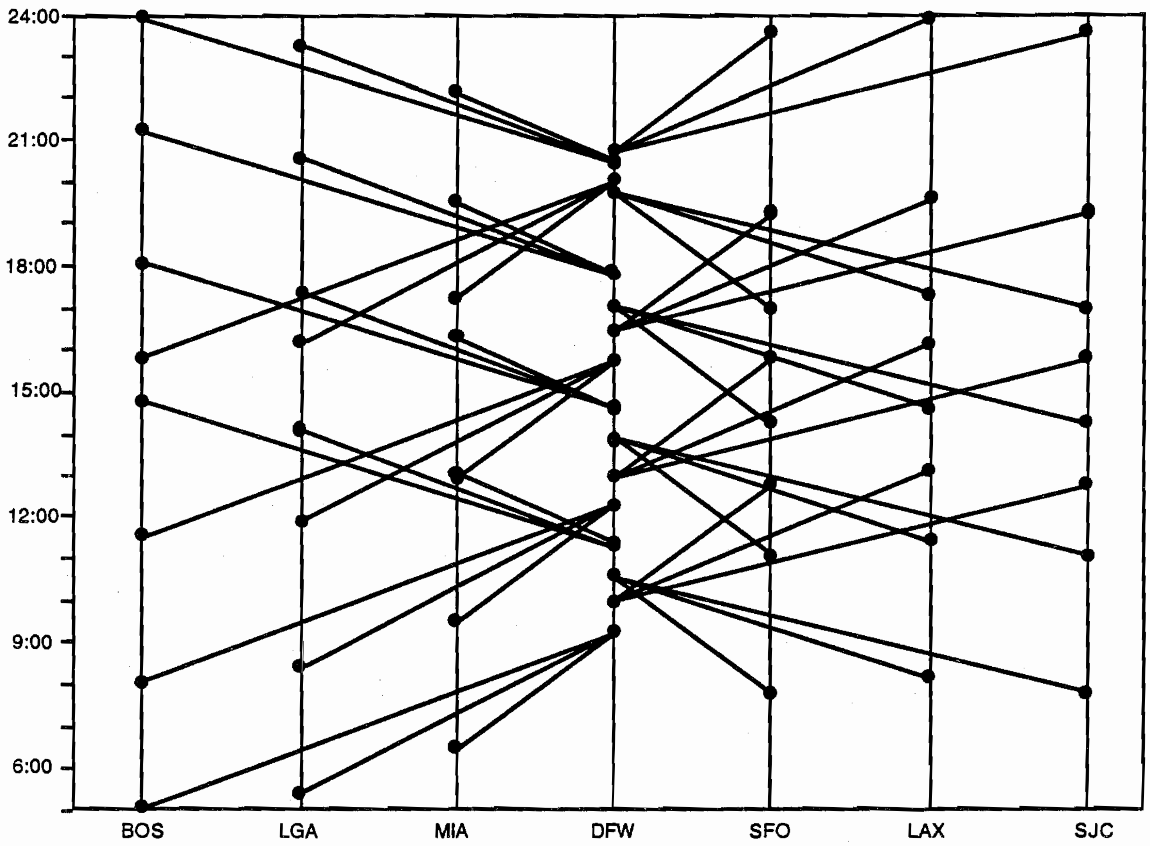


Figure 7-1 Space-time network representation for an airline schedule example

7.1.1 Multicommodity Flows

However, passengers can not simply be modeled using the analogy of water being pumped through a system of pipes. Each passenger is intent on reaching a pre-determined destination and needs to be handled as such. This is achieved through application of the multicommodity flow problem (Ahuja et al, 1993) where commodities are grouped into different categories depending on their final destination, but still sharing the same common network with all other commodities.

7.1.2 Network Representation Assumptions

Along with applying multicommodity flow, the following two assumptions are made in the network representation:

Homogeneous goods assumption

Every unit of flow, be it a passenger or aircraft uses 1 unit of capacity on each arc. A flight link would for instance have a capacity equal to the seats of that aircraft flying the sector in terms of passengers, but have a capacity of one in terms of aircraft.

No congestion assumption

We assume that up to the upper bound of capacity on any given arc, the flow through it is linear and no interaction exists. The cost can therefore always be expressed as a linear function of unit cost and flow.

The cost associated with moving 1 unit of aircraft (also the maximum capacity) over a flight arc is therefore equal to the trip cost of operating a specific aircraft on that sector. A reasonably good approximation of this cost would be the product of the block time and the hourly direct operating cost of the aircraft.

Passengers are assumed to yield revenue only as they are transported over a link, since nearly all the costs of transporting them is included in the aircraft operating cost. Thus the (negative) cost of passenger revenue, is approximated by the product of the number of passengers flowing over a link and the average fare attributable to the provision of that service.

7.2 INTER-DEPENDENT NATURE OF THE AIRLINE SYSTEM

From the previous discussion it becomes apparent that a model of an airline schedule involves the transportation of at least two commodities, passengers and aircraft. A more complicated model might for instance add baggage and flight crew as well. In the light of the complicated nature of the problem we will at this stage limit this analysis only to the first two, assuming that the crew scheduling problem is independently solvable given an aircraft allocation. In the macro scale of the system, baggage is assumed to form part of the passenger and does not require separate analysis at this level.

Unfortunately, this still leaves us with two inter-dependent systems. The aircraft schedule depends on the expected passenger demand, but the demand itself is a function of the capacity offered on the various flight links. A possible method is to invoke an iterative scheme, where the two systems are alternately analyzed, and the results for each previous iteration are used as input values for the next. In such a scheme, one hopes that the system is inherently stable and that the solution converges to some steady state value. By merely repeating these steps sufficient number of times, a final solution is found.

If this is not the case, a method is needed after each iteration to point the direction of the next set of input variables to ensure ultimate convergence. In very complex system having a multitude of decision variables this may be a daunting task. In this study, a genetic algoritm implementation was used to drive the system towards optimality.

7.3 FLEET AND SCHEDULE OPTIMIZATION

The problem of optimal fleet assignment to meet fluctuating demand and recover from schedule disturbances, impacts sufficiently on operating costs to warrant considerable attention by transport providers and various researchers. Some larger airlines, notably American and Delta have implemented such systems based on linear or integer programming techniques to optimize their fleet allocation, providing a net cost reduction of between 1-5%.

However, the success of dynamic, demand-driven dispatch strategies depends to a large extent on the accuracy of the expected demand for each sector of the service to be provided. With the wide-spread use of computerized flight reservations systems in the airline industry, this information generally becomes more accurately determinable as the time of departure approaches. Conversely, as restrictions imposed by aircraft and flight crew availability are progressively set as the departure approaches, aircraft re-assignment opportunities become more limited. This is unfortunate, limiting the window of decision to some finite time before departure. Most probably, this means that the exact demand for a particular flight is not known at this time, and that an estimation has to be made.

Table 7-1 lists a selection from American Airlines' DFW Schedule showing the fleet assignments it makes on various routes. Generally aircraft with less capacity are assigned to thinner markets, but may also be assigned to larger markets for the sake of improving frequency of service. Normally though, larger aircraft assigned between larger hub airports, since those aircraft are generally needed for assignment to international routes.

TABLE 7-1 SELECTION FROM AMERICAN AIRLINES' DFW SCHEDULE

Flight	Dep City	Arr City	Dep Time	Arr Time	Aircraft
817	DFW	SEA	344P	613P	S80
821	MIA	DFW	349P	602P	72S
824	LAX	DFW	1110A	411P	S80
825	MIA	DFW	1240P	303P	S80
826	DFW	BOS	1235P	514P	S80
828	DFW	BOS	629A	1107A	S80
847	DFW	SEA	644P	901P	757
854	DFW	MIA	821P	1207A+1	757
859	MIA	DFW	1116A	133P	72S
862	DFW	SFO	1225P	218P	S80
878	SEA	DFW	1202P	554P	S80
900	MIA	DFW	745A	955A	M11
900	DFW	LAX	1055A	1219P	M11
901	DFW	MIA	510P	856P	M11
933	DFW	MIA	1240P	426P	757
941	DFW	MIA	630A	958A	72S
942	MIA	DFW	630P	842P	72S
953	DFW	MIA	623A	955A	757
958	MIA	DFW	328P	545P	72S
960	MIA	DFW	150P	405P	757
962	DFW	SFO	918A	1110A	763
963	SFO	DFW	152P	727P	S80
968	MIA	DFW	710P	921P	72S
1001	LGA	DFW	605A	901A	S80
1025	MIA	DFW	430P	646P	72S
1048	LAX	DFW	1140A	444P	S80
1119	BOS	DFW	705P	1036P	S80
1201	MIA	DFW	615A	824A	72S
1205	DFW	LAX	800A	923A	S80
1206	LAX	DFW	100A	547A	S80
1208	DFW	MIA	632P	1004P	72S

7.3.1 Traditional Solution Methods

Unfortunately, the Dynamic Fleet Assignment problem is very difficult to solve because it is NP-hard. (Ahuha et al, 1993, pp.792) In linear programming (LP) terms, a large domestic airline could generate a problem with as many as 100,000 variables and 50,000 constraints. (Berge and Hopperstad, 1993) Additionally, these decision variables are restricted to integer values. The combined scale and combinatorial nature of the problem, the required daily frequency of the solution and the multitude operational constraints imposed by the nature of the system make this a daunting task indeed.

Subramanian et al, 1994 use a mixed-integer programming method to solve the fleet assignment problem for Delta Airlines. They first employ some algebraic reduction techniques to reduce the problem size from some 40,000 constraints and 60,000 variables to 12,000 constraints and 33,000 variables. This LP solution initially assigns about aircraft to about 2500 legs taking between 1 and 3 hours after which various smaller problem subsets are run to resolve problems. They estimate direct savings attributable to the model to be more than $100,000 per day.

Berge and Hopperstad, 1993 mention the usefulness of heuristic solution techniques as an efficient way to solve the problem. A heuristic algorithm makes use of a cleverly defined instruction set of operations, strategically arranged to coax the solution towards optimality, although not guaranteed to reach the ultimate optimal solution. However, the greater simplicity and speed of implementation when compared to LP-programming techniques has provoked active interest and research on this topic.

7.4 GENETIC ALGORITHM APPROACH

The original genetic algorithm (GA) was developed by John Holland in 1975 as a new type of search algorithm. They are based on an analogy with natural selection and population genetics by evaluating a set of mapped strings, called chromosomes, and synthetically mimicking the process of natural selection and Darwinian evolution theory. This provides a unique and fascinating way of optimizing a de-coupled system without any understanding of it's underlying structure.

7.4.1 Why Use a Genetic Algorithm?

Figure 7-2 illustrates the close-coupling that exists within the main aspects of transport provision. It shows the main relationships between the demand, service (operations), resources and infrastructure within the operation. Traditionally, each aspect has been treated and analyzed individually. For Instance. a operator would rely on a service demand model taking into account various economic, geographic and historic data factors in a similar fashion to that used in the four-step planning method used in Transportation analysis. Only then is a operations research optimization performed, usually to maximize profits with given resources. A shortcoming of this approach is that the resultant service would necessarily influence the customer's perception in such a way that the demand for the service would then change (usually adversely). This would then require in a revision of the service provided to retain profitability, leading to an ever decreasing demand/supply spiral until some equilibrium is found.

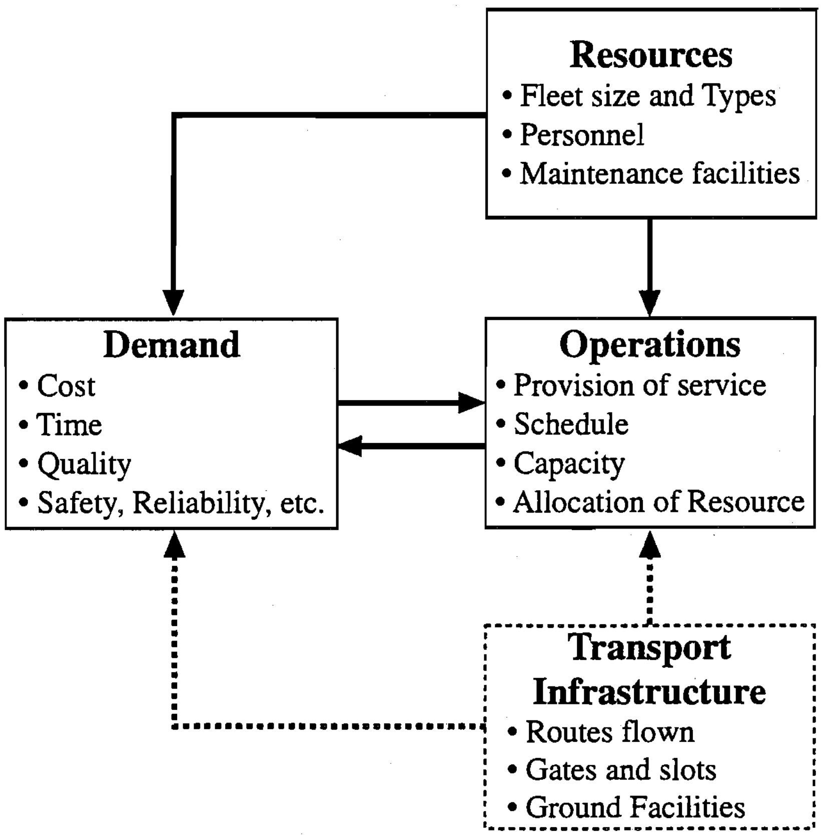


Figure 7-2 Main aspects of a transport service

One of the goals of this study was to find a method to model the network optimization and logistics of an air transport provider which takes into consideration the coupling between the various demand/service parameters to not only maximize cost effectiveness, but to possibly even analyze growth and movement of market share carriers. When analyzing the operation, alternatives must be chosen from among the very large number of possibilities to minimize cost, satisfy operational constraints and also fulfill the interests of the customer. A good model would allow demand, costs and level of service to be optimized within such constraints and goals as:

1. Fleet size, composure and the performance, size and cost properties of the individual aircraft;
2. Pilot/Crew Schedules and rotations;
3. Schedule and Frequency of service;
4. Service speed and comfort;
5. Resource utilization;
6. Routing and Transfer alternatives;

Genetic algorithms coupled with modern computer based simulation or modeling technique hold promise for enhanced solution techniques for transportation problems. It is hoped that by using a genetic algorithm, a powerful, non linear optimization of non linear models with stochastic parameters may be possible, a scenario that is frequently encountered in the quantification of transport properties. Genetic algorithms also appear to be more robust and are not as prone as some other optimization techniques to the pitfalls associated with local maxima/minima problems.

7.5 OVERVIEW OF THE ALGORITHM

The genetic algorithm is a general-purpose stochastic search technique applicable to a broad range of optimization problems. It works using a population of mapped strings, called chromosomes, each which corresponds to a single possible solution or function value of the problem. Using the terminology of genetics as a naming convention, we call each string in the population a *chromosome*, and each element or bit in it a *gene*. Obviously the way in which this mapping takes place is very important to the success of the implementation. Using the most basic example this may be a binary representation of a set of numbers within the domain of the solution area of some function for which we hope to find, say the local maximum. In practice, however, a coding scheme may take on any combination of symbols or characters arranged as a linear string, which in some way maps to a possible solution.

The first step of the optimization process is to generate an initial population set. Though poor performing, each element in the set should at least represent a feasible solution to the problem. This initial problem set may be generated in a random fashion, similar to the procedure used in Monté Carlo simulation, or may be generated manually or by some other modeling process.

The next step would entail characterizing each chromosome and assigning to it a fitness value which will be used in the "natural selection process". In simple cases this fitness could simply be the objective function value we wish to optimize. As will be seen later, in many cases a more complex definition here may be necessary, especially when performing multi-objective optimization.

After each chromosome has been assigned a fitness value, selections are made from the population in proportion to the fitness and then paired for reproduction purposes. The probability of selection, and thereby contributing to the next generation's genepool is therefore a function of each chromosome's fitness value.

A new population chromosomes are then created by using some crossover scheme *(mating)*, thus creating a *child* chromosome having some properties of both parents. The fundamental assumption is that these properties are somehow encoded in the individual genes, or in combinations of them, called *alleles*, and are not all lost during the reproduction process. Obviously this depends to a large degree on the method of mapping used to characterize the genes. Indeed, it is hoped that some chromosomes, inheriting various properties from both parents will yield a better overall fitness value than either parent. If this is not the case, the whole algorithm would merely become a random search procedure.

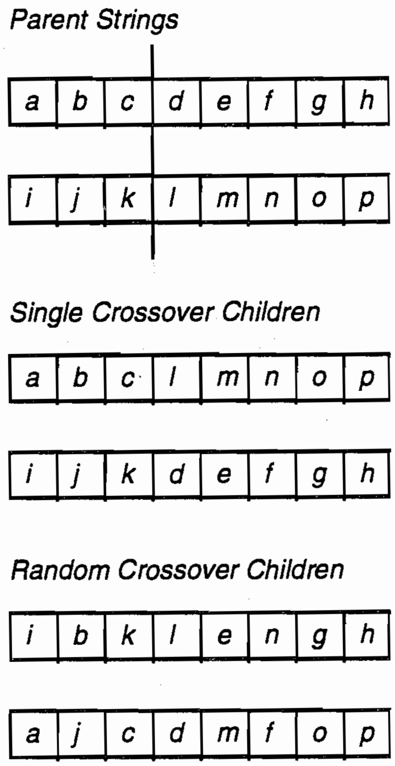


Figure 7-3 Schematic illustration of single and random crossover chromosome reproduction

Figure 7-3 shows 2 possible ways by which a child chromosome is produced. Random crossover, where each gene in the child string is inherited from either parent by a probabilistic mechanism, somewhat resembles the mechanism by which basic life forms reproduce. However, studies have found that a simple single crossover scheme, using the first portion of one parent and the latter of the other, normally yields better results. This is ascribed the to the better probability of gene combinations representing some good quality to be maintained in subsequent generations. (Glodberg, 1989)

Having produced a new generation of chromosomes, a small degree of *mutation* may be introduced to provide at least a small measure of randomness. This is necessary to theoretically to ensure that a given gene could take on any feasible value, although a particular gene value might not be present in any chromosomes in the initial genepool. This mutation normally takes the form of some small probability, say 0.05% that any given gene in each chromosome will change to some other value.

These steps make up the operations performed in each generation and at this stage the algorithm repeats itself again, starting with the fitness assignment step. Unlike nature, where there is no real end to the evolutionary process, the algorithm should keep on improving itself until it converges. This happens when it has exhausted all possibilities attainable with the initial genepool, or the most optimal value is reached, after which no further improvement is possible. It is important to understand that as with heuristic methods, a genetic algorithm does not guarantee optimality to be reached, it merely improves an initial solution set towards more optimal values.

This only describes the most basic strokes of Genetic Algorithms. Many variations and different implementations are possible and have been implemented for specific problems. (Goldberg, 1989)

7.6 ADAPTING THE METHOD TO THE SCHEDULING PROBLEM

In this study a new implementation approach to used to apply a genetic algorithm to the airline schedule optimization problem. This implementation involved a different way of mapping the flight schedule decision variables to a chromosome string as was found in the literature of similar studies. As discussed under the space-time network representation section, the airline system is modeled as a multicommodity flow problem on a space-time network. This in fact amounts to two models, one for passenger flow and the other for aircraft flow. The linkage occurs in that the capacity of each flight arc on the passenger flow network maps to the physical passenger capacity of the type of aircraft used on the corresponding aircraft flow network.

To explain the method used in this study to map chromosomes to an airline schedule, let us a imagine to be an aircraft dispatcher that assigns aircraft to flight sectors in real time. For each departure our imaginary "scheduler" has to assign an aircraft from the available number parked at the gate at say, 15 minutes before departure. Let us imagine that the scheduler knows with a reasonable degree of certainty the number of passengers wishing to travel on that flight. This assumes that the passengers are able to connect within a reasonable time onto a connecting flight to their final destination, if it is different from the destination of the departing flight.

Using a so-called "greedy" heuristic, the scheduler would assign the available aircraft that most closely matches the capacity of the expected demand for that flight, or for instance that aircraft that would maximize net revenue on that flight. This would be repeated for all subsequent departures, even when only one or no aircraft are available. In such a case the scheduler would make the most greedy choice available, be it to schedule a flight with a 400-seat Boeing 747 when there are only 50 passengers Only when no aircraft is available will a flight be canceled.

If we expand this concept a little, let's broaden the scheduler's choices to further options. He may choose to dispatch the second, or third most optimal aircraft for that specific flight leg, or cancel the flight, even when an aircraft is available. Although these choices may seem sub-optimal in the short run, they may be beneficial in the overall scheme of things, since an aircraft that would otherwise have been assigned earlier is held back for assignment to a later more profitable route. Seen over the complete network, a single scheduling decision also has a far-reaching effect on later scheduling, by effecting fleet availability and distribution at subsequent airports.

Let's denote these scheduling options by the following natural numbers:

0 - Cancel the flight

1 - Assign the best aircraft available (Greedy heuristic)

2 - Assign the second best aircraft available

3 - Assign the third best aircraft available

4 - Fourth Best etc.

In the case that the scheduler is instructed to perform option 3 (Schedule the third best aircraft available), and only two types of aircraft are available for dispatch, we define the second best aircraft to be selected. If only one is available and non zero instruction is encountered, that aircraft is always selected, unless no aircraft are available, in which case the flight gets canceled. In a real case scenario the flight may be delayed until an aircraft does become available later, but for the sake of our algorithm we disregard that option. It is after all possible to include dummy links at later stages to represent delayed flights.

Starting with the first departure in the morning, the scheduler is given a set of instructions with which all flights during that day are dispatched. This may for example take the form:

11121123120114312211412011321115120211121311112321 etc.

Since an action is defined to cover all combinations of the instruction and system state (i.e. available aircraft at that time), each string maps out to only one possible solution, although more than one string may map out to the same solution.

This type of coding scheme is very useful for implementation using a genetic algorithm, since it is possible to randomly generate a population of initial starting chromosomes. According to this definition, all subsequent child chromosomes would always be feasible solutions themselves. Also, since each bit (or gene) represents the same flight in the daily schedule, a particular scheduling complex is represented by a combination of genes, called *schemata*. This is a very powerful property and allows genes representing a schedule solution with a particular good complex to propagate in subsequent generations according to the fundamental theorem of genetic algorithms. This theorem according to Holland, states that schemata of short length and low order and above average fitness are propagated in exponential numbers throughout the generations. (Goldberg, 1989)

7.7 CUMULATIVE GENETIC ALGORITHM

The problem was first implemented using the standard algorithm described under section 7.5, and did indeed find successive improvements as the generations passed. However, optimization occurred fairly slowly, and on occasion, the trend toward improvement even reversed itself for a couple of generations. This was not unexpected, since one can not always expect a child chromosome to perform better than both parents. Also, the selection procedure for the standard genetic algorithm implementation is after all probabilistic, and it does not always guarantee a good chromosome automatic reproduction.

By using a cumulative chromosome population, the best performing portion of each chromosome generation was retained into subsequent generations. To a certain extent this guaranteed the survival of good candidates, and therefore greatly enhance their probability for contributing to the genepool. A immediate improvement in optimization speed was found, in accordance with the findings of Xiong and Schneider(1993). They labelled this set of high-fitness chromosomes the historical nondominated solution set (HNDSS). The definition of a nondomonated solution will be discussed further under the section multi-objective optimization.

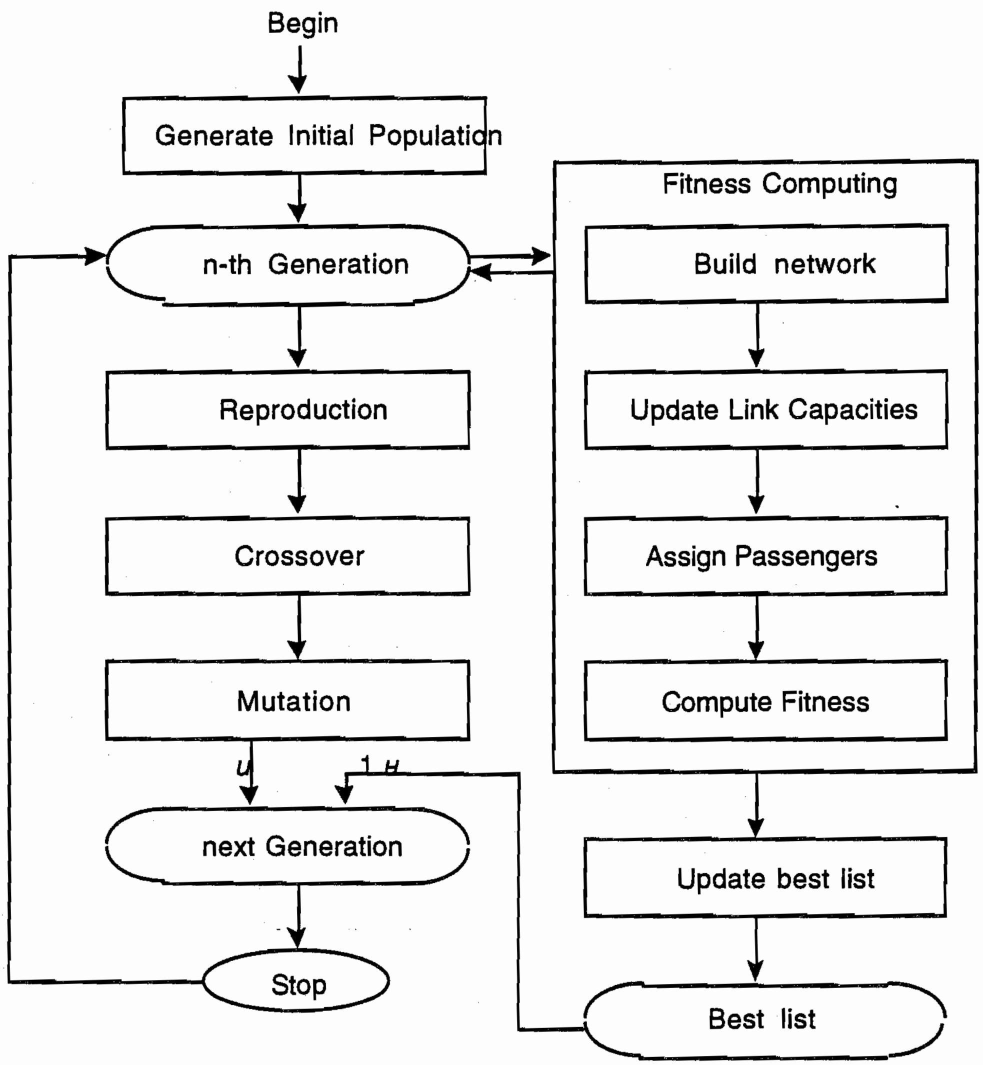


Figure 7-4 Genetic algorithm implementation for the airline network problem

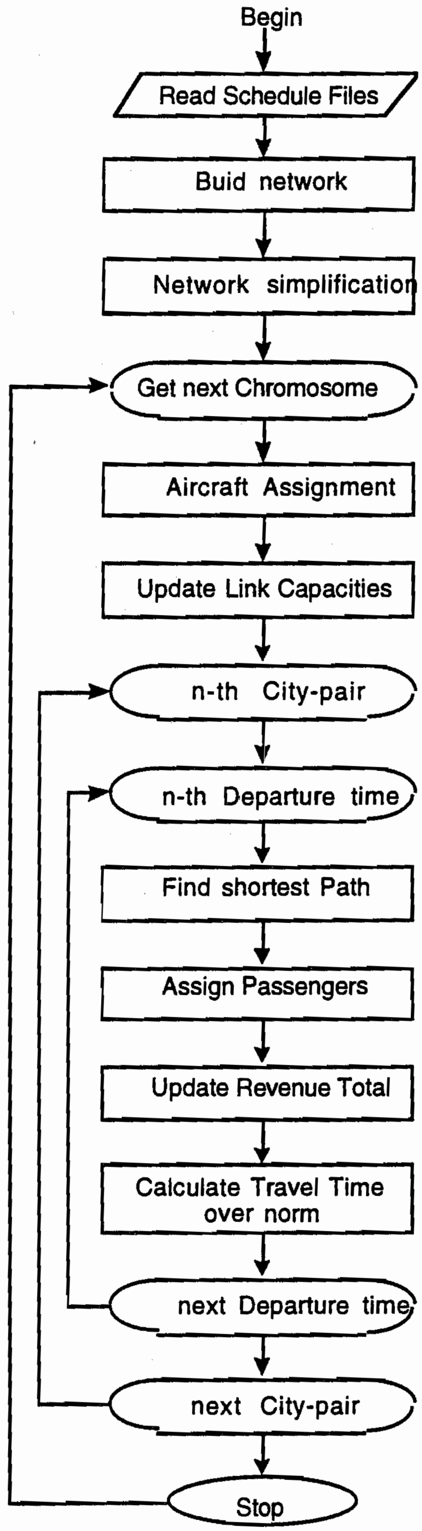


Figure 7-5 Algorithm for computing the fitness of each chromosome string

The downside of maintaining a list of super-chromosomes is that after a while they tend to dominate the gene properties of the population as a whole. Although they might increase the average fitness of a population, the probability of introducing new genetic information is lessened in a similar fashion as in nature when too much inbreeding occurs. Therefore a certain balance exists between the ratio, *u*, of this subgroup and the total population size. Xiong and Schneider (1993) Found the best value for their HNDSS to be 0.5. This coincided with tests performed in this study to maximize optimization speed while still preventing early convergence.

Figure 7-4 illustrates the structure of the genetic algorithm implementation by using a generalized flowchart representation. The Fitness computation of each individual string involved the solution of the airline network flow model as described in the flowchart in Figure 7-5. Starting with the first passengers early in the morning, flight assignments are made, thereby decreasing the remaining capacity on the arcs representing those flights. At some time the point may be reached where certain flights are filled to capacity and passengers need to be booked on later departures. This is achieved evaluating the shortest way a passenger can reach his final destination for each passenger as it is assigned flights.

A slightly modified version of the Dijkstra label setting algorithm (Ahuja, Magnanti and Orlin, 1993, pp. 108) was used for the shortest path subroutine used for passenger assignment. Using pseudo-Pascal coding, this algorithm can be stated as:

begin

$S: = 0; \bar{S} := N;$

$d(i) : = \infty$ **for each node** $i \in N;$

$d(s) := 0$ **and pred**$(s) : = 0;$

while $S \notin t$ do

begin

let $i \in \bar{S}$ **be a node for which** $d(i) = \min\{d(j) : j \in \bar{S}\};$

$S: = S \cup \{i\};$

$\bar{S} := \bar{S} - \{i\};$

for each $(i,j) \in A(i)$ **do**

if $d(j) > d(i) + c_{ij}$ **then** $d(j) := d(i) + c_{ij}$ **and pred**$(j) := i$;

end;

end;

where:

S = set of nodes already labeled with shortest path distance

$\bar{S}$ = set of nodes reachable (i.e. forward in time) from the starting node, n_s

N = complete set of nodes evaluated, $S \cup \bar{S}$

s = *shortest path starting node, i.e. the one from which the shortest path is sought*

t = *shortest path ending node, i.e. the one to which the shortest path is sought*

$d(s)$ = *distance to node s, starting node*

$d(t)$ = *distance to node t, ending node (this is per definition the value we seek)*

i = *starting or tail node of arc under consideration*

j = *ending or head node of the arc under consideration*

$d(i)$ = *distance to node i*

$d(j)$ = distance to node j

$pred(s)$ = *predecessor node to node s*

$pred(j)$ = *predecessor node to node j*

$A(i)$ = *set of arcs adjacent to node i, i.e. all arcs with node i as the tail node*

c_{ij} = *the distance of the shortest path found thus far from node i to j*

This Dijkstra shortest-path algorithm was chosen to solve the shortest path problem since it was hoped that it would take the least time in doing so. This is very important, since the shortest path algorithm is performed many times during the passenger assignment routine. Unlike most other shortest path algorithms, this adaptation can terminate as soon as the shortest path label of the ending node is set permanently. Although the worst case scenario may not necessary provide a advantage over all other algorithms, the network structure under consideration has been designed such that this node should normally be reached before most other modes in the network, thus saving valuable computing time.

7.7 MULTIOBJECTIVE OPTIMIZATION

In our discussion of genetic algorithms thus far, we have assumed that a chromosome's fitness is clearly defined by some measure of some parameter or objective criterion . When there are more than one criterion or objective which need to be optimized simultaneously, such as is typical of transportation problems where we wish to maximize revenue while still maintaining the highest possible levels of service, this becomes more difficult. One approach is to simply collapse the various criteria into one single utility or monetary value according to some weighted function and then proceed to optimize this value.

This approach works well in many problems, but for this study it deemed too restrictive to impose a general monetary value on, say passenger time, and then proceed with a optimization routine. Defining such a utility value could become a contentious issue which might vary widely between airlines and the markets they operate in. It was therefore decided to treat this problem as a multiobjective or multicriteria optimization problem.

In general, when a set of possible solutions is plotted on a set of axis (in n-dimensional space) according to respective performance on the n criteria to be optimized, the better solutions are those that appear closest to the corner of the quadrant of the best values for each dimension. In the case of two-criteria optimization this can easily be represented on a two-dimensional plane graph as in Figure 7-6. In this case the best values are those towards the top, left-hand side corner of the graph.

Those solutions represented by the points forming the outer boundary towards the top-left of the graph are *nondominated*, because there are no points in the solution set that perform better on all the criteria under consideration. The other solutions represented by points towards the bottom-right of this boundary, also called the *efficiency frontier*, are said to be *dominated,* because at least one of the nondominated solutions performs better on all the objective criteria. The nondominated values are therefore clearly better than the dominated ones, but selecting the best solution among all nondominated solutions would involve a subjective weighting amongst the objective criteria.

To be totally unbiased when assigning a fitness value for each chromosome, the genetic algorithm should, therefore, attempt to assign a value that corresponds to the distance away from this efficiency frontier, and assign the same level of fitness to all solutions on the frontier. There are various ways of doing this, most notably by assigning a ranking by the number of times a solution is dominated, or the n^{th} - dominated ranking method described in Goldberg, 1989 and used by Xiong and Schneider, 1993. This scheme was also attempted for this study, but another method described under the section 7.8 was ultimately chosen, since it yielded similar results but was considerably faster in execution.

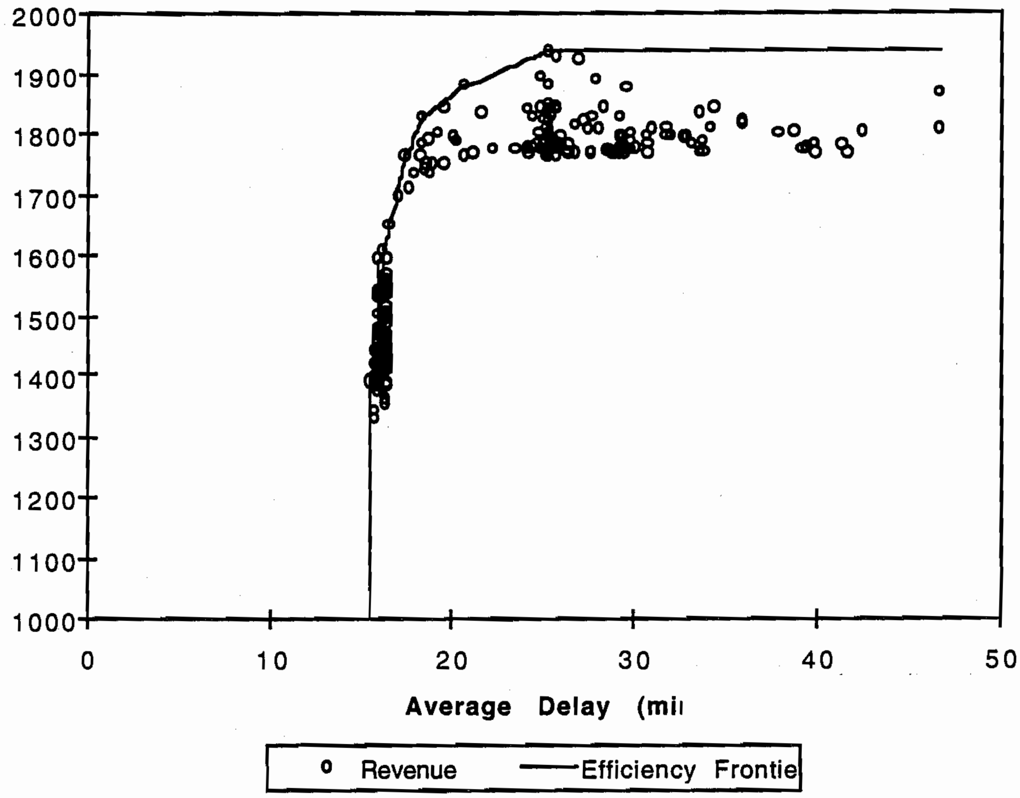


Figure 7-6 Definition of efficiency frontier bounding all dominated solutions

7.8 SCALING OF THE EVALUATION CRITERIA

At the start and during the early execution of genetic algorithm runs, it is common that a couple of extraordinary individuals in a population of mediocre colleagues dominate excessively, producing nearly all subsequent genetic material, causing premature convergence. Late in a run, the opposite may become true, when most chromosomes in the population have a fitness very close to the mean, i.e. a low variance exists. This may cause reproduction selection to become too random, not providing sufficient bias to the better individuals.

A useful procedure to counteract this is linear scaling as described in Goldberg, 1989 on pp. 77. Defining the raw fitness f and the scaled fitness as f' linear scaling provides a linear relationship in the form:

$$f' = a f + b \tag{7-1}$$

The coefficients were chosen in a number of ways, and for this study they were based on the statistical sample properties of each generation such that:

$$f' = \frac{f}{2\sigma_f + \mu_f} + 1 \tag{7-2}$$

where μ_f and σ_f are the generation mean value and standard deviation respectively.

Per this definition, very good individuals will approach 2 and very bad ones will be close to zero. This implies that the really good ones have about twice the probability of being selected for reproduction and the bad individuals have nearly no chance whatsoever. In the cases where a value may actually fall outside of the range $[\mu_f - 2\sigma_f ; \mu_f + 2\sigma_f]$, the scaled fitness, which becomes negative on the low end, is simply taken as 0 and has therefore no chance at all of being selected. On the high side, the scaled fitness value would then become larger than 2.

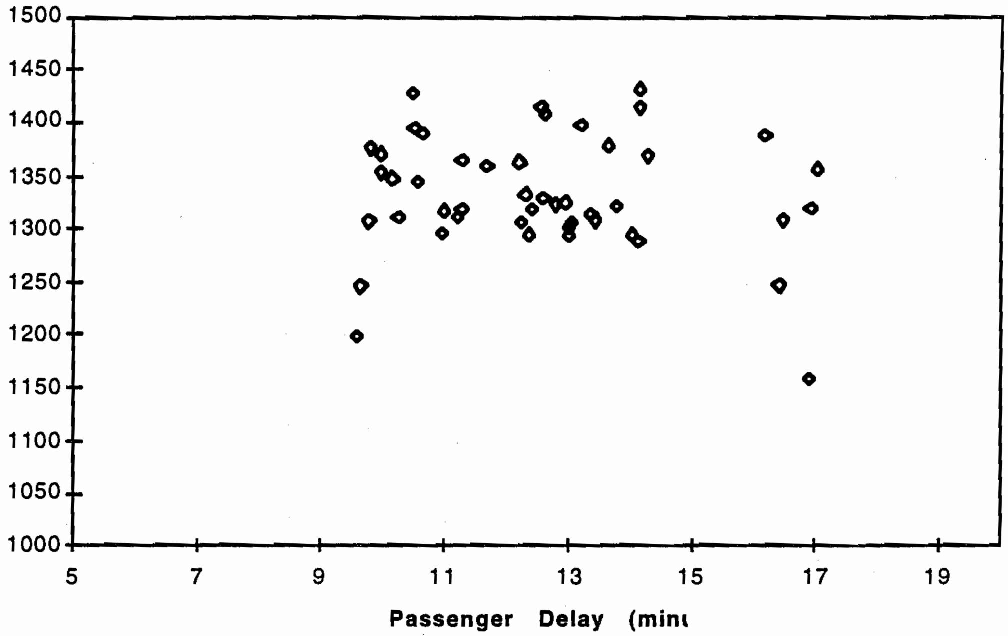


Figure 7-7 Solution distribution of unscaled revenue and passenger delay parameters

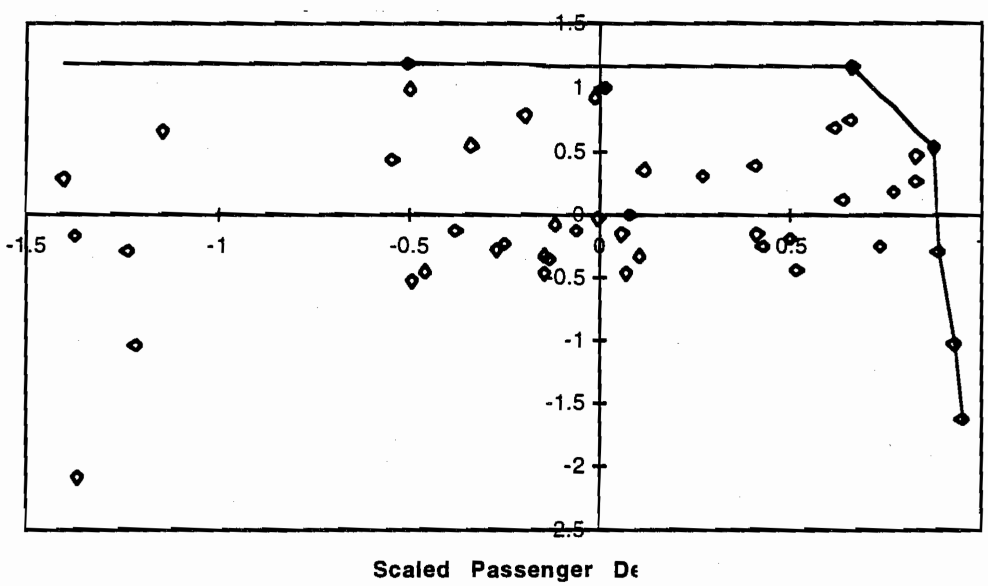


Figure 7-8 Solution distribution after applying scaling scheme

Figures 7-7 and 7-8 illustrate a unscaled and scaled generation sample. As in Figure 7-5, Figure 7-6 plots the two-dimensional relationship between average passenger delay time and net airline revenue for a set of solutions representing a pool of chromosomes at any given generation. In Figure 7-8 the objective parameters have been scaled according to:

$$f' = \frac{f}{2\sigma_f + \mu_f} \tag{7-3}$$

where the scaled values have not yet been offset by 1 as in Equation 7-2. This clearly shows how the scaling normalizes the distribution in a fairly uniform manner around the mean values of each parameter. The best values in the solution set on the upper right-hand side boundary. A general fitness value associated with each chromosome is then defined as:

$$f'' = \sqrt{\left(f_1'^2 + f_2'^2\right)} \quad \textbf{if } f_1' \textbf{ and } f_2' > 0$$

$$f'' = \max(f_1', f_2') \textbf{ otherwise} \tag{7-4}$$

This formulation should impose very little bias on the overall fitness of each chromosome, no matter if it performs better on a single parameter or provides a good compromise of both. Finally, to ensure that all nondominated solutions receive equal fitness ratings, they are all assigned the maximum general fitness value of the generation population or set equal to 2, whatever may be larger.

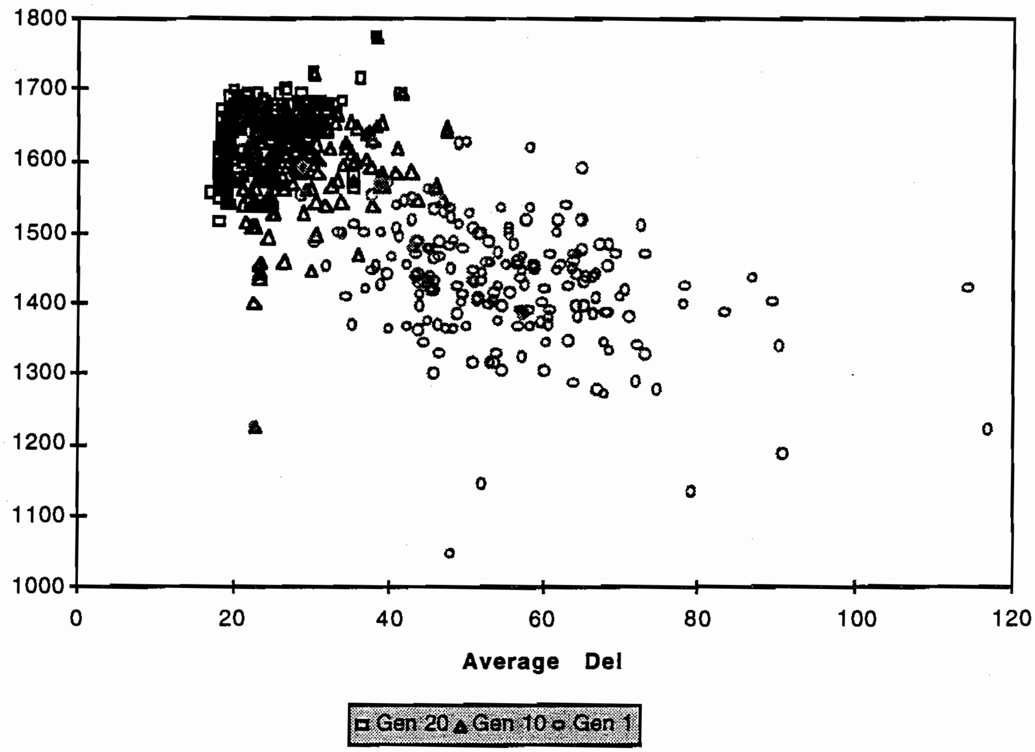


Figure 7-9 Solution space showing progression of populations at 1, 10, and 20 generations

7.4 OPTIMIZATION PERFORMANCE

Figure 7.9 shows how the optimization progresses from the initial starting solution set at generation 1 for a test case of about 100 flights on a route network of seven cities. It clearly shows how the set of solutions for each generation gradually moves towards the upper, left-hand side of the graph denoting better optimality. Even after 20 generations a significant improvement of the solution set is found.

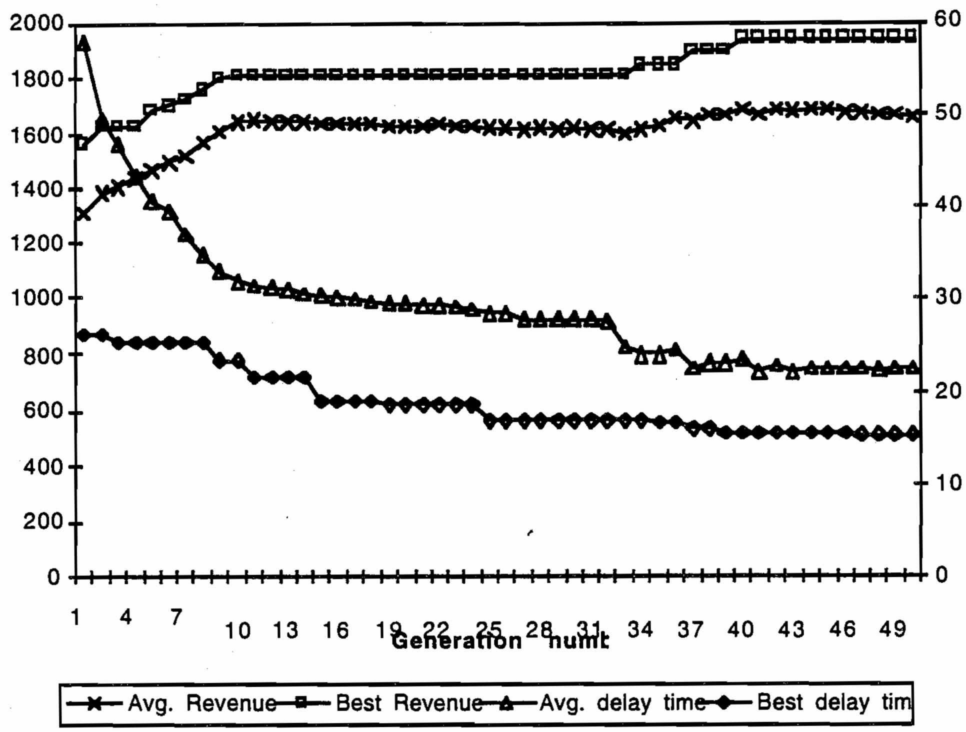


Figure 7-10 Optimization progress for the average and maximum fitness parameter values as a function of generation number

Figure 7.10 shows the improvement in the various objective parameters as a function of generation number. As expected, initial progress is fairly rapid, after which further improvements occur more slowly as more generations pass. When no more improvement is found after a dozen or so generations, the process is assumed to have converged.

The genetic algorithm optimizer program was coded using *Pascal* with the Borland Delphi 2.0 32-bit compiler on a PentiumPro Windows NT workstation. For the 100-flight test case, each single chromosome evaluation took about a second to run. Runs with population sizes of up to 500 over 100 generations were tested and took nearly 7 hours to run to completion. This seems disappointingly slow, but each chromosome evaluation does require a network flow analysis of the 100 flight airline over a 24-hour period, assigning thousands of passengers and a fleet of nearly 30 aircraft.

Actually the network flow assignment module which calculated each chromosome's fitness, proved to be the main culprit in consuming runtime, and compared to it, the actual genetic optimizer portion required negligible processor time. No doubt significant speed increases are possible with some code optimization, or with a more efficient network assignment implementation. However, within the scope of this study the results were deemed acceptable, and the problems could be solved to a acceptable level of optimization.

It was found that a larger initial population size with less generations produced better final values within a given time frame, and after some experimentation subsequent runs were done using a population size of 500 over 30 generations. This provided a fair compromise, especially since some of the larger schedule examples evaluated had up to 200 flights and 13 cities, which took about 6 seconds to run each fitness calculation.

7.5 DEMAND MODELING

To evaluate the operational feasibility of the alternative hub concept, it was necessary to construct a representative airline sample case over a 24-hour period. In a similar fashion to the geographic location analysis described in chapter 5, a airline was chosen having a hub at Dallas/Ft. Worth International airport (DFW). The new Austin-Bergstrom International Airport was chosen as the alternative hub since the infrastructure cost analysis and capacity studies showed that it was a reasonable choice.

A study of the top 13 Markets served by American Airlines from their Dallas hub showed a predominance of longer ranged east and west-coast markets. Some of these markets are also currently served by direct flights from Austin indicating a healthy demand exists to the alternative hub in addition to the passengers that normally transfer at DFW. This effect of this demand on the attractiveness of each alternative hub candidate was not included in the analysis done in Chapter 5 since a mechanism did not exist to do so at the time. Obviously, passenger demand at the alternative hub could influence the geographic selection of an alternative hub.

TABLE 7-2 TOP MARKETS SERVED BY AMERICAN AIRLINES FROM THEIR DALLAS HUB IN '93 RANKED BY REVENUE PASSENGER MILES (RPM)

Market	Miles	Departures Performed	Onboard Passengers	Available Seats	RPM's (000's)	ASM's (000's)	Load-Factor
DFW-LAX	1,235	7,380	986,367	1571,685	1218,163	1941,031	62.76
DFW-HNL	3,784	1,434	302,799	401,371	1145,791	1518,788	75.44
DFW-LGA	1,389	6,952	768,375	1262,359	1067,273	1753,417	60.87
DFW-SFO	1,464	5,631	639,269	1022,201	935,891	1496,503	62.54
DFW-ORD	802	11,778	1115,958	2011,769	894,998	1613,439	55.47
DFW-MIA	1,121	6,506	772,029	1196,984	865,445	1341,819	64.5
DFW-SJC	1,438	5,323	555,295	842,695	798,514	1211,795	65.9
DFW-DCA	1,192	6,204	622,559	1054,140	742,090	1256,535	59.06
DFW-SEA	1,660	4,207	446,431	668,146	741,075	1109,122	66.82
DFW-BOS	1,562	4,270	451,925	771,936	705,907	1205,764	58.54
DFW-SNA	1,205	4,767	572,268	890,641	689,583	1073,222	64.25
DFW-LAS	1,055	4,628	603,750	861,233	636,957	908,602	70.1
DFW-SAN	1,171	4,491	529,479	807,418	620,020	945,486	65.58

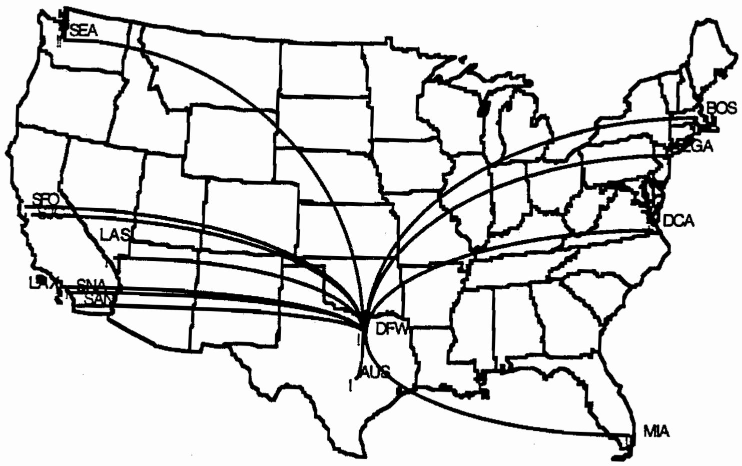


Figure 7-11 Selected routes considered for model

When an airline uses a fleet assignment model it would normally have access to considerable passenger demand data from it's flight reservations system. Of late these systems have been equipped with elaborate passenger characteristic statistical modeling tools, and airlines have become quite good at estimating demand for a given flight.

For the purposes of this study it is assumed that the airline would posses perfect information on passenger demand characteristics for a given 24-hour time period. This may be overly optimistic, but since the various aircraft type capacities typically differ by more than 20 seats, deviations within these bounds should generally not affect the aircraft assignment.

For the schedule modeling and evaluation purposes real passenger demand data is not available and it needs to be generated using some other model. In this study a simple gravity model was used to model passenger demand using weighting factors derived from the available seats offered by American Airlines to those markets from their DFW hub. The gravity model included a random component and has the form:

$$\delta\ k_1 k_2 \left[1+\alpha \left\{ \frac{2\ asin(2\,rnd\#-1)}{\pi} \right\} \right] \left[1+\beta \left\{ \frac{abs(60t-720)}{720} \right\} \right] \qquad (7\text{-}4)$$

where k_1 and k_2 are the weighting factors for the origin end destination cities respectably as listed in Table 7-3, t is the departure time in hours , *rnd#* is a random number between 0 and 1, and α, β and δ are constants taken to be 0.5, 0.3 and 154 respectively. These constant values where chosen to simulate passenger demand variability over a 24-hour period giving a system wide average aircraft demand equal to about a 65% load factor of available seats.

TABLE 7- 3 DERIVED WEIGHT FACTORS AS USED IN GRAVITY MODEL TO CALCULATE DEMAND

Market	Avg. Seats/Flight	Daily Departures	Daily Passengers	Weight factor
DFW-LAX	213	20	2702	1.000
DFW-MIA	184	18	2115	0.783
DFW-LGA	182	19	2105	0.779
DFW-SFO	182	15	1751	0.648
DFW-DCA	170	17	1706	0.631
DFW-LAS	186	13	1654	0.612
DFW-SNA	187	13	1568	0.580
DFW-SJC	158	15	1521	0.563
DFW-SAN	180	12	1451	0.537
DFW-BOS	181	12	1238	0.458
DFW-SEA	159	12	1223	0.453

8.0 CONCLUSION AND RECOMMENDATIONS

The Scheduling model and optimizer was run with 3 sample studies representing:

1. Normal hubbed operations, typical of a large transcontinental carrier with a hub at Dallas-Ft. Worth international airport (DFW)
2. Two canceled flight banks due to the DFW hub being closed for 2 hours between 14H00 and 16H00
3. Alternative hub operations at Austin given the same hub closure as under case 2

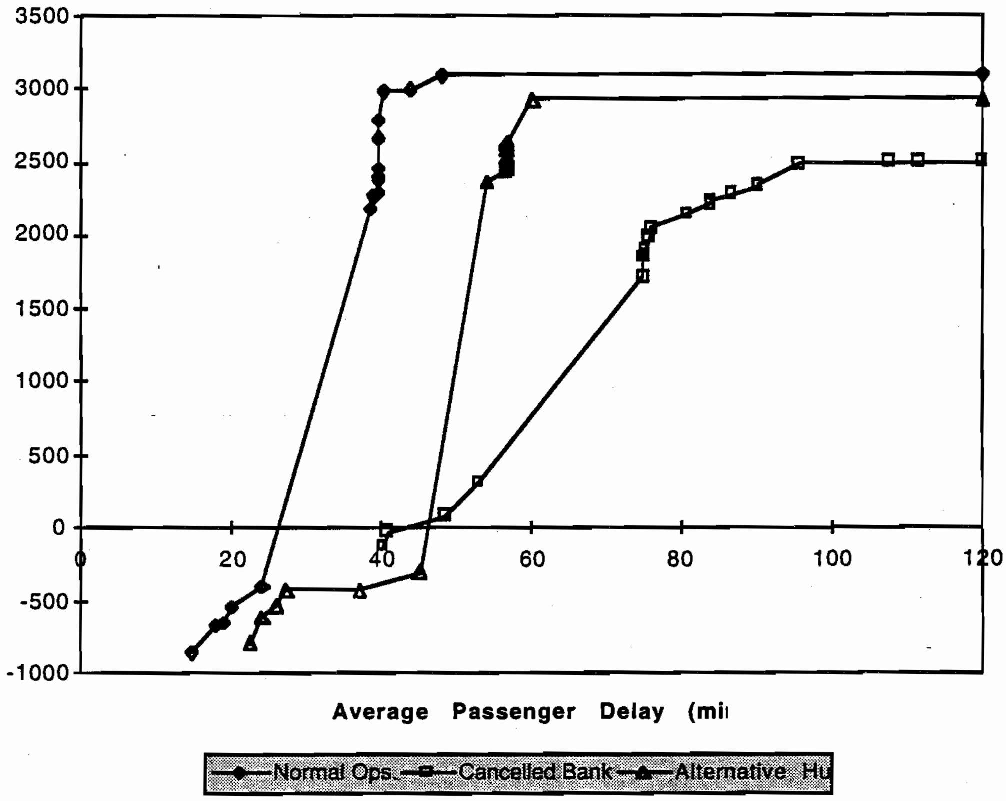


Figure 8-1 Efficiency frontiers for the model example showing normal hubbed operations, effect of canceled banks and alternative hub operations

The flight schedule included 197 flights over a 24-hour period serving 13 cities. This is representative of a sub-portion of the schedule of a large carrier such as American or Delta Airlines operating from a hub at Dallas-Ft. Worth (DFW) International Airport. The 13 cities were chosen as possible markets for alternative hub operations to Austin-Bergstom International Airport.

Figure 8-1 shows the efficient frontier curves for each of the three plotted as net revenue versus average passenger delay cost. Net revenue was calculated as the total revenue from all passengers whom completed their journeys minus the product of the hourly direct operating cost of utilized aircraft times the actual number of block hours flown. Average passenger-delay is calculated as the average excess travel time in minutes over and above the minimum travel time for the markets served. This is typically defined as the actual flying time from the origin to the hub airport, a 15 minute transfer and the actual flying time to the destination of each trip. Single stage trips simply have the actual flying time as the reference time. Delay can be caused by a waiting time at the origin airport, the hub airport or both. In flight delays were not considered unless it included extra flying distance, for example a extra 30 minutes was added to all flights diverting to Austin from northerly originating cities.

The genetic algorithm optimizer typically locates some solutions for each case with a very low average delay time, but very low or negative net revenue. These solutions represent a strategy whereby only those flights giving a very short and optimal transfer time are flown and all others are canceled. Since this involves only accepting a small portion of the inherent passenger demand, the result is a low revenue base. Although interesting from a multicriteria optimization point of view, such solutions are of academic interest only.

For evaluation purposes the interesting solutions are those found near the top, left-hand side of the curve. Although these solutions do incur some delay, they yield a fair revenue for the air carrier. Since even the normal operations have a average delay of the order of 30 minutes, these portions of each curve can be compared for each case. As can be seen from Figure 8-1 the best case scenario is the normal hubbed operations. This is to be expected since the original schedule was designed around this operation strategy and it represents the baseline case when comparing the effects of weather delays. The worst case is the one where all flights arriving or leaving DFW during the 14H00 to 16H00 curfew are simply canceled. Especially noticeable is the decrease in slope in the revenue/delay relationship. This implies that a the cost of maintaining reasonable service is quite severe from an operating viewpoint. The alternative hub operations case, although slightly poorer performing as the baseline case in both revenue and average delay time, still offers a significant improvement over the cancellation alternative. In terms of revenue the difference is between $0.5 and $1 million with a improvement in average passenger delay time of between 20-50 minutes.

TABLE 8-1 FLEET SCHEDULE ASSIGNMENT FOR ALTERNATIVE HUB OPERATIONS USING AUSTIN DURING A CLOSURE OF DFW AIRPORT FROM 14H00 TO 16H00

Departures From Hub Airport						Arrivals To Hub Airport					
Fl	Dep City	Dep Time	Arr City	Arr Time	Fleet ass.	Fl	Dep City	Dep Time	Arr City	Arr Time	Fleet ass. Assi
47	DFW	13H00	DCA	16H00	MD8	178	SJC	9H00	DFW	12H15	MD8
61	DFW	13H00	LAX	16H15	MD8	124	LAS	10H40	AUS	14H00	757
72	DFW	13H00	LGA	16H30	757	131	LAX	10H10	AUS	14H00	MD8
91	DFW	13H00	SAN	16H00	MD8	172	SFO	10H00	AUS	14H00	MD8
103	DFW	13H00	SFO	16H45	MD8	179	SJC	10H15	AUS	14H00	MD8
110	DFW	13H00	SJC	16H30	MD8	186	SNA	10H30	AUS	14H00	MD8
118	DFW	13H00	SNA	16H00	MD8	152	MIA	10H45	AUS	14H15	MD8
30	DFW	14H00	AUS	14H45	D10	166	SEA	9H45	AUS	14H15	MD8
199	AUS	15H15	DFW	16H00	MD8	13	BOS	11H00	AUS	15H30	MD8
48	AUS	15H30	DCA	18H30	MD8	22	DCA	11H45	AUS	15H30	MD8
7	AUS	15H30	DFW	16H15	757	142	LGA	11H15	AUS	15H30	MD8
40	AUS	15H45	BOS	19H30	MD8	153	MIA	12H00	AUS	15H30	MD8
73	AUS	15H45	LGA	19H15	MD8	160	SAN	12H00	AUS	15H30	MD8
62	AUS	16H30	LAX	18H45	MD8	173	SFO	11H30	AUS	15H30	MD8
8	AUS	17H00	DFW	17H45	MD8	132	LAX	12H00	AUS	15H45	MD8
53	AUS	17H00	LAS	19H45	MD8	125	LAS	13H30	DFW	16H15	757
63	AUS	17H00	LAX	20H15	MD8	154	MIA	13H15	DFW	16H15	D10
74	AUS	17H00	LGA	20H30	MD8	174	SFO	12H45	DFW	16H15	757
84	AUS	17H00	MIA	19H45	MD8	14	BOS	12H30	DFW	16H30	757
92	AUS	17H00	SAN	20H00	MD8	23	DCA	13H15	DFW	16H30	MD8
97	AUS	17H00	SEA	21H15	MD8	133	LAX	13H15	DFW	16H30	MD8
104	AUS	17H00	SFO	20H45	MD8	143	LGA	12H45	DFW	16H30	MD8
112	AUS	17H00	SJC	20H30	MD8	167	SEA	12H30	DFW	16H30	MD8
119	AUS	17H00	SNA	20H00	D10	187	SNA	13H30	DFW	16H30	MD8
41	DFW	17H15	BOS	21H00	MD8	134	LAX	14H15	DFW	17H30	MD8
49	DFW	17H15	DCA	20H15	D10	144	LGA	13H45	DFW	17H30	MD8
64	DFW	17H15	LAX	20H30	MD8	161	SAN	14H30	DFW	17H30	MD8

Table 8-1 shows the flight assignments for arrivals and departures for one of the efficient alternative hub solutions around the time of the 14H00-16H00 curfew at DFW. It is interesting to note that flight 30, from DFW to Austin (AUS) is allocated a DC-10, the largest capacity aircraft for the test case. This is done to ferry DFW originating passengers to the alternate hub, allowing them to connect to those flights diverted to Austin for this purpose.

As demonstrated by these studies, using an alternative or reliever hub is definitely an effective way of reducing airline schedule disturbances caused by inclement weather and Austin/Bergstrom would be an good location for such a hub. This study also has shown that infrastructure investment costs along with operating costs are significant when evaluating reliever hub location. For infrastructure investment costs, only costs associated with construction materials were considered; costs for construction and the actual financing of the project were not included. Investigation into the Austin/Bergstrom construction scenario showed that financing and project management costs could increase the total infrastructure investment cost by more than 70%. Since all airports would require these extra costs, the ideal locations selected by the model in the solution should not change, assuming little variation in constructions costs between various cities.

Using Austin/Bergstrom as a reliever-hub would be ideal for a medium-sized, average airline hub. Attempting to relocate a larger hub would be more difficult. For larger facilities, infrastructure costs per square foot are projected to increase more steeply. For example, at Austin/Bergstrom, simply adding 20-30 gates to the existing terminal would be relatively easy. To accommodate 30-50 aircraft, remote terminal(s) would have to be constructed. As demonstrated by the Bergstrom case-study, a remote terminal would be more costly, compared with adding to the existing terminal.

Austin/Bergstrom was found to be a promising candidate, since it is currently under construction and as future expansion plans for doubling of gate capacity are being considered. With widely spaced parallel runways, Austin/Bergstrom can handle nearly 120 operations per hour in all but the most severe weather. Although choosing Tulsa would slightly reduce airline direct operating costs, Austin/Bergstrom is perhaps still the better choice since it offers a much stronger passenger home market. American Airlines has an average of 24 daily jet departures from Austin to 6 cities. At Tulsa, American operates only 8 daily jet departures and 15 commuter flights. Austin is a larger city than Tulsa and enplanements are increasing at 5% annually. American has 13 flights per day to Dallas/Ft. Worth and passengers can be easily ferried to Dallas when the weather clears. At Austin's current growth rate, many markets are now being served nonstop from Austin including Miami, San Francisco, Los Angeles, San Jose, Boston, Orlando, Nashville, Phoenix, Las Vegas and other southwestern cities. This is in addition to service offered to the main hubs of the nearly all of the large US carriers.

American and Delta Airlines could also use Austin as a normal, congestion reliever hub for Dallas Ft. Worth. Currently, American has non-stop flights between Austin and Los Angeles, San Jose, Dallas/Ft. Worth, Boston, Miami, and Chicago. A passenger traveling from Los Angeles to Miami could conceivably connect in Austin. American could offer passengers the option of connecting in Austin or in Dallas. Since Austin is less congested than DFW, this passenger could arrive in Miami 30 or more minutes sooner than if he connected through DFW. Taxi-out and airspace delays at DFW are commonly more than 15 minutes, particularly during peak times. If infrastructure for a weather reliever hub is constructed at Austin, no additional infrastructure would be needed to use Austin as a congestion reliever hub.

Developing a reliever hub-system is an effective way of reducing airline schedule disturbances caused by weather. The infrastructure investment required would be recovered quickly with significant reductions in delay experienced by the airline and its passengers. The attractiveness of the reliever-hub concept depends on how an airline values delay experienced by its passengers. Unforeseen delays are very stressful for passengers; nobody likes to be delayed. Passengers would feel more secure by knowing that an hour or two of potential weather delay could be avoided by simply connecting at a different location. Because of this fact, airlines who implement a reliever hub system could become more attractive to consumers.

BIBLIOGRAPHY

Ahuja, Ravindra and Thomas Magnanti. Network Flows: Theory, Algorithms, and Applications. New York: Prentice Hall, 1993.

Ashford, Norman and Martin Stanton. Airport Operations. London: Pitman Publishing, 1991.

Berge, Matthew and Craig Hopperstad. "Demand Driven Dispatch: A Method for Dynamic Aircraft Capacity Assignment, Models, and Algorithms," Operations Research, January-February 1993, pp 153-168.

Doganis, Rigas. Flying Off Course: The Economics of International Airlines. New York: Routledge, 1993.

Dobson, Gregory and Phillip J, Lederer. "Airline Scheduling and Routing in a Hub-and-Spoke System," Transportation Science, August 1993, pp. 281-297.

Federal Aviation Administration. Airport Capacity Enhancement Plan, Washington, DC, 1996.

Goldberg, David E. Genetic Algorithms in Search, Optimization, and Machine Learning, Reading, Massachusetts: Addison-Wesley, 1989.

Horonjeff, Robert and Francis McKelvey. Planning and Design of Airports. New York: McGraw and Hill, 1994.

Goldberg, David E. Genetic Algorithms in Search, Optimization, and Machine Learning. Boston: Addison-Wesley Publishing, 1994.

Kanafani, Adib and Atef Ghobrial. "Airline Hubbing - Some Implications for Airport Economics," Transportation Research, Volume 19A, pp 15-27.

Klincewicz, John and Moshe B. Rosenwein. "The Airline Exception Scheduling Problem", Transportation Science, February 1985, pp 4-16.

Levine, David. "Application of a Hybrid Genetic Algorithm to Airline Crew Scheduling", Computers and Operations Research, Vol. 23, No. 6, pp 547-558.

Ruckel, Dick. Operations Analyst, American Airlines. Phone Interviews.

Subramanian, Radhika and Richard P. Scheff. "Coldstart: Fleet Assignment at Delta Air Lines," Interfaces, January-February 1994, pp. 104-120.

Talluri, Kalyan. "Swapping Applications in a Daily Airline Fleet Assignment," Transportation Science, August 1996, pp 237- 248.

Teodorovic, Dusan and Goran Stojkovic. "Model to Reduce Airline Schedule Disturbances," Journal of Transportation Engineering, July/August 1985, pp 324-331.

Teodorovic, Dusan and Goran Stojkovic. "Model for Operational Daily Airline Scheduling," Transportation Planning and Technology, Vol. 14, pp. 273-285.

Turner, Thomas. Weather Patterns and Phenomenon. New York: TAB Books, 1995.

Waring, Dick. System Operations, American Airlines. Phone Interview, 1997.

Williams, George. Airline Industry and the Impact of Deregulation. Cambridge, England: University Press, 1993.

Xiong, Yihua and Jerry B. Schneider. "Transportation Network Design using a Cumulative Genetic Algorithm and Neural Network," Transportation Research Record 1364, 1993 pp 37-44.

APPENDIX A - AMERICAN AIRLINES DELAY STATISTICS

HUB PERFORMANCE BY COMPLEX
May 19, 1997

JB DFW

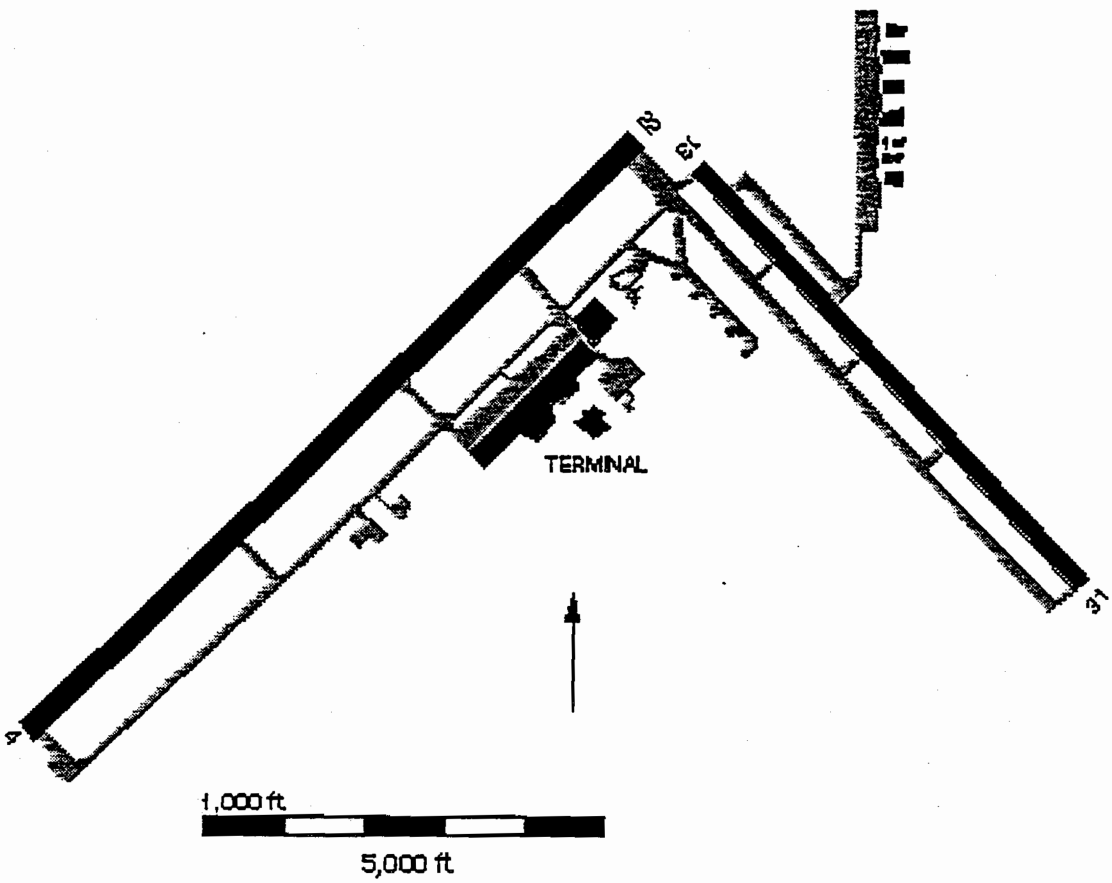
TYPE	CPLX	TIME	FREQUENCY TTL OPNS	NBR DLYS	NBR UPL	PERFORMANCE STATISTICS D+0	D+5	A+5	A+15	B+0	B+5	TXOUT PCT	PCT IN AIR	TXIN PCT	AVERAGE VARIANCE IN MINUTES DEPT VAR	TXOT VAR	AIR VAR	TXIN VAR	BLK VAR	ARVL VAR
DEPTS	01-E	0620	21	5	0	47.6	76.2	47.6	71.4	28.6	47.6	38.1	38.1	47.6	13	3	2	0	5	18
	02-E	0800	34	5	1	52.9	85.3	73.5	91.2	76.5	82.4	67.6	76.5	52.9	3	-2	-3	0	-5	-1
	03-W	0905	41	11	0	48.8	73.2	73.2	90.2	63.4	80.5	48.8	75.6	63.4	6	1	-5	1	-3	3
	04-O	0950	4	2	1	25.0	50.0	25.0	50.0	25.0	50.0	25.0	50.0	100.0	6	12	6	-2	16	22
	05-W	1030	52	14	2	57.7	73.1	46.2	67.3	40.4	57.7	23.1	69.2	59.6	9	7	-5	1	3	13
	06-O	1137	16	15	2	0.0	6.3	12.5	31.3	37.5	50.0	37.5	43.8	81.3	19	[illegible]	3	-1	3	26
	07-E	1225	48	25	8	29.3	47.9	25.0	45.8	27.1	47.9	22.9	64.6	68.8	17	9	-2	0	7	24
	08-O	1326	5	4	2	20.0	20.0	20.0	80.0	60.0	80.0	20.0	80.0	60.0	9	4	-1	1	4	13
	09-E	1400	52	24	6	26.9	53.8	63.5	76.9	69.2	88.3	61.5	69.2	65.4	9	-4	-5	0	-5	3
	10-W	1530	46	11	1	43.5	76.1	45.7	67.4	58.7	63.0	50.0	71.7	56.5	7	7	-8	2	1	8
	11-E	1700	49	29	9	46.3	59.2	62.5	79.2	62.5	79.2	32.7	91.7	72.9	13	7	-8	-4	-1	13
	12-W	1830	51	40	6	11.8	21.6	0.0	2.0	2.0	3.9	0.0	68.6	54.9	29	76	-4	1	73	103
	13-E	2005	49	49	11	0.0	0.0	0.0	0.0	70.6	79.4	62.5	81.1	70.6	141	0	-6	-0	-5	109
	14-W	2135	31	31	5	0.0	0.0	0.0	0.0	35.3	58.8	32.3	55.6	52.9	31	4	-2	5	3	67
	NON	****	15	4	1	53.3	73.3	57.1	71.4	57.1	64.3	53.3	85.7	71.4	6	22	-4	-1	17	26
	DIRECTION																			
	EAST		253	128	35	28.5	49.4	46.4	61.6	57.0	70.9	47.6	72.7	65.0	36	3	-4	0	-1	25
	OMNI		25	21	5	8.0	16.0	16.0	44.0	40.0	56.0	32.0	52.0	80.0	15	7	2	-1	8	23
	WEST		221	107	14	34.4	51.6	36.2	50.2	39.1	50.2	29.4	69.7	58.0	23	21	-5	1	17	36
	NON		15	4	1	53.3	73.3	57.1	71.4	57.1	64.3	53.3	85.7	71.4	6	22	-4	-1	19	26
	ALL		514	260	55	30.7	49.4	40.8	56.1	46.4	61.1	39.2	70.8	62.9	29	12	-4	0	9	39
ARVLS	CPLX	TIME																		
	01-E	0620	14	4	2	71.4	71.4	61.5	69.2	7.7	46.2	64.3	0.0	69.2	26	0	7	-0	6	29
	02-E	0800	9	1	0	77.8	88.9	50.0	66.7	0.0	66.7	33.3	0.0	66.7	-1	4	5	1	12	14
	03-W	0905	38	2	0	73.7	94.7	86.8	94.7	73.7	92.1	50.0	78.9	57.9	2	1	-5	-4	-4	-2
	04-O	0950	3	1	0	0.0	66.7	66.7	100.0	66.7	100.0	100.0	100.0	66.7	4	-2	-6	1	-7	-3
	05-W	1030	48	12	3	50.0	75.0	77.1	91.7	70.8	87.5	58.3	70.8	58.3	7	-4	-6	-0	-7	0
	06-O	1137	16	1	0	68.8	93.8	31.3	62.5	31.3	37.5	62.5	43.8	12.5	1	1	2	7	9	10
	07-E	1225	50	7	0	74.0	86.0	38.0	64.0	18.0	36.0	66.0	42.0	36.0	12	0	7	4	19	22
	08-O	1326	6	0	0	66.7	100.0	0.0	50.0	0.0	0.0	66.7	0.0	16.7	-1	1	6	12	18	18
	09-E	1400	47	5	2	72.3	89.4	51.1	70.2	25.5	51.1	51.1	23.4	57.4	1	1	7	-0	7	7
	10-W	1530	48	10	5	60.4	79.2	70.8	89.6	70.8	89.6	50.0	77.1	70.8	9	2	-6	-1	-4	4
	11-E	1700	46	10	7	66.9	78.3	47.8	78.3	45.7	60.9	71.7	23.9	76.1	3	-1	7	-2	3	6
	12-W	1830	48	9	5	56.3	81.3	54.2	75.0	47.9	54.2	50.0	43.8	68.3	6	2	5	-1	6	11
	13-E	2005	25	9	2	60.0	64.0	8.0	12.0	0.0	0.0	40.0	4.2	62.5	30	3	58	2	58	89
	14-W	2135	62	22	7	51.6	64.5	1.6	4.8	4.9	9.7	43.5	4.8	32.3	24	24	29	7	51	75
	NON	****	26	6	1	65.4	76.9	38.5	57.7	36.5	38.5	46.2	50.0	46.2	4	8	5	4	16	21
	DIRECTION																			
	EAST		191	36	13	68.6	81.2	41.7	62.6	23.0	44.4	58.6	23.7	58.1	9	0	13	1	14	23
	OMNI		25	2	0	60.0	92.0	28.0	64.0	28.0	36.0	68.0	40.0	20.0	1	0	2	7	9	10
	WEST		244	55	20	57.4	77.5	53.7	66.4	50.0	62.3	59.0	51.2	56.1	11	7	3	1	11	22
	NON		26	6	1	65.4	76.9	38.5	57.7	38.5	38.5	46.2	50.0	46.2	4	8	5	4	16	21
	ALL		486	99	34	62.3	79.6	46.7	64.3	37.8	52.7	54.1	39.7	54.5	9	4	7	2	12	22

EXCLUDES CONTINUING SEGMENTS OF DIVERSIONS

APPENDIX B - AIRPORT LAYOUT PLANS

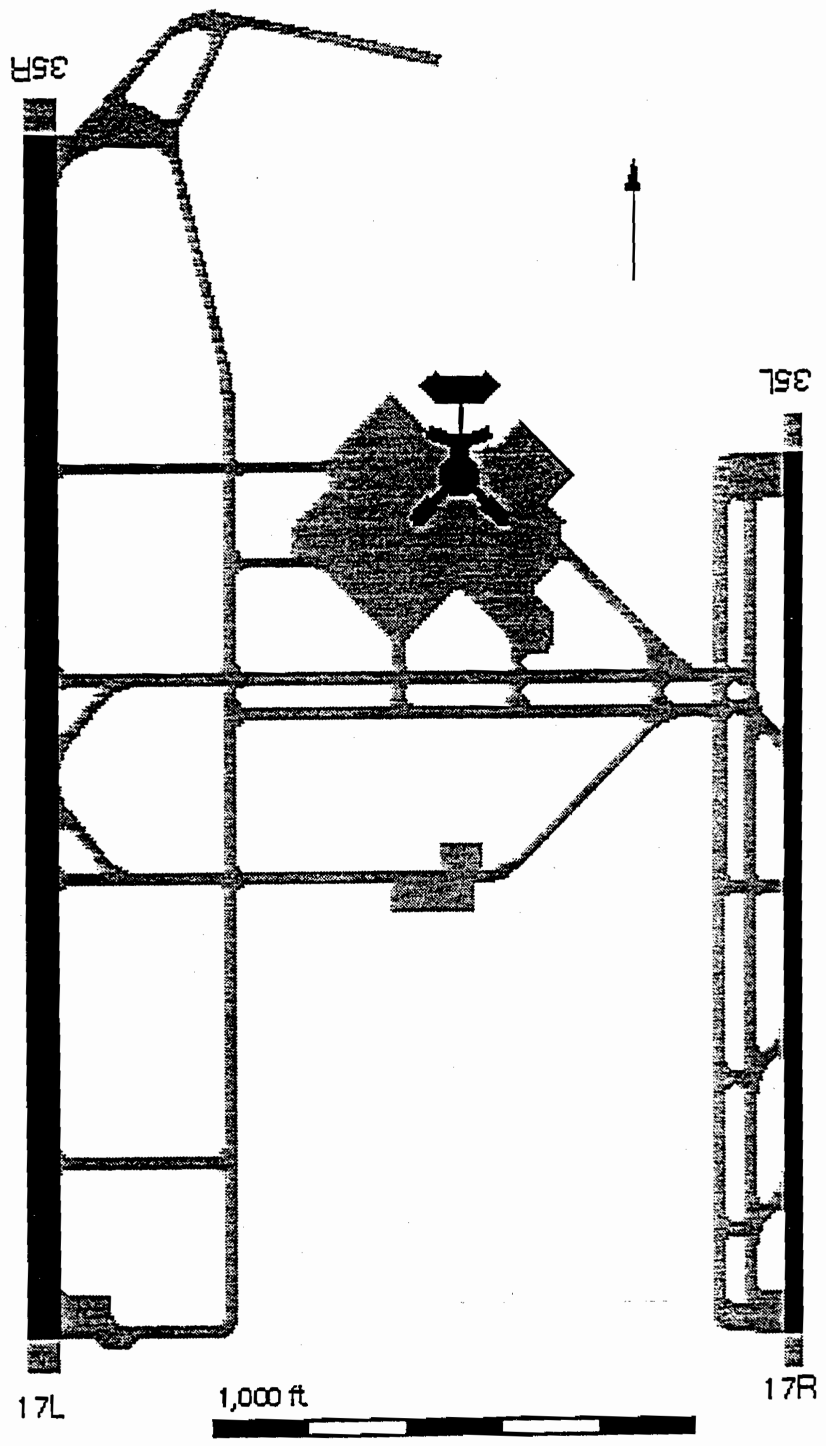
Airport Diagram

Airport Name Amarillo International Airport **Airport ID** AMA

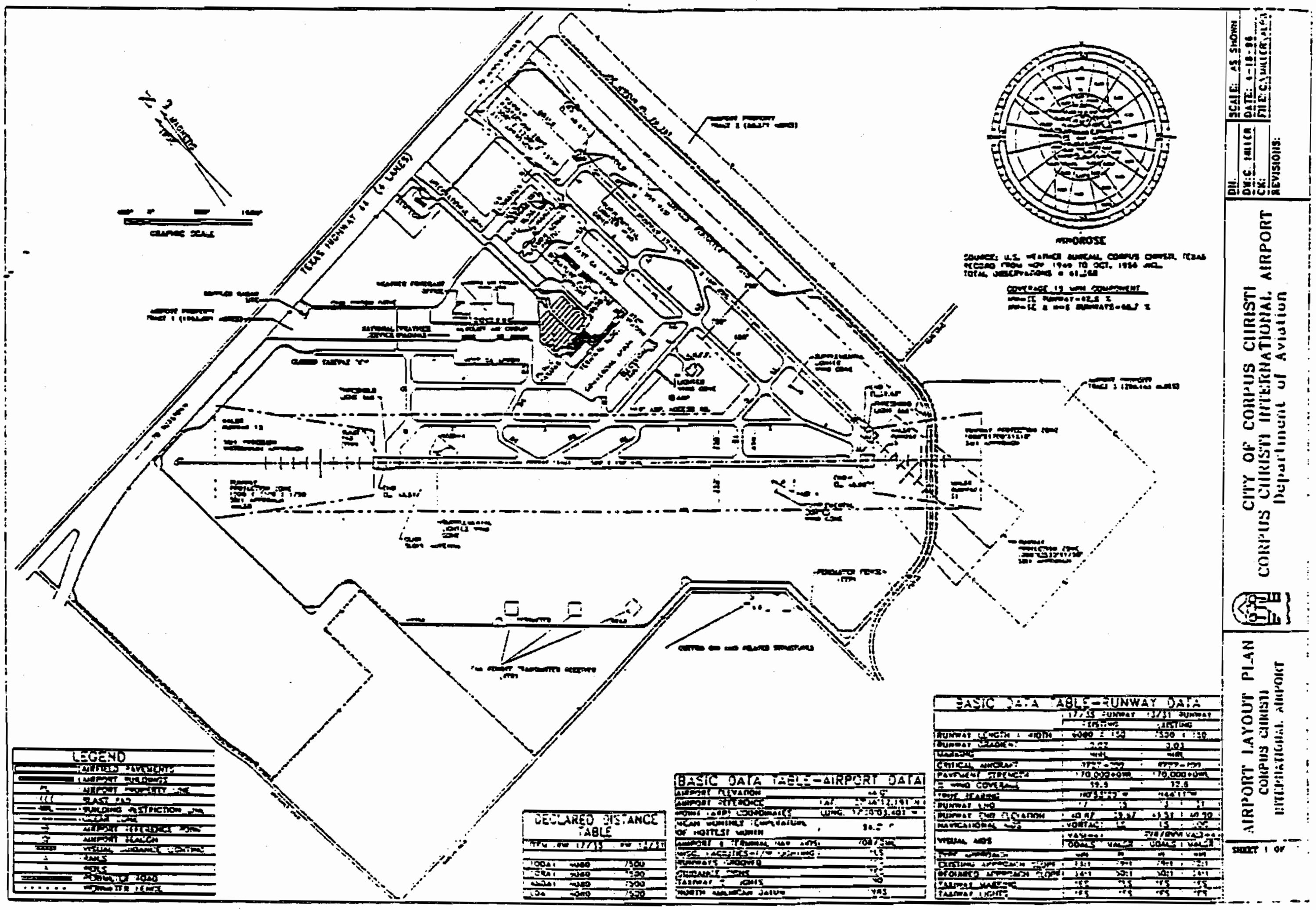


Airport Diagram

Airport Name Bergstrom AFB (new Austin) **Airport ID** BSM

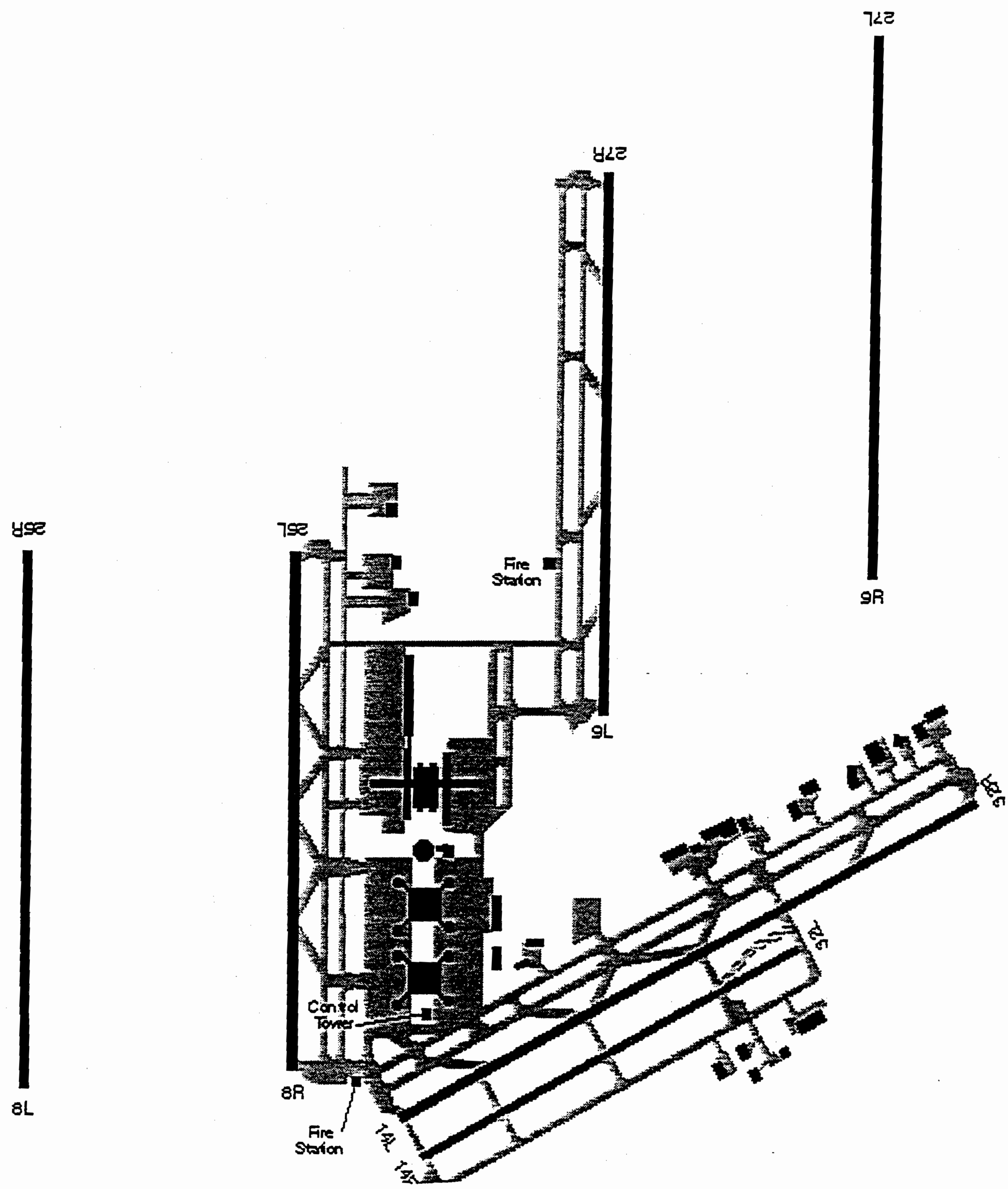


Bergstrom Air Force Base Conversion
Opening Day Layout Plan


AIRPORT LAYOUT PLAN
CORPUS CHRISTI INTERNATIONAL AIRPORT
CITY OF CORPUS CHRISTI
CORPUS CHRISTI INTERNATIONAL AIRPORT
Department of Aviation
SCALE: AS SHOWN
REVISIONS:
WINDROSE
TEXAS HIGHWAY 44 (4 LANES)
LEGEND
DECLARED DISTANCE TABLE
BASIC DATA TABLE—AIRPORT DATA
BASIC DATA TABLE—RUNWAY DATA

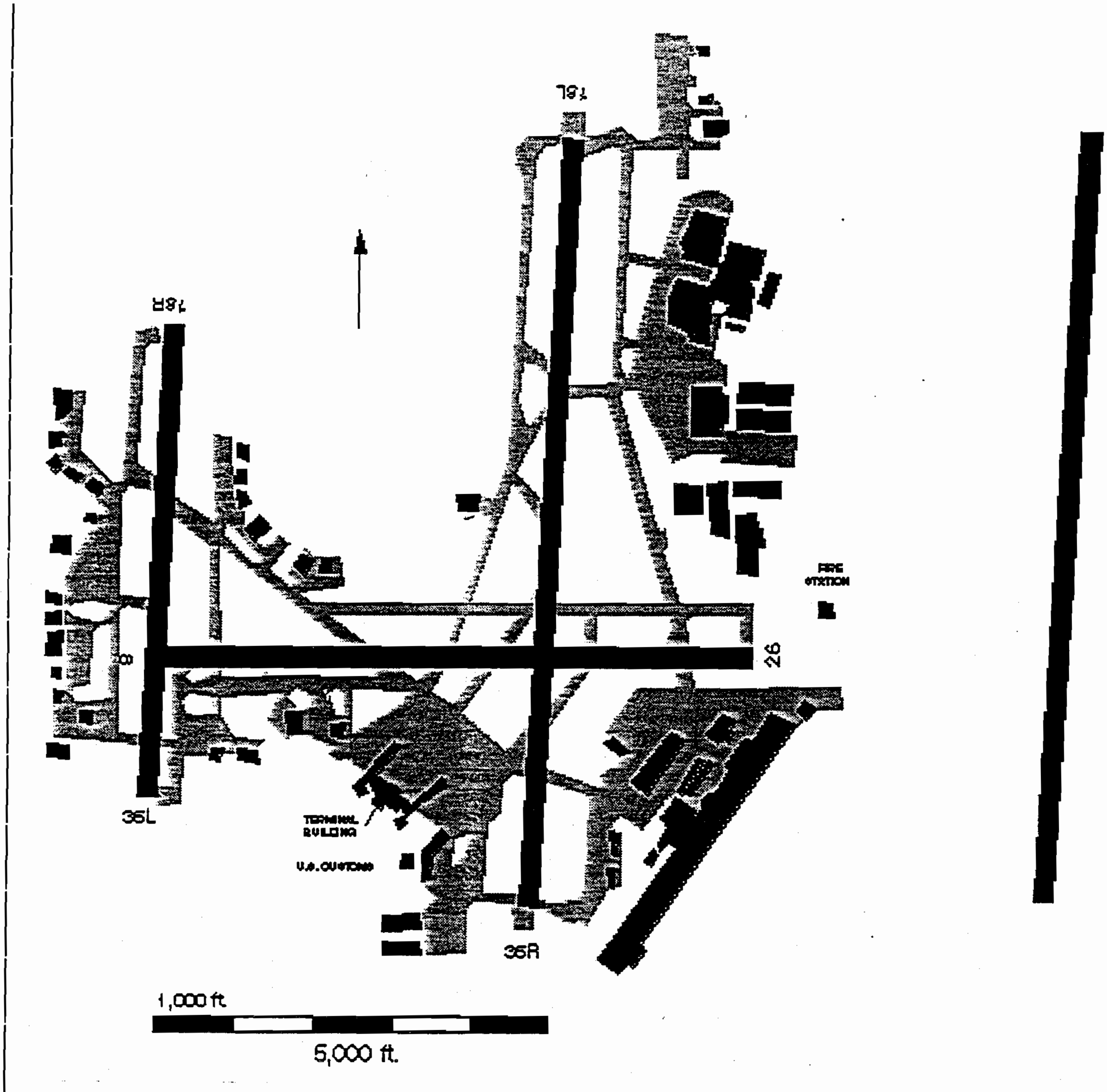
Airport Diagram

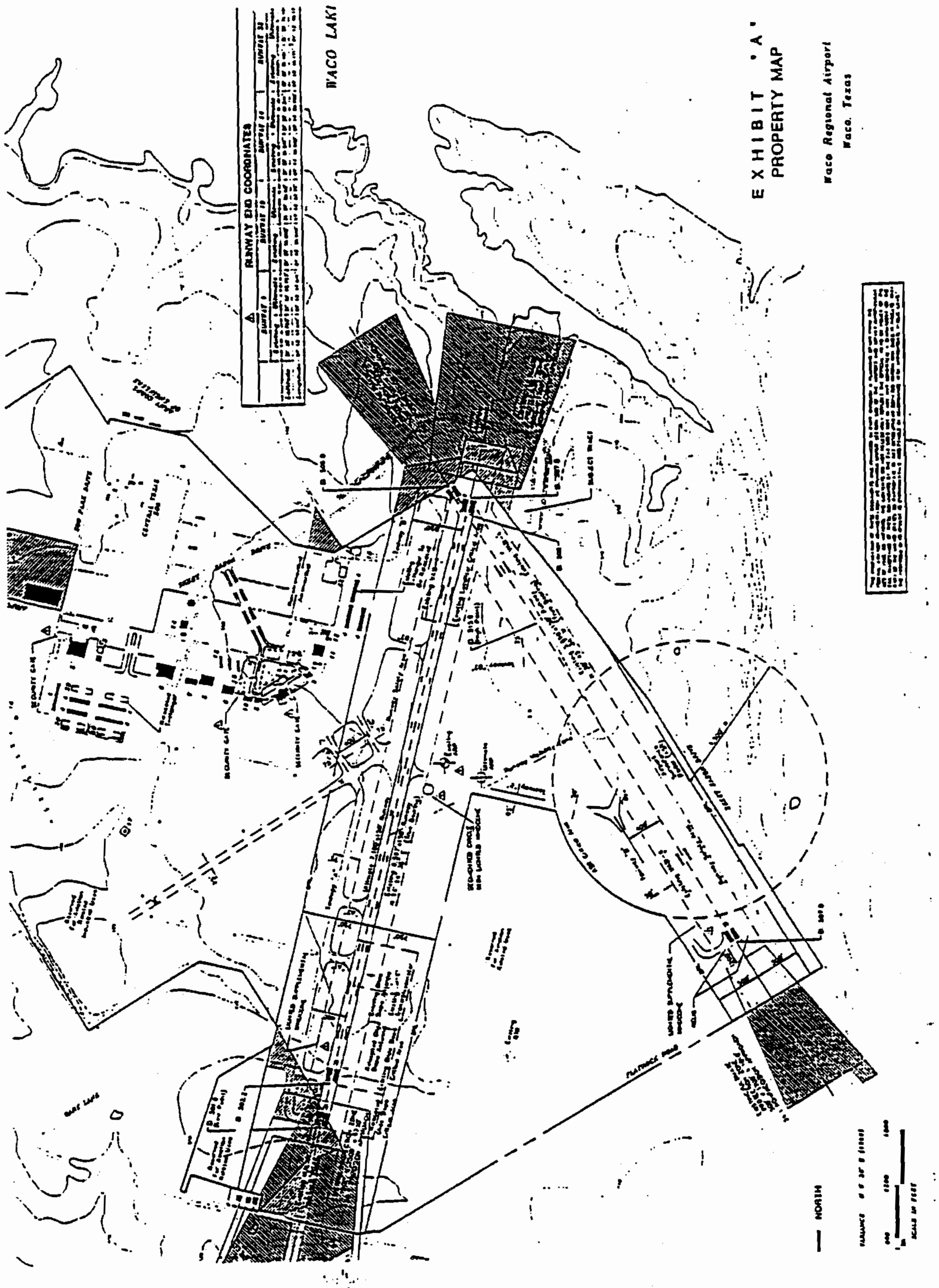
Airport Name: Houston Intercontinental Airport **Airport ID:** IAH



Airport Diagram

Airport Name Tulsa International Airport **Airport ID** TUL




RUNWAY END COORDINATES
EXHIBIT 'A'
PROPERTY MAP
Waco Regional Airport
Waco, Texas
NORTH

APPENDIX C - INFRASTRUCTURE INVESTMENT COSTS

Airport	Addition Ft2/Gate	Cost Per Ft2	Terminal Bldg (Per Gate)	Add Bridge	2 Gates/3 Aircraft	Total Terminal Cost (Per Aircraft)	
Amarillo	5700	234	1,333,800	250,000	0.667	1,056,395	
Austin/ Bergstrom	5700	234	1,333,800	250,000	0.667	1,056,395	
Corpus Christi	6100	254	1,549,400	250,000	0.667	1,200,200	
Houston	6100	254	1,549,400	250,000	0.667	1,200,200	
Tulsa	5700	234	1,333,800	250,000	0.667	1,056,395	
Waco	6100	254	1,549,400	250,000	0.667	1,200,200	
	Apron Size/ Aircraft Yd2	Cost $/Yd2	Apron Cost (Per Aircraft)	Ground Equip		Total Cost Per Aircraft	Annual Equiv. Cost 5 Yr, I=3%
Amarillo	7750	75	581,000	34500		1,671,895	365,142
Austin/ Bergstrom	7750	75	303,000	34500		1,393,895	304,427
Corpus Christi	7750	75	581,000	34500		1,815,700	396,549
Houston	7750	75	581,000	34500		1,815,700	396,549
Tulsa	7750	75	581,000	34500		1,671,895	365,142
Waco	7750	75	581,000	34500		1,815,700	396,549

APPENDIX D - EXAMPLE OF GENETIC ALGORITHM OUTPUT

Chrom #	Avg. delay	Revenue	Chromosome
1	15.12	1393	11111110221111111211111121111111111111111111111101111102111110111211100111111111111111121111
2	15.39	1390	11111110211111111211121121111111111111111111111101112102111110111211100111111111111111121111
3	15.51	1385	11111110221111111211111111111111111111111111111101111102111110121111100111111111111111121111
4	15.7	1447	11111110131111011111111111111111111111112111111101111101111110111111101111111111111111122111
5	15.71	1417	11111110211111021211111111111211111111112111111101111101111110111111100111111111111120121211
6	15.78	1330	11111110131111111111111111111111111111111111111101111001111110121211100111111111111101121111
7	15.78	1345	11111110131111111111111111111111111111111111111101111001111110121211100111111111111101121111
8	15.78	1443	11111110131111111111111111111111111111111111111101111001111110121211100111111111111101121111
9	15.87	1377	11111110221111011211111111111111111111111111111101111102111110121111100111111111111111121111
10	15.87	1386	11111110221111011211111111111111111111111111111101111102111110121111100111111111111111121111
11	15.87	1389	11111110221111011211111111111111111111111111111101111102111110121111100111111111111111121111
12	15.87	1456	11111110221111011211111111111111111111111111111101111102111110121111100111111111111111121111
13	15.87	1591	11111110221111011211111111111111111111111111111101111102111110121111100111111111111111121111
14	15.88	1455	11111110131111111111121111111211111111111111111101101102111110111111111111111111111111122111
15	15.97	1395	11111110221111012211111111111111111111111111111101111102111110121111100111111111111111121111
16	15.97	1428	11111110211121111111111111111111111111112111111101111102111110121211101111111111111111121211
17	15.97	1471	11111110211121111111111111111111111111112111111101111102111110121211101111111111111111121211
18	15.97	1502	11111110211121111111111111111111111111112111111101111102111110121211101111111111111111121211
19	15.98	1410	11111110111121111211111111111111111111112111111101111101111110121211101111111111111111121211
20	15.99	1417	11111110221111111211111111111111111111111111111111111102111110121121100111111111111111121111
21	16	1386	11111110131111011211111121111111111111112111111101111102111110121111100111111111111111121111
22	16	1389	11111110131111011211111121111111111111112111111101111102111110121111100111111111111111121111
23	16.01	1418	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
24	16.01	1423	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
25	16.01	1425	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
26	16.01	1426	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
27	16.01	1457	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
28	16.01	1530	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
29	16.01	1533	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
30	16.01	1535	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
31	16.01	1538	11111110131111111211121121111211111111111121112101111102111110111111111111111111111111121111
32	16.02	1402	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
33	16.02	1404	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
34	16.02	1405	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
35	16.02	1407	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
36	16.02	1408	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
37	16.02	1438	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
38	16.02	1464	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
39	16.02	1475	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
40	16.02	1477	11111110221111021211111111111111111111111111111101111102111110121111100111111111111111121111
41	16.06	1408	11111110221111021211111111111112111111111111111101111102111110121111100111111111111111121111
42	16.1	1375	11111110221111211211111111111111111111211111111101111102111110121111100111111111111111121111
43	16.15	1449	11111110211111011211111111111111111111111111111101111101111110111111101111111111111111122111
44	16.16	1464	11111110111111111111111121111211111111111111111101111102111110111111111111111111111111121111
45	16.16	1490	11111110111111111111111121111211111111111111111101111102111110111111111111111111111111121111
46	16.16	1495	11111110111111111111111121111211111111111111111101111102111110111111111111111111111111121111
47	16.16	1497	11111110111111111111111121111211111111111111111101111102111110211111111111111111111111121111
48	16.16	1604	11111110111111111112111121111211111111111111112101121102111110111111111111111111111111121111
49	16.16	1607	11111110111111111111111121111211111111111111111101111102111110111111111111111111111111121111
50	16.2	1464	11111110131111011111111121111211111111111111111101111102111110111111111111111111111111221111
51	16.24	1558	11111110211121111211121121111211111111111111112101111102111110111211111111111111111111121111
52	16.25	1356	11111110211111021211111121111111111112111111112111111101111101111110111111111001111111111111201211
53	16.25	1362	11111110211111021211111121111111111112111111112111111101111101111110111111111001111111111111201211
54	16.25	1363	11111110211111021211111121111111111112111111112111111101111101111110111111111001111111111111201211
55	16.27	1502	11111110221111011211121111111211111111111111111111111102111110111211111111111111111111121111
56	16.3	1415	11111110111121011211111121111111111111112111111101111101121110111111101111111111111111121211
57	16.3	1464	11111110111121011211111121111111111111112111111101111101121110111111101111111111111111111111
58	16.3	1538	11111110111121011211111121111111111111112111111101111101111110111111101111111111111111121211
59	16.3	1545	11111110131111011211111111111111111111112111111101101101111110111111101111111111111111121211
60	16.3	1545	11111110111121011211111121111111111111112111111101111101121110111111101111111111111111111111
61	16.31	1443	11111110111111011111111111111111111111112111111101111101111110111111101111111111111111122111
62	16.31	1445	11111110111111011111111111111111111111112111111101111101111110111111101111111111111111122111
63	16.31	1446	11111110111111011111111111111111111111112111111101111101111110111111101111111111111111122111
64	16.31	1552	11111110111111011111111111111111111111112111111101111101111110111111101111111111111111122111
65	16.31	1560	11111110111111011111111111111111111111112111111101111101111110111111101111111111111111122111
66	16.36	1415	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
67	16.36	1421	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
68	16.36	1425	11111110131111011211111111111111111211111111111101111101111110111111101111111111111111221111
69	16.36	1428	11111110131111011211111111111111111211111111111101111101111110111111101111111111111111221111
70	16.36	1429	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
71	16.36	1430	11111110131111011211111111111111111211111111111101111101111110111111101111111111111111221111
72	16.36	1460	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
73	16.36	1533	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
74	16.36	1535	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
75	16.36	1536	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
76	16.36	1541	11111110131111011211111111111111111211111111111101111101111110111111101111111111111111221111
77	16.36	1543	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
78	16.36	1544	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
79	16.36	1592	11111110131111011111111121111111111211111111111101111101111110111111101111111111111111221111
80	16.37	1437	11111110131111111111111111111211111111112121112101111101111110111111111111111111111111121111
81	16.38	1408	11111110111111011211111211111111111111112111111101111101111110111111101111111111111111122111
82	16.38	1459	11111110131121111111111121111111111111111111111101111102111110121111101111111111111111221111
83	16.38	1495	11111110131121111111111121111111111111111111111101111102111110121111101111111111111111221111
84	16.39	1391	11111110211111111211111121111111111111111111111101112101111110121111100111111111111111121111
85	16.39	1506	11111110221111011211111111111111211111111111111111111101111110111211101111111111111111121111
86	16.39	1512	11111110211111111211111111111111111111111111111101111102111110121211101111111111111111121111
87	16.39	1542	11111110221111011211111111111111211111111111111111111101111110111211101111111111111111121111
88	16.4	1453	11111110211111111111111121111111111111112111111101111101111110121211101111111111111111121211
89	16.42	1422	11111110131111011211111111111111111211112111111101111101111110111111101111111111111111221111
90	16.42	1425	11111110131111011211111111111111111211112111111101111101111110111111101111111111111111221111
91	16.42	1428	11111110131111011211111111111111111211112111111101111101111110111111101111111111111111221111
92	16.42	1549	11111110111111011111111121111211111111111111111101111102111110111111101111111111111111121111
93	16.43	1435	11111110131111011111111221111111111211111111111101111101111110111111101111111111111111221111
94	16.44	1384	11111110231111011211121121111111111111111111111101111102111110111211100111111111111111221111
95	16.44	1387	11111110131111011111111121111111111111112111111101111101111110111111101111111111111111121111
96	16.44	1444	11111110131111011211111121111111111111111111111101111101111110111111101111111111111111121111
97	16.44	1445	11111110131111011211111121111111111111111111111101111101111110111111101111111111111111121111
98	16.44	1446	11111110131111011111111121111111111111112111111101111101111110111111101111111111111111121111
99	16.44	1451	11111110131111011111111111111111111111112111111101111101111110111111101111111111111111121111

APPENDIX E - FLIGHT SCHEDULE ASSIGNMENT EXAMPLE

	Assignments					
Flight	Depart		Arrive		Aircraft	Remain cap
1	AUS	6H45	DFW	7H30	MD8	21
2	AUS	7H45	DFW	8H30	MD8	0
3	AUS	9H15	DFW	10H00	MD8	0
4	AUS	11H30	DFW	12H15	757	10
7	AUS	15H30	DFW	16H15	757	0
8	AUS	17H000	DFW	17H45	MD8	0
9	AUS	18H15	DFW	19H00	CNL	0
10	AUS	20H00	DFW	20H45	MD8	0
11	BOS	6H00	DFW	10H00	MD8	0
12	BOS	8H00	DFW	12H00	MD8	0
13	BOS	11H00	AUS	15H30	MD8	29
14	BOS	12H30	DFW	16H30	757	74
15	BOS	14H00	DFW	18H00	MD8	0
16	BOS	15H30	DFW	19H30	D10	139
17	BOS	17H00	DFW	21H00	CNL	0
18	DCA	5H30	DFW	8H45	757	3
19	DCA	6H45	DFW	10H00	MD8	0
20	DCA	8H45	DFW	12H00	MD8	0
21	DCA	10H30	AUS	14H15	CNL	0
22	DCA	11H45	AUS	15H30	MD8	0
23	DCA	13H15	DFW	16H30	MD8	0
24	DCA	16H15	DFW	19H30	757	0
25	DCA	17H15	DFW	20H30	MD8	0
26	DFW	7H00	AUS	7H45	MD8	67
27	DFW	9H30	AUS	10H15	D10	210
28	DFW	11H00	AUS	11H45	MD8	0
29	DFW	13H00	AUS	13H45	CNL	0
30	DFW	14H30	AUS	15H15	D10	33
32	DFW	17H15	AUS	18H00	CNL	0
33	DFW	18H30	AUS	19H15	MD8	0
34	DFW	20H15	AUS	21H00	CNL	0
35	DFW	22H00	AUS	22H45	MD8	0
36	DFW	6H45	BOS	10H30	D10	172
37	DFW	8H00	BOS	11H45	CNL	0
38	DFW	9H15	BOS	13H00	MD8	0
39	DFW	13H00	BOS	16H45	MD8	0
40	AUS	15H45	BOS	19H30	MD8	0
41	DFW	17H15	BOS	21H00	MD8	0
42	DFW	20H15	BOS	24H00	757	0
43	DFW	7H00	DCA	10H00	MD8	5
44	DFW	8H00	DCA	11H00	MD8	0
45	DFW	9H15	DCA	12H15	D10	212
46	DFW	11H00	DCA	14H00	757	128
47	DFW	13H00	DCA	16H00	MD8	0
48	AUS	15H30	DCA	18H30	MD8	0
49	DFW	17H15	DCA	20H15	D10	65
50	DFW	18H30	DCA	21H30	757	0
51	DFW	8H15	LAS	11H00	757	103
52	DFW	11H15	LAS	14H00	D10	104
53	AUS	17H00	LAS	19H45	MD8	0
54	DFW	18H45	LAS	21H30	MD8	0
55	DFW	20H00	LAS	22H45	MD8	0
56	DFW	22H00	LAS	24H30	D10	0
57	DFW	22H00	LAS	24H30	MD8	139
58	DFW	8H00	LAX	11H15	MD8	0
59	DFW	9H30	LAX	12H45	MD8	0
60	DFW	11H00	LAX	14H15	757	0
61	DFW	13H00	LAX	16H15	MD8	0
62	AUS	16H30	LAX	18H45	MD8	0
63	AUS	17H00	LAX	20H15	MD8	0
64	DFW	17H15	LAX	20H30	MD8	0
65	DFW	18H45	LAX	22H00	MD8	0
66	DFW	20H00	LAX	23H15	757	0
67	DFW	22H00	LAX	24H30	MD8	0
68	DFW	7H00	LGA	10H30	MD8	0
69	DFW	8H15	LGA	11H45	MD8	39
70	DFW	9H30	LGA	13H00	MD8	33
71	DFW	10H45	LGA	14H15	MD8	58
72	DFW	13H00	LGA	16H30	757	0
73	AUS	15H45	LGA	19H15	MD8	0
74	AUS	17H00	LGA	20H30	MD8	0
75	DFW	17H15	LGA	20H45	MD8	0
76	DFW	17H15	LGA	20H45	MD8	139
77	DFW	18H15	LGA	21H45	757	0
78	DFW	20H15	LGA	23H45	757	0
79	DFW	6H45	MIA	9H30	MD8	3
80	DFW	8H15	MIA	11H00	D10	202
81	DFW	10H45	MIA	13H30	MD8	53
82	DFW	12H45	MIA	15H30	757	0
83	AUS	17H30	MIA	18H15	CNL	0
84	AUS	17H00	MIA	19H45	MD8	0
85	DFW	17H15	MIA	20H00	MD8	0
86	DFW	18H30	MIA	21H15	D10	0
87	DFW	20H15	MIA	23H00	757	0
88	DFW	8H00	SAN	11H00	MD8	72
89	DFW	9H30	SAN	12H30	MD8	35
90	DFW	11H15	SAN	14H15	D10	206
91	DFW	13H00	SAN	16H00	MD8	43
92	AUS	17H00	SAN	20H00	MD8	39
93	DFW	18H30	SAN	21H30	MD8	0
94	DFW	22H00	SAN	24H30	MD8	0
95	DFW	9H30	SEA	13H45	757	102
96	DFW	11H00	SEA	15H15	757	110
97	AUS	17H00	SEA	21H15	MD8	0
98	DFW	18H30	SEA	22H45	CNL	0
99	DFW	22H00	SEA	24H30	MD8	0
100	DFW	8H15	SFO	12H00	CNL	0

101	DFW	9H30	SFO	13H15	757	35
102	DFW	11H00	SFO	14H45	757	86
103	DFW	13H00	SFO	16H45	MD8	11
104	AUS	17H00	SFO	20H45	MD8	20
105	DFW	17H15	SFO	21H00	MD8	0
106	DFW	18H45	SFO	22H30	757	85
107	DFW	22H00	SFO	24H30	CNL	0
108	DFW	9H30	SJC	13H00	757	121
109	DFW	11H15	SJC	14H45	D10	212
110	DFW	13H00	SJC	16H30	MD8	12
111	AUS	16H45	SJC	4H15	D10	287
112	AUS	17H00	SJC	20H30	MD8	0
113	DFW	18H30	SJC	22H00	757	14
114	DFW	20H00	SJC	23H30	MD8	12
115	DFW	8H15	SNA	11H15	MD8	62
116	DFW	9H30	SNA	12H30	757	114
117	DFW	11H00	SNA	14H00	D10	199
118	DFW	13H00	SNA	16H00	MD8	0
119	AUS	17H00	SNA	20H00	D10	194
120	DFW	18H45	SNA	21H45	CNL	0
121	LAS	3H00	DFW	5H45	MD8	0
122	LAS	4H45	DFW	7H30	MD8	0
123	LAS	9H15	DFW	12H00	MD8	0
124	LAS	10H45	AUS	14H00	757	117
125	LAS	13H30	DFW	16H15	757	0
126	LAS	16H30	DFW	19H15	D10	194
127	LAS	19H45	DFW	22H30	CNL	0
128	LAX	2H15	DFW	5H30	D10	4
129	LAX	4H00	DFW	7H15	D10	0
130	LAX	8H45	DFW	12H00	D10	24
131	LAX	10H15	AUS	14H00	MD8	0
132	LAX	12H00	AUS	15H45	MD8	2
133	LAX	13H15	DFW	16H30	MD8	0
134	LAX	14H15	DFW	17H30	MD8	0
135	LAX	15H45	DFW	19H00	757	0
136	LAX	17H45	DFW	21H00	MD8	0
137	LAX	19H15	DFW	22H30	MD8	0
138	LGA	5H00	DFW	8H45	MD8	0
139	LGA	6H30	DFW	10H15	D10	0
140	LGA	8H15	DFW	12H00	MD8	0
141	LGA	9H45	AUS	14H00	CNL	0
142	LGA	11H15	AUS	15H30	MD8	0
143	LGA	12H45	DFW	16H30	MD8	0
144	LGA	13H45	DFW	17H30	MD8	0
145	LGA	15H15	DFW	19H00	MD8	0
146	LGA	17H15	DFW	21H00	757	0
147	LGA	17H15	DFW	21H00	757	0
148	LGA	19H00	DFW	22H45	CNL	0
149	MIA	5H45	DFW	8H45	CNL	0
150	MIA	7H15	DFW	10H15	757	0
151	MIA	9H00	DFW	12H00	757	0
152	MIA	10H45	AUS	14H15	MD8	35
153	MIA	12H00	AUS	15H30	MD8	0
154	MIA	13H15	DFW	16H15	D10	105
155	MIA	14H45	DFW	17H45	MD8	0
156	MIA	16H15	DFW	19H15	757	0
157	MIA	16H15	DFW	21H15	CNL	0
158	SAN	8H45	DFW	11H45	MD8	30
159	SAN	10H30	AUS	14H00	CNL	0
160	SAN	12H00	AUS	15H30	MD8	0
161	SAN	14H30	DFW	17H30	MD8	0
162	SAN	16H00	DFW	19H00	MD8	22
163	SAN	17H45	DFW	20H45	MD8	64
164	SAN	18H45	DFW	21H45	MD8	53
165	SEA	8H15	DFW	12H15	CNL	0
166	SEA	9H45	AUS	14H15	MD8	0
167	SEA	12H30	DFW	16H30	MD8	1
168	SEA	15H30	DFW	19H30	CNL	0
169	SEA	17H00	DFW	21H00	757	27
170	SFO	2H15	DFW	5H45	757	0
171	SFO	6H30	DFW	12H00	CNL	0
172	SFO	10H00	AUS	14H00	MD8	39
173	SFO	11H30	AUS	15H30	MD8	0
174	SFO	12H45	DFW	16H15	757	0
175	SFO	14H15	DFW	17H45	757	9
176	SFO	15H45	DFW	19H15	757	22
177	SFO	17H30	DFW	21H00	MD8	27
178	SJC	9H00	DFW	12H15	MD8	7
179	SJC	10H15	AUS	14H00	MD8	7
180	SJC	13H15	DFW	16H30	CNL	0
181	SJC	14H15	DFW	17H30	MD8	0
182	SJC	15H45	DFW	19H00	MD8	0
183	SJC	17H30	DFW	20H45	MD8	25
184	SJC	19H15	DFW	22H30	757	100
185	SNA	9H00	DFW	12H00	MD8	0
186	SNA	10H30	AUS	14H00	MD8	76
187	SNA	13H30	DFW	16H30	MD8	0
188	SNA	14H30	DFW	17H30	757	71
189	SNA	16H00	DFW	19H00	D10	139
190	SNA	17H45	DFW	20H45	CNL	0
199	AUS	15H15	DFW	16H00	MD8	0
200	DFW	16H00	AUS	16H45	CNL	0

Tot passengers = 16105

Tot travel time = 1194525 (minutes)

Tot Revenue = $3.659.963