Policy-Level Decision Support for Airport Passenger Terminal Design

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Errors in the initial stages of airport passenger terminal design can be enormously expensive. Thus, providing airport planners with decision support at the policy level can prevent costly errors made on the basis of rules of thumb or "standard" practice. The two traditional approaches for assessing potential terminal performance are inadequate. Detailed, microsimulation programs require large amounts of data and presuppose a strictly defined initial configuration. Analytic formulas, expressing airport performance in terms of one or more decision variables, can be developed and optimized using differential calculus to find the best configuration—unfortunately, this method can oversimplify the problem. A new methodology is presented for providing decision support for assessing airport terminal performance in terms of expected passenger walking distances. It has the advantages of capturing the most important elements of airport operations and being fast and flexible. To achieve such speed, simple mathematical expressions (based on sophisticated analyses) are used that can be computed very quickly so that potential performance can be assessed for a variety of forecasts. Performance can thus be assessed for many possible futures to get an idea of the robustness of a particular configuration, that is, whether it exhibits similar characteristics over a wide range of conditions.

Errors in the initial stages of airport passenger terminal design can be enormously expensive. From a purely economic perspective, preventing avoidable design errors for a single airport passenger terminal can save tens of millions of dollars (*1*). It is believed, for instance, that avoidable design errors at the Air France terminal in Paris (Aerogare 2) resulted in an additional $75 million in expenses. Overdesign of the corridor in the International Terminal Building in Sydney, Australia, unnecessarily increased construction expenditures by an estimated $10 million.

Moreover, inappropriate terminal configuration selection can inconvenience passengers with unnecessarily long walking distances. The linear design of the Dallas–Fort Worth Airport was chosen under the assumption that future passenger traffic would consist largely of originating and terminating passengers. Under such an assumption, a design that provides short distances between ground transportation access and aircraft gates is highly desirable. Traffic patterns changed dramatically after airline deregulation, however, as carriers such as American and Delta Air Lines established large hub-and-spoke operations in Dallas. As a result, much passenger traffic there became transfer traffic, for whom the street-to-gate distance metric is not nearly as important as the average distance between arrival and departure gates. In terms of average gate-to-gate distances, the linear design is inappropriate for large volumes of transfer traffic (*2*).

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To illustrate this point, consider the two curves shown in Figure 1. The lines represent average walking distances for each of two terminal configurations as a function of passenger traffic mix. Note that for low levels of transfer traffic the Dallas configuration performs well, but that as the proportion of transfers increases, walking distances increase steadily. The second line shows the potential performance of some other configuration. As transfer traffic increases, walking distances increase as before, though not nearly as steeply. The second configuration is thus more robust, that is, it performs well over a wide range of circumstances rather than just one.

Basing configuration selection on a single forecast, as is often done, may lead to inflexible selections—ones that are appropriate only for a very limited range of future conditions. Given the enormous uncertainty associated with forecasting conditions 10 to 15 years away, it is crucial to select the most robust design on the basis of a wide range of forecasts. To accomplish such a selection, however, we need to be able to evaluate the potential performance of several different configurations over a variety of conditions.

In short, the process of selecting an initial configuration can benefit greatly from decision-support tools that can assess a priori measures of airport performance such as passenger walking distances. Arriving at an individual estimate, however, is not sufficient. To be effective, the tool must provide performance estimates for a range of future conditions in order to help select a robust design. As shown in Figure 1, the linear configuration performs better over a very restricted range of passenger mix forecasts. But a more complete analysis exposes its inflexibility to the level of transfer traffic.

Computer-based simulation tools are one means of providing decision support for airport terminal design. These programs focus on a detailed minute-by-minute or passenger-by-passenger analysis of a configuration in order to arrive at one or more performance measures. The programs can provide important information for improving designs, but they generally require large amounts of detailed input data that must presuppose a particular initial configuration. Moreover, these microsimulation programs require large setup times for even minor changes to the initial layout, making them cumbersome for performing extensive sensitivity analyses. What results from a series of "design-simulate-redesign" iterations is often an improved layout, though of a very strictly defined initial configuration, with no indication of whether the initial configuration was the most appropriate in the first place.

Other approaches attempt to provide analytic solutions to finding optimal passenger terminal geometries in terms of minimizing performance measures such as passenger walking distances (*3,4*). Bandara (*5*) and Bandara, Wirasinghe et al.

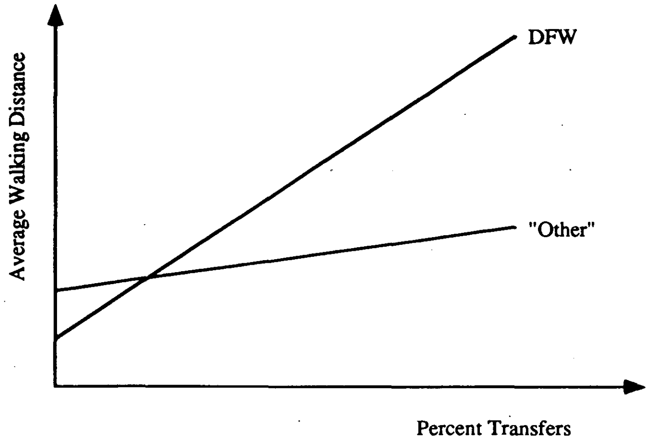


FIGURE 1 Average walking distance (as a function of passenger mix).

(*6–9*) present expressions for expected walking distances in terms of different decision variables for different terminal configuration concepts. Using differential calculus, they find the optimal parameter that minimizes the expected walking distance. Unfortunately, these approaches must make several simplifying assumptions to develop a single expression; examples include universal gate capacity and uniform gate spacing throughout the entire airport, uniform probabilities of arrival and departure at all gates within a terminal, and similarly shaped terminals for a given configuration. Under these assumptions optimal parameters can be determined, and the results from the expressions provide a good first cut for assessing configuration performance. Relaxing assumptions such as universal gate capacity is difficult, however, because of the special structure of the equations.

Absent from the overall terminal design process is a decision-support tool that can quickly evaluate the approximate performance of several very different terminal configurations in order to determine the one most appropriate for a given range of assumptions. Such a tool can be thought of as a front end to more-detailed microsimulations, providing valuable information early on for screening and eliminating inappropriate design alternatives. The remaining alternatives can then be analyzed using a more precise tool, when rapid response times are not as critical and precision becomes important.

This paper describes a new approach for assessing passenger terminal performance during the selection of the initial configuration concept. The method departs from more traditional techniques of discrete-event simulations and analytic formulas, relying instead on the incorporation of the essential elements of airport operations (which affect such performance characteristics as expected walking distances) into a model that can determine performance measures quickly for any given forecast. To achieve such speed, the method uses simple expressions that can be solved on a computer.

With such a fast and flexible tool, we can test the performance of several configurations over a variety of forecasts in the time that it takes to evaluate just one using other methods. The technique reduces the risk associated with making decisions under great uncertainty or with limited evidence. Such high-level decision support during the early phases of terminal design is likely to prevent costly errors that are made because of reliance on intuition and so-called standard practice.

After a brief overview of the quality of service, or performance, of airport terminals, this paper describes the primary types of terminal configurations and the types of passengers who use them. It then presents a model for estimating passenger walking distances and demonstrates how the model can be used to assess configuration robustness. The numerical values used to introduce the methodology are presented only to illustrate the principle of the technique and intentionally are not taken from actual sources, so as to divorce the reader from the notion that the validity of the technique itself somehow depends on specific values of the input data.

AIRPORT PERFORMANCE

The topic of airport performance is one of much study and debate. Lemer provides a comprehensive discussion of the characterization and measurement of performance for airport passenger terminals (*10*). He identifies specific quantifiable measures for assessing airport performance from the perspective of the three principal users of airport services: airport operators, airlines, and passengers. Each group has its own set of often conflicting measures by which to assess airport terminal performance. Thus, it is the task of the airport designer/planner to achieve a balance among the needs of all three groups when designing a passenger terminal.

From the perspective of the airport operator, issues of operational effectiveness, efficiency, and flexibility are of primary importance. Good utilization of gates, labor, and overall space adds to the airport's functionality while keeping operational costs down. Large projects such as airport expansions are often financed through the issue of bonds, and debt coverage is an important financial factor that airport operators also consider when measuring the performance of an airport.

Debt coverage is frequently handled, at least in part, by the airlines that use airport services. Station costs such as terminal and landing fees are important considerations from the perspective of the airlines. Other issues such as operational effectiveness (aircraft turnaround times, baggage transfer reliability, etc.), flexibility, and corporate image are also important, particularly in the United States, where carriers sometimes own their own terminal areas.

From a passenger's perspective, issues of terminal compactness, service area delays, and reliability are among the most important measures of airport performance. Ideally, passengers want to minimize walking distances and waiting times at check-in and baggage claim facilities and never miss a connecting flight. Moreover, they would like good signage and spatial logic to help them get around easily, and they would like the prices at concession areas to be competitive.

Of these measures of performance, policy-level decision makers exert considerable control over passenger walking distances when selecting the initial terminal configuration. Indeed, the physical geometry of a terminal configuration is the largest factor influencing passenger walking distances.

TERMINAL CONFIGURATION TYPES

Airport terminal configurations are as numerous as airports, yet nearly all can be placed in four primary categories based on their underlying philosophies of function: the centralized terminal, the linear (or gate-arrival) terminal, the midfield terminal, and the remote (or transporter) terminal (*11*).

The centralized terminal is characterized by a large common area containing check-in and baggage facilities as well as concession areas and other auxiliary services. Passengers reach departure gates through corridors. If aircraft interfaces (gates) are located along the corridors, the terminal is considered a finger pier [Figure 2(*a*)]. If the aircraft interface is at the end of the corridor, the terminal is considered a satellite [Figure 2(*b*)]. Large airports may comprise several centralized terminal areas with finger piers or satellites extending from each, such as at Chicago O'Hare International Airport.

A more fundamental type of configuration is the linear, or gate-arrival, terminal (Kansas City, new Munich). Represented by one or more simple rectangles [Figure 2(*c*)], the linear configuration provides a more immediate interface between local passengers and aircraft, though it requires the duplication of services (e.g., baggage handling and check-in facilities) for each separate terminal.

An increasingly prevalent configuration is the midfield terminal concept (Atlanta Hartsfield, new Denver), characterized by a centralized terminal and one or more separate concourses connected by an underground people mover or moving walkway [Figure 2(*d*)]. Each of the separate concourses can have aircraft interfaces on virtually all sides, providing good use of terminal space.

The final type of terminal configuration is the remote, or transporter, terminal (Washington Dulles). Passengers board a bus or transporter at a centralized terminal and are taken either directly to their aircraft or to a remote terminal at which the aircraft is parked. The remote terminal can be represented by a simple box, and any of the previous configurations can house remote exit points. The transporter concept is appealing for managing peak traffic because it eliminates fixed structural costs in lieu of smaller variable costs for transporter equipment and labor.

Strict adherence to a particular concept is not required. Indeed, many hybrid terminal configurations embody two or more of the previous concepts. Thus, we can think of a hybrid configuration as a fifth concept.

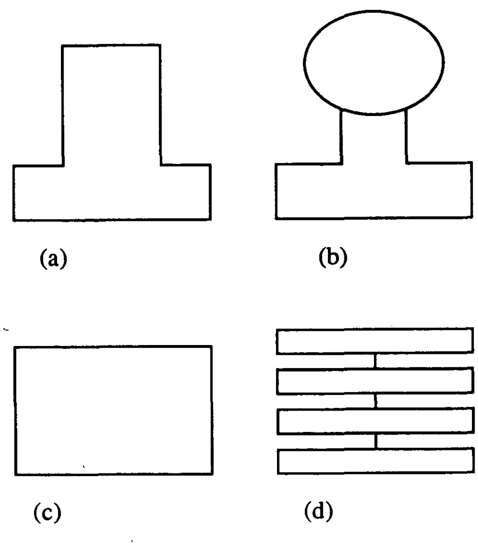


FIGURE 2 Terminal configuration concepts: (*a*) finger pier, (*b*) satellite, (*c*) gate-arrival, and (*d*) midfield.

PASSENGER TYPES

Passengers who either begin or complete their journey at an airport are known as originating or terminating passengers, respectively. Originating passengers are assumed to arrive at the airport entrance nearest to the terminal containing their departure gate. Their required walking distance, therefore, can be modeled as the distance between the terminal entrance and the departure gate. Check-in facilities are generally located somewhere along this path (or nearby), so we make no explicit distinction between the walking distances for passengers who have advance seat assignments and those who must check in. Furthermore, we do not distinguish between walking distances for originating passengers who are carrying luggage and walking distances for those who are not.

Similarly, terminating passengers are assumed to leave the airport through the exit nearest their arrival terminal. Required walking beyond the exit is not necessarily affected by the configuration concept, so it is not considered. Like check-in services, baggage claim services are often located along the path from the arrival gate to the terminal exit, so we do not make a distinction between terminating passengers with and without baggage.

Thus, we model the required walking distances for both originating and terminating passengers as the distance between the departure (arrival) gate and the nearest entrance (exit). Such an approximation helps in performing calculations quickly, though there is also a strong intuitive argument for its use.

Passengers who neither begin nor end their journeys at an airport are considered transfer passengers. Transfer passengers are required to travel some path from their arrival gate to their departure gate. The length and direction of the path depends both on the physical geometry of the terminal and whether the passenger is making a direct or indirect transfer. The more common type of transfer is a direct, or hub, transfer: passengers go directly from their arrival to their departure gates. The required walking distance for a direct transfer is the length of the most direct path between the respective gates, determined by the geometry of the terminal. Indirect, or nonhub, transfers, on the other hand, must include in their path some intermediate service point, which is likely to increase the required walking distance. Most interline connections and international flights with domestic connections can be considered indirect transfers.

ESTIMATING WALKING DISTANCES

We estimate expected walking distances by calculating weighted averages of the absolute distances walked by each of the passenger classifications. Absolute distances are calculated using the right-angle or Manhattan metric and reflect the actual walking distances required of a passenger to get between two locations in the airport, on the basis of terminal geometry. In practice, passengers often divert from the most direct path (to use concession areas, for example). We do not consider such diversions, because they do not reflect the choice of a terminal configuration as much as they do passenger behavior.

For interterminal transitions, we assume each terminal has a waypoint through which passengers must pass when walking between terminals. We can therefore determine all absolute gate-to-gate as well as gate-to-entrance (or exit) distances on the basis of the physical geometry of the terminal configuration. Determining the overall expected walking distance for a particular configuration, however, requires additional information.

The overall expected walking distance is a weighted average of all the individual gate-to-gate and gate-to-entrance/exit distances walked. The frequency that each path is walked depends on the forecast of the passenger mix. Thus, if we anticipate that 60 percent of the traffic will be originating or terminating and 40 percent will be transfers (of which 90 percent are direct and 10 percent are indirect), the expression for the expected overall walking distance is

$$D = 0.60d_{ot} + 0.40(0.90d_{td} + 0.10d_{ti}) \quad (1)$$

where

D = overall expected walking distance,
d_{ot} = expected walking distance for originating and terminating passengers,
d_{td} = expected walking distance for direct transfers, and
d_{ti} = expected walking distance for indirect transfers.

Each distance term on the right in Expression 1 is a weighted average of walking distances estimated on the basis of other assumptions regarding frequency of use. The rest of the paper describes in detail a conceptual approach used to estimate the distance factors in Expression 1.

Direct Transfer Walking Distances

To illustrate our approach, we begin by developing a model for estimating the expected walking distance for direct transfers, d_{td}, from Expression 1. Consider direct transfers within Terminal 1 of the two-terminal airport configuration shown in Figure 3: passengers arriving at Gate 1 can depart from any one of the three gates, and the absolute distance from Gate 1 to Gate 2 is 30 m and from Gate 1 to Gate 3, 20 m.

If we assume that each gate is equally likely for departure, the expected walking distance for Gate 1 direct transfers, d_{td1}, is

$$d_{td1} = (0.33) \times 0 + (0.33) \times 30 + (0.33) \times 20 = 16.7 \text{ m}$$

Now consider all possible direct transfers, which include those to Terminal 2, a satellite terminal containing two gates (for simplicity) located along the perimeter of the circular aircraft interface.

Gate 1 arrivals may now depart from any one of five gates. We assume (though it is not necessary) that passengers arriving in Terminal 1 are more likely to depart from Terminal 1, reflecting, for instance, the territorial nature of gate occupancy at most U.S. airports. The matrix of transition probabilities (T_{ij}) for passengers arriving at a Terminal i and departing from a Terminal j might look like

To	1	2	
From	1	0.80	0.20
	2	0.30	0.70

Note that we have not assumed the matrix to be symmetrical. One explanation may be that, because Terminal 2 contains only two of the five departure gates, it is slightly more likely that Terminal 2 arrivals will need to make an interterminal connection. Maintaining a uniform gate use assumption, the expected walking distance for Gate 1 arrivals becomes

$$d_{td1} = 0.80\ (16.7) + 0.20\ (0.50 \times 240 + 0.50 \times 240)$$
$$= 61.3 \text{ m}$$

The expected walking distance increases considerably because of the 20 percent chance of passengers' having to depart from Terminal 2. Similar analyses can be performed for all five potential arrival gates.

Intelligent Scheduling

Our primary assumption so far has been that gate transitions are uniform, that each gate is equally likely for departure. In reality, airport operators and the airlines exercise much control over flight-to-gate assignments and can reduce transfer walking distances by scheduling arrival gates closer to connecting departure gates (*12,13*). It is reasonable, therefore, to consider that under such "intelligent scheduling" conditions, the probability of departing closer to one's arrival gate is greater than that of departing from far away. We refer to transition probabilities based on flight-to-gate assignments as "gate affinity."

A simple method of capturing such effects of intelligent scheduling is to model the probability of departing from a gate as being inversely proportional to the distance to the arrival gate. This assumption is only one of many possibilities, however. The actual transfer probabilities used can be obtained from more complex analyses involving anticipated flight schedules, or they can simply be estimated and input by the user individually. Appendix A demonstrates how to calculate transition probabilities based on our simple model of intelligent scheduling.

Under the assumption that intraterminal transitions are inversely proportional to distances walked and that interterminal transitions remain uniformly distributed, the transition probabilities for Gate 1 arrivals become

$$t_{11} = 0.32$$
$$t_{12} = 0.19$$
$$t_{13} = 0.29$$
$$t_{14} = 0.10$$
$$t_{15} = 0.10$$

The new direct transfer walking distance estimate becomes

$$d_{td1} = 59.5 \text{ m}$$

Note the reduction from the uniform assumption used before.

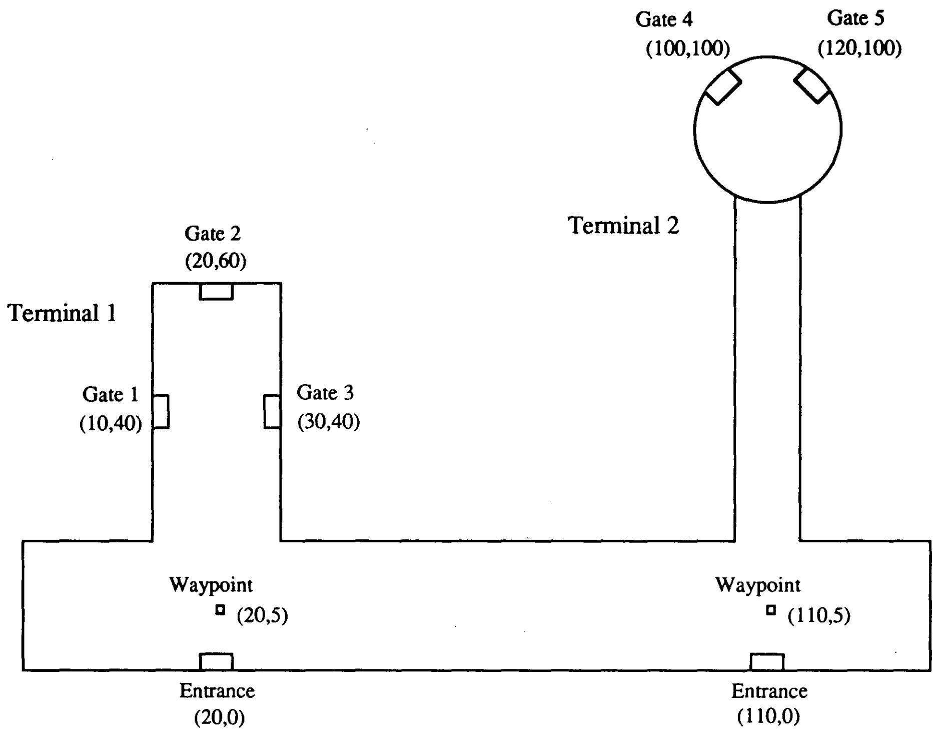


FIGURE 3 Two-terminal airport configuration.

Aircraft Effects

The assumption behind the determination of the transition probabilities calculated thus far has been that each gate handles the same volume of passengers per unit time—that for an airport with *n* gates, the probability of a random passenger arriving at or departing from any gate is $1/n$. Under such an assumption, differences in gate affinity arise only from the desire of the airport operators or airlines to assign gates for connecting flights closer together.

An important element is missing from such an assumption, though: namely, the capacity of different gates in terms of aircraft use. Different classes of aircraft naturally require different amounts of gate parking space, primarily because of the aircraft's wingspan. Certain gates can handle only small and medium-sized aircraft. Passenger volumes at a gate thus depend on the type and mix of aircraft serviced there throughout the day. We refer to the probability of a passenger's arriving or departing from a gate solely on the basis of the mix of aircraft serviced there as the "demand rate."

The capacity of a gate is often expressed in terms of the largest aircraft that it can service: gates able to accommodate large aircraft, for instance, can also generally accommodate medium-sized and small aircraft. The breakdown of aircraft utilization at a gate is primarily determined by some gate assignment policy—a "Large" gate, for example, may serve 40 percent large aircraft, 50 percent medium-sized aircraft, and only 10 percent small aircraft, whereas a "Medium" gate may service 70 percent medium-sized and 30 percent small aircraft.

Given the gate use by aircraft type, two remaining factors influence the demand rate: the expected number of passengers and the turnaround time for each aircraft type. Aircraft turnaround time is the time required for services such as cleaning and refueling between an arrival and the next departure. In general, larger aircraft may carry more passengers, but they have longer turnaround times. Conversely, smaller aircraft carry fewer passengers but can be turned around more quickly, thus allowing more operations per unit time. The net effect of these two factors on the demand rate can be determined using information about average aircraft use as well as the size and average turnaround times associated with each aircraft type.

Appendix B illustrates how so-called aircraft effects can be used to calculate demand rates. For our example, we use the following data on aircraft size and turnaround times, but the model is entirely general:

Aircraft Type	*Number of Seats*	*Turnaround Time (min)*
Large	400	90
Medium	200	60
Small	150	40

We also assume that the three gates in Terminal 1 are Medium gates and the two gates in Terminal 2 are Large gates, with aircraft utilizations equal to those previously described for Large and Medium gates. From Appendix B, we get the following demand rates:

Gates	*P(Depart)*
1, 2, 3	.19
4, 5	.21

To incorporate demand rates into our original transition probabilities, we weight the two sets of probabilities together. The resulting transition probabilities for Gate 1 arrivals are given in Table 1. The expected walking distance for Gate 1 direct

TABLE 1 Transition Probabilities for Gate 1

T_{ij}	Gate Affinity	Demand Rate	Weighted Transition	Walking Distance (m)
t_{11}	0.32	0.19	0.309	0
t_{12}	0.19	0.19	0.185	30
t_{13}	0.29	0.19	0.278	20
t_{14}	0.10	0.21	0.114	240
t_{15}	0.10	0.21	0.114	240

transfers is the weighted average of the combined transition probabilities and the absolute walking distances, or 65.9 m. On the basis of intelligent scheduling alone, the expected walking distance would be slightly lower, 59.5 m. The increase is due to the higher probability of a passenger's departing from the Large gates in Terminal 2. Similar analyses can be performed for all five gates.

To obtain a single estimate for all direct transfers, we weight the individual direct transfer estimates by the probability of arriving at a given gate. This probability is simply the demand rate based on aircraft effects alone. The implicit assumption is that symmetry exists between departures and arrivals; however, if there is reason to believe that arrival load factors are very different from departure load factors, a similar analysis can be performed to obtain arrival-specific demand rates. We assume symmetry here, and the resulting calculations yield the following:

Gate	*Expected Distance (m)*	*P(Arrival)*
1	65.9	.19
2	71.0	.19
3	65.9	.19
4	73.5	.21
5	73.5	.21

The overall expected walking distance for direct transfer passengers is the weighted average of the individual distances, or 70.2 m.

Other Walking Distances

From this point it is possible to obtain walking distance estimates for originating, terminating, and indirect transfer passengers using similar analyses. The expected originating (terminating) passenger walking distance is the weighted average of the absolute distances walked by such passengers, depending on the probability of departure from (or arrival at) a particular gate. This probability is simply the demand rate based on aircraft effects. Using the demand rates calculated previously, the overall expected walking distance for originating or terminating passengers in the two-terminal airport example is 78.3 m.

Indirect transfers who require intermediate services before departure often must cross greater distances than direct transfers. Given the location of these intermediate service points, we can determine indirect transfer walking distances for all possible gate-to-gate transitions. The overall estimate is the weighted average of all such walking distances.

For our example, we assume services for indirect transfers are located at the waypoint of the respective arrival terminal. Thus, the required walking distance for a Gate 1 arrival departing from Gate 2 is 100 m. Transition probabilities for indirect transfers are calculated similarly to those for direct transfers. Gate-to-gate transition probabilities for indirect transfers are driven almost entirely by interterminal transitions, however, because walking distances to and from intermediate service points are large in relation to gate spacing. Thus, for our example we assume that departure gate affinity for indirect transfers is uniform.

It can be shown that the overall expected walking distance for indirect transfers is 169.3 m. The considerable increase over direct transfer walking distances is explained by the additional walking required for intermediate services.

We now return to Expression 1 and solve for the overall expected walking distance by substituting values calculated previously:

$$D = 0.60(78.3) + 0.40(0.90 \times 70.2 + 0.10 \times 169.3) = 79\,\text{m}$$

Thus, the overall expected walking distance for all traffic weighted by passenger mix is 79 m.

The preceding analysis completes our model for estimating passenger walking distances for a given configuration. But another element of control for airport operators can greatly affect passenger walking distances: namely, dynamic gate selection. The next section details how exploiting demand fluctuations can help reduce walking distances during periods of low demand.

Dynamic Gate Selection

Varying levels of passenger demand place different requirements on an airport and its services throughout the day. Two typical passenger demand profiles faced by airport owners are shown in Figure 4. The first profile is characterized by an almost constant level of demand. The second profile is characterized by distinct peaks in the morning and in the evening. Airport operators facing the second demand profile can exploit such volatility by using only a subset of gates during off-peak periods of demand.

The ability to allocate gate use dynamically on the basis of demand patterns can have significant effects on expected walking distances. By using gates in only one terminal, for instance, direct transfer walking distances are reduced by eliminating lengthy interterminal connections. In Salt Lake City, Delta Air Lines will dynamically reduce gate use along its piers in order to centralize operations and passenger flows during periods of low demand.

Returning to our example, let us assume that during periods of low demand, the airport is used primarily by transfer traffic and that only gates in Terminal 2 are used for arrival and departure operations. To incorporate this new low-demand policy into our expected walking distance model, we perform an independent walking distance analysis as if we were dealing with a new airport consisting only of Terminal 2. We then weight the two overall estimates by the fraction of time that the airport operator uses each configuration to obtain an overall estimate for the given demand profile.

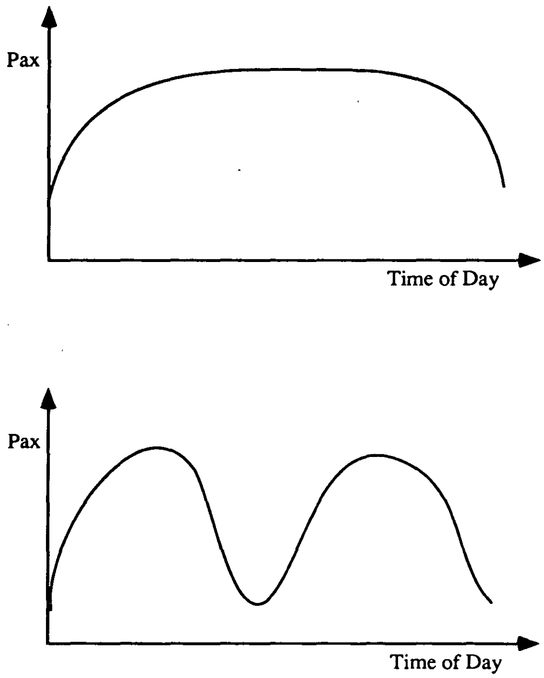


FIGURE 4 Characteristic demand profiles: *top*, constant demand profile; *bottom*, two-peaked demand profile.

Performing a similar walking distance analysis on our Terminal 2 airport yields the following overall walking distance estimates:

Traffic Type	*Passenger Mix*	*Expected Distance (m)*
Originating/terminating	0.30	110.0
Transfer (direct)	0.63	12.0
Transfer (indirect)	0.07	210.0
Overall		55.3

Combining high and low estimates depends on the fraction of time that the airport faces each demand condition. For simplicity, assume that only Terminal 2 is used when the demand level is less than half the highest demand peak, and the full two-terminal configuration is used otherwise. For the demand profile shown in Figure 4 (*top*), this policy translates approximately to a 90/10 demand split. The overall walking distance is thus $(0.90 \times 79.0) + (0.10 \times 55.3) = 76.6$ m.

For the second profile [Figure 4 (*bottom*)], high demand conditions prevail for a smaller fraction of time, so we would expect a greater reduction in walking distances because of our low-demand policy. Indeed, the high/low demand split is approximately 60/40, which translates to an overall expected walking distance of 69.5 m.

To summarize, two factors related to passenger demand profiles influence walking distances. The first is the actual profile of demand, or how much fluctuation exists between high and low demand. The second and perhaps more important factor is the policy used for addressing such volatility. It is the judicious selection of gates used during low demand conditions that reduces walking distances and thus improves performance, not the variability in the demand pattern itself.

SENSITIVITY ANALYSES AND CONFIGURATION ROBUSTNESS

Forecasts are by nature imprecise and often incorrect. Making a decision as important as selecting a terminal configuration on the basis of a single "snapshot" of what might occur can have devastating effects in the face of great uncertainty. More important to decision makers is the robustness of a configuration, a measure of how the configuration will perform over a variety of conditions.

To test configuration robustness for our example, we systematically vary two separate parameters and note their effects on our estimates for expected walking distances. The first parameter is passenger mix, which we vary in terms of the fraction of total traffic made up by transfer passengers. The second parameter is the volatility of the passenger demand profile, which we vary in terms of the fraction of time that the airport faces low demand conditions.

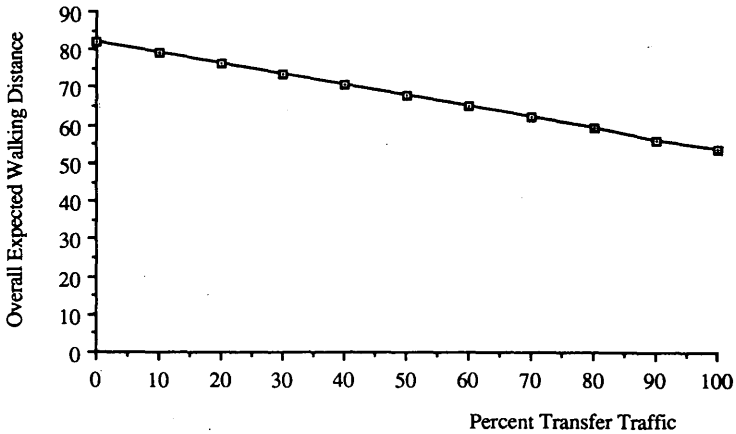
By varying the percentage of transfer traffic, we can determine the sensitivity of our configuration to our original passenger mix assumption. Holding all other parameters constant, we vary the percentage of transfer traffic between 0 and 100 [Figure 5 (*top*)]. Note that as the fraction of transfer traffic increases, the overall expected walking distance decreases, as we would expect given the intermediate values that we calculated for each passenger type.

A similar sensitivity analysis was performed to test configuration robustness to changes in the daily demand profile. Figure 5 (*bottom*) shows the results of varying the fraction of time that the airport faces low demand while holding all other parameters constant. Note that as we increase the fraction of time that the airport faces low demand conditions, the overall expected walking distance decreases, which is precisely the goal of our gate selection policy.

FURTHER RESEARCH AND CONCLUSIONS

This paper has presented a new methodology for estimating passenger walking distances. Unlike other, more traditional models that make restrictive and sometimes inappropriate assumptions, our model allows for a great deal of flexibility and provides the opportunity to assess the effects of not only the physical geometry of a terminal but also the actions of airport operators in a highly dynamic environment. Rather than providing a definitive answer as to the "best" airport configuration for all circumstances (it is unlikely such a configuration exists), the model provides an approach for assessing the robustness of many different designs to determine which configuration is most appropriate in the face of great uncertainty.

The most natural application of our model is as a decision-support tool for airport planners to be used during the earliest stages of the design process. Because the model requires only minimal input, walking distance estimates can be obtained quickly and various sensitivity analyses can be performed to determine the robustness of many candidate designs. Such analyses may help prevent costly design errors that are made early in the planning process. The model can also be used to establish general rules of thumb for initial configuration selection based on forecasts of passenger mix, gate capacity and



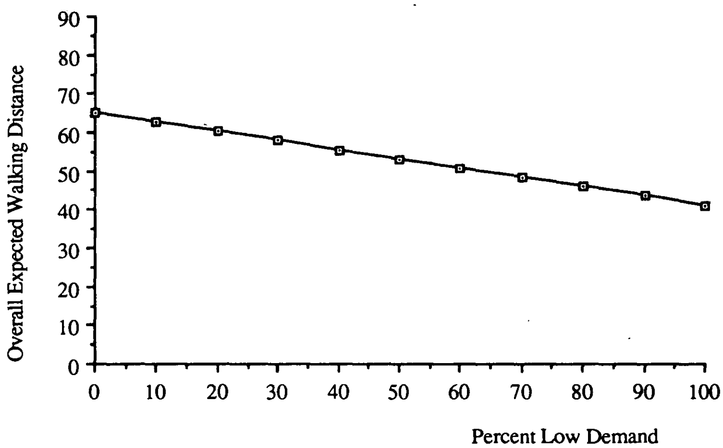


FIGURE 5 Sensitivity analyses and terminal robustness: *top*, robustness to passenger mix; *bottom*, robustness to demand profile volatility.

use, and expected daily demand profiles for future airport construction.

Finally, once an initial configuration is selected, it is possible to test different gate selection policies for handling fluctuations in daily demand. Such sensitivity analyses are not restricted to future airport construction projects. Indeed, many current airports facing high variability in daily demand patterns can benefit greatly from such analyses to decide how best to use existing facilities.

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APPENDIX A
Intelligent Scheduling

To calculate gate affinities on the basis of the assumption that the probability of departure from a gate is inversely proportional to the distance walked, we first need an estimate for through passengers (whose required walking distance is zero). This estimate can be obtained from historical or forecast data. Returning to our example of Gate 1 arrivals connecting within Terminal 1, let us assume that 40 percent of arrivals are through passengers. Thus, the remaining 60 percent of traffic will depart from either Gate 2 or Gate 3.

If transition probabilities are inversely proportional to distance, then the following relation will hold:

$$\frac{d_{12}}{d_{13}} = \frac{t_{13}}{t_{12}}$$

The sum of t_{12} and t_{13} must total the remaining proportion of traffic, which from the preceding is 0.60, or

$$t_{12} + t_{13} = (1 - t_{11})$$

Solving for t_{12} and t_{13} for our example yields

$$t_{12} = \frac{20}{50} * 0.60 = 0.24$$

$$t_{13} = \frac{30}{50} * 0.60 = 0.36$$

In general, for an arrival gate i and a given proportion of through traffic, t_{ii}, the following expressions describe our simple intelligent scheduling model for calculating gate affinities for a terminal with n gates:

$$t_{ij} = \left(1 - \frac{d_{ij}}{d_{\text{tot}i}}\right)(1 - t_{ii})$$

where

t_{ij} = probability that a Gate i arrival departs from Gate j,
d_{ij} = absolute distance from Gate i to Gate j, and
$d_{\text{tot}i} = \sum_{j=1}^{n} d_{ij}$

APPENDIX B
Aircraft Effects

To calculate demand rates on the basis of aircraft effects, consider the following data:

Aircraft Type	*Number of Seats*	*Turnaround Time (min)*
Large	400	90
Medium	200	60
Small	150	40

A gate operating continuously throughout a 12-hr period servicing only large aircraft will thus "witness" 3,200 arrival/departure seats. Similarly, gates servicing only medium-sized or only small aircraft would witness 2,400 or 2,700 seats, respectively. The expected number of passengers witnessed by each gate can be determined by multiplying total seats by the average load factor for each aircraft type. Thus, if large aircraft are generally 67 percent full, our dedicated gate will witness (3,200 × 0.67) or 2,144 passengers. Making a similar load factor assumption for medium-sized and small aircraft yields 1,608 and 1,800 passengers, respectively.

For an individual gate, the expected number of passengers witnessed depends on gate use by aircraft type. Recall our use description of Large and Medium Gates:

Large Gate

Aircraft Type	*Passengers per Day*	*Use*	*Total*
Large	2,144	0.40	858
Medium	1,608	0.50	804
Small	1,800	0.10	181
Total			1,843

Medium Gate

Aircraft Type	*Passengers per Day*	*Use*	*Total*
Medium	1,608	0.70	1,126
Small	1,800	0.30	543
Total			1,669

In our two-terminal airport configuration there are two Large and three Medium gates, for a total of 8,693 passengers witnessed per 12-hr period.

The demand rate is defined as the probability that a passenger will arrive at or depart from a particular gate. This probability is the fraction of total passengers witnessed by a particular gate. Thus, we can determine demand rates for all gates by dividing the number of passengers witnessed by a single gate by the total number of passengers witnessed at the entire airport per time period. Such calculations yield the following:

Gates	*Fraction of Total Pass. Departures*	*Demand Rate*
1, 2, 3	1,669/8,693	0.192
4, 5	1,843/8,693	0.212

Note that since we are dividing one time-dependent figure by another, the actual time period assumed has no effect on the demand rate estimates.