

## Research Article

# Distribution Optimization Model for Passenger Departure via Multimodal Transit

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International airports in China have become a complex hub between airport and multimodal transit stations. Dissimilar passenger departure demands in different transit mode cause wide gaps among departure times from airport to these modes. In this context, hub managers need to balance the distribution of air passengers to transit modes in order to reduce departure delays and alleviate the congestion in transit stations, even though they cannot change the operating plan of airport or transit stations. However, few research efforts have addressed this distribution. Therefore, we developed a distribution optimization model for passenger departure that minimizes the average departure time and is solved by Genetic Algorithm. To describe differences in passenger choices, without taking into consideration the metropolitan transportation network outside the airport, we introduced the concept of rigid and elastic departures. To reflect the tendency of elastic passengers to choose different transit modes, we assume that the passengers change to other modes in different proportions. A case revealed that the presence of rigid passengers allows managers to partly balance the distribution of passengers and improve the average departure time. When the volume of passengers approaches the peak volume, the optimized distribution significantly improves the departure time.

## 1. Introduction

International airports in China are designed as mega-hubs, which function not only as an airport but also as terminals for metropolitan transportation networks. In some cases, the airport is even a complex hub for airport, railway station, and multimodal transit stations. Thus, taking Shanghai Hongqiao International Airport and Beijing Capital International Airport as examples, serious delays occur in the transit stations of airports at peak hours because of the limited capacity of the stations and complex passenger flows departing from the airport to metropolitan areas. In addition, dissimilar passenger departure demands in different transit mode cause wide gaps among passenger departure times from airport to these transit modes. Taking our survey as an example, taxi passengers are far more than bus riders in Shanghai Hongqiao International Airport. Under this circumstance, although nearly 10 taxis arrive simultaneously with an average 20-second departure interval, exceptionally long queues occur at the taxi stop while a lot of seats are available at the waiting room of bus station. In this context, in order to

reduce departure delays and alleviate the congestion in transit stations, hub managers and operators need to balance the distribution of departure passengers using each transit mode, even though they cannot change the operating plan of the airport or transit stations. Unfortunately, there has been little research on determining the distribution of passengers for each transit mode to significantly reduce departure delays. Therefore, it is worthwhile to quantify the relationship between the passenger distribution for each transit mode and average departure time to theoretically determine the minimum departure time.

Many studies have considered factors in the successful operation of airport terminals. For example, one approach involves measuring the level of service (LOS) for airport passenger terminals [1–3]. Useful indices have been proposed for objective LOS measurement for a single operational component at an airport according to user perceptions [1]. In another study, a global index was used to assess the overall LOS for the airport performance after obtaining weighted values for individual operational components [2]. The LOS has also been measured for transfer passengers who did not

use airport access roads [3]. This revealed that the courtesy of security staff and the quality of flight information displays are among the factors most valued by transfer passengers.

Researchers have also investigated airport gate assignment [4–6], operation of check-in facilities [7, 8], and people flows in airport terminals [9, 10]. However, because many international airports are hubs for both airline travel and multimodal transit, improved operation of the airport itself is not sufficient to minimize passenger departure time. Hub managers need to coordinate passenger departure from the airport with multimodal transit stations.

In order to fully understand passenger distribution among different transport modes in an airport, railway station, or metro station, researchers have focused on three main aspects: volume forecasts, transfer efficiency, and evaluation and implementation of improvements.

To forecast the volume of passengers taking each transit mode, Ameen and Kamga [11] forecast airport ground access and egress trips at John F. Kennedy International Airport using an incremental logit or pivot-point model. They predicted the impact of the change in waiting and transfer time in the AirTrain system on transit mode chosen by air passengers and employees traveling to and from the airport.

In addition, to evaluate transfer efficiency, Leng et al. [12] proposed various criteria and a hierarchy index system for the transfer conditions in Beijing South Railway Station. They compared the ranking results for transfer efficiency among different transfer modes. Duncan [13] used an approach called “nanosimulation” to contribute the following: (1) analyzing airport access by comparing multiple parking options, rail transit, drop-off, and taxi access and (2) visualizing the generalized cost, taking into account time, distance, and price factors. However, few studies have managed to optimize transfer conditions after evaluating the current performance.

Furthermore, Engel-Yan et al. [14] analyzed a case study in which they adapted and applied a planning process for station access to a commuter rail network. This process was helpful in identifying multimodal access priorities at high-capacity transit stations and in weighing benefits and trade-offs. So transit agencies could balance investment in park-and-ride facilities with other more sustainable access modes. Cherry and Townsend [15] identified actions that could improve connections between metro and bus transit modes in Bangkok. Chen et al. [16] suggested bicycling as a mode of access to or egress from the metro system in Nanjing, China, to increase use of the metro system and alleviate traffic loads on the urban road network. They investigated the determinants of bicycle transfer demand as a valuable factor for policy designing. Chowdhury and Chien [17] proposed a plan for vehicle dispatch at transfer stations to reduce the transfer time. They developed a procedure for dynamic optimization of the dispatch time for each ready vehicle to minimize connection delays and missed-connection costs. Their results showed that the method could be used to improve dispatch strategies for transit vehicles and reduce transfer time.

Unlike governors, airport managers, and transit agencies, hub managers cannot change the operating plan of airports or transit stations. To the best of our knowledge, none of the

research efforts has attempted to balance the distribution of departing passengers using each transit mode, which could improve the departure time within the airport and transit stations. This research gap motivated our development of a distribution optimization model for passenger departure.

The choice of departure mode is mainly determined by the travel cost, travel time, and accessibility outside the airport. Departure time within the hub cannot have great impact on every passenger. However, when attempting to quantify the “time-choice” relationship, it is extraordinarily complicated to take the metropolitan transportation network outside the terminal into consideration. To describe differences in passenger choice and emphasize the impact of departure time within the hub, we introduce the concept of rigid and elastic departures. Rigid passengers are not inclined to change their choice of transit mode for departure from the airport, regardless of the waiting and walking time in the hub and transit station. For these passengers, apart from individual preference, their rigidity is determined by the fact that other transit modes to their destination are inaccessible, far more time-consuming, or more expensive. In contrast, elastic passengers have a tendency to change their departure choice, after comparing departure times within the hub and transit station among various transit modes. These passengers have other choices available that are comparable to their first choice in travel time and cost outside the airport, and their choice is primarily affected by departure time within the hub.

Therefore, we need to optimize average passenger departure time within the hub and transit stations.

Based on the above discussion, we performed the following research: (i) developing a mathematical model to quantify the relationship between the passenger distribution of each transit mode and average departure time within the hub, (ii) taking into account the rigidity and elasticity of passenger choice behavior and proposing a transfer matrix of transit modes based on the varieties in the inclination of elastic passengers to choose different transit modes, and (iii) applying our model to a case study of Shanghai Hongqiao International Airport, China, optimizing the departure passenger distribution for each transit mode that minimizes average departure time within the hub.

## 2. Distribution Optimization Model for Passenger Departure

*2.1. Framework.* To improve waiting and walking time in the hub and transit stations, we develop a distribution optimization model that minimizes the average passenger departure time under the capacities of the departure chain, including transfer routes, platforms (or waiting rooms), and transit modes (subway, bus, and taxi). The main model considerations are described below.

First, we categorize the departing passengers as rigid or elastic. Rigid passengers scarcely change their choice of transit mode for departing from the airport, regardless of waiting and walking time in the hub. For example, for a passenger whose destination is quite far from the airport and for which only bus transit provides direct access, change

in choice to subway or taxi while seated in the waiting room is very unappealing. In contrast, elastic passengers can choose to change their departure option, after comparing departure times among various transit modes. For instance, bus, subway, and taxi modes are all available for passengers who live in metropolitan Shanghai, and the taxi fare in Shanghai is acceptable to air passengers. Thus the waiting times in the hub and transit station always determine departure behaviors of these passengers. Therefore, optimization involves appropriate distribution of the proportion of elastic passengers in each transit mode.

Drivers of private cars are considered to be rigid passengers because they take their own cars to leave the airport, even if there is severe congestion at parking garage exit. Therefore, we exclude private car drivers from the factors affecting average departure time within the hub.

Second, to simplify the model, we assume that the total volume of departure passengers during a period is constant, even though the flow fluctuates in reality. In addition, we assume that the capacities of transfer routes, platforms (or waiting rooms), and transit modes are all constant during a certain interval.

Third, elastic passengers who choose one transit mode can retain their original choice or switch to another mode. To describe the differences in the tendency of elastic passengers to choose different transit modes, we propose a transfer matrix of transit modes and assume the transfer matrix to be constant.

Finally, because of the narrow price gap between taxi and other transit modes in Shanghai, we suppose that the passenger distribution for each transit mode is only determined by the average departure time from the airport to transit stations. The average departure time is for all passengers, both rigid and elastic. In addition, the time of each departure chain is determined by (i) walking time, platform (or waiting room) waiting time, and queuing time at the fare gates of the subway station (if a passenger takes the subway) and (ii) the volume (or number) of passengers in the departure chain and the capacity of the chain.

The optimization model is derived using system optimization, which minimizes the average departure time for all passengers by balancing the proportion of elastic passengers in each transit mode. The model framework is presented in Figure 1.

**2.2. Model Assumptions.** The model is developed based on the following assumptions.

- (1) The total volume of departure passengers  $Q$  during period  $T$  is a constant function.
- (2) Passengers in each transit mode are divided into rigid and elastic passengers. The proportion of rigid passengers among all passengers using mode  $i$ ,  $\alpha_i$ , is considered to be constant.
- (3) Elastic passengers who choose one transit mode can retain their original choice or switch to another mode. The transfer ratio  $\gamma_{i,j}$  ( $j \neq i$ ) for mode  $i$  is considered to be constant. Among the total passengers who

transfer from mode  $i$  to other modes,  $\gamma_{i,j}$  is the proportion of passengers changing to mode  $j$ .

- (4) Passengers who drive private cars are all considered as rigid passengers and their impacts on departure time are neglected.

**2.3. Model Formulation.** The model aims to minimize the average passenger departure time under the capacities of the departure chain, including transfer routes, platforms (or waiting room), and transit modes (subway, bus, taxi, and car). Thus, the model is formulated as follows:

Minimize

$$T = \sum_i \eta_i T_i, \quad i = 1, 2, 3, \quad (1)$$

subject to

$$\begin{aligned} Q_i &\leq C_i \\ \sum_{i=1}^4 \eta_i &= 1, \end{aligned} \quad (2)$$

where

$T$  = the average departure time for all departing passengers;

$\eta_i$  = the percentage of passengers using transit mode  $i$  among all passengers;

$T_i$  = the average departure time of passengers using transit mode  $i$ , and  $T_i = T_{wk,i} + T_{q,i} + T_{wt,i}$ , where  $T_{wk,i}$ ,  $T_{q,i}$ , and  $T_{wt,i}$  are the average walking time, queuing time, and waiting time, respectively;

$Q_i$  = the total volume of passengers using transit mode  $i$ ;

$C_i$  = the capacity of transit mode  $i$ , including the departure routes, platforms (or waiting room), and transit modes;

$i$  = the transit modes and 1–4 are subway, bus, taxi, and private car, respectively.

In the model, (1) is the objective function; formula (2) is the constraint conditions. Detailed expressions for the objective function and the constraint conditions are discussed in the following subsections.

### 2.3.1. Objective Function

**(1) Average Departure Time for Each Transit Mode.** The departure time is the time that passengers spend in the entire departure chain, specifically, from the moment when passengers leave the luggage area to the moment they board their transit mode of choice. Therefore, the average departure time covers the average walking time, average queuing time at the fare gates of subway station (if a passenger takes the subway), and average platform (or waiting room) waiting time.

**Average Walking Time.** The average walking time is derived from the pedestrian walking speed, which is highly dependent

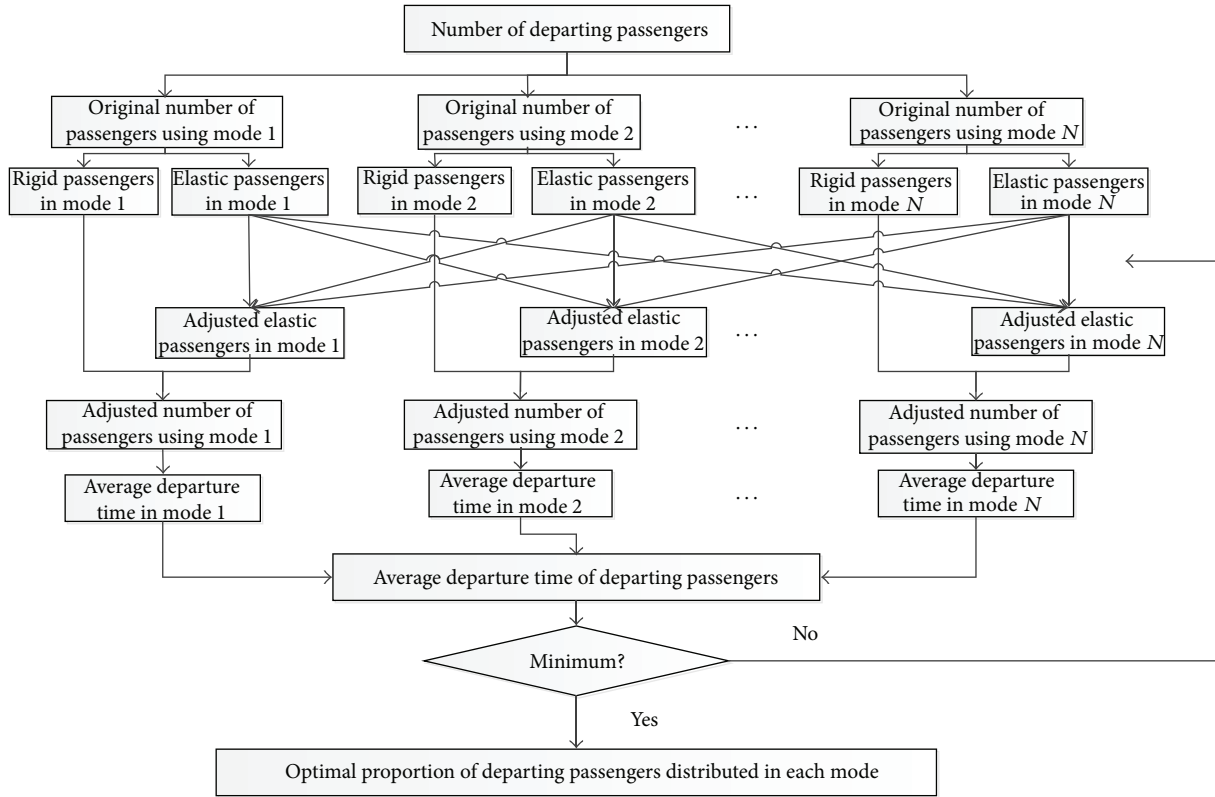


FIGURE 1: Framework of the distribution optimization model for passenger departure.

on the characteristics of the walking population and the walking environment [18–22]. To explain the pedestrian flow parameters, researchers have investigated speed density [21, 23–30], flow density [21, 31–36], and speed flow [21, 30, 32–39], as summarized in the *Highway Capacity Manual* [19].

Passenger volume is the most important independent parameter in the objective function, so we identify the relationship between passenger volume and walking time via regression analysis. This means that the model is formulated in a black-box manner, which hides other important parameters and converts them to constant coefficients. However, the model can directly yield final results and reflects actual walking by passengers under given conditions. Through field observations and data collection in Shanghai Hongqiao International Airport, we obtained a walking time-flow relationship, equivalent to the Bureau of Public Roads function [38, 39]:

$$T_{wk,i} = \frac{L_i}{S_f} + 4.2 \times \left( \frac{v_i}{c_i} \right)^{2.1}, \quad (3)$$

where

$T_{wk,i}$  = the average walking time for passengers selecting transit mode  $i$  (s);

$L_i$  = the distance from the luggage area to the platform (or waiting room) for transit mode  $i$  (m);

$S_f$  = the passenger free flow speed (1.32 m/s according to field observation);

$v_i$  = the average flow rate (ped/m/min);

$c_i$  = the capacity of the departure route (ped/m/min).

Equation (3) implies that when there are few pedestrians on a departure route, there is space available to choose a higher walking speed. As flow increases, the walking speed declines because of closer interactions among pedestrians.

*Average Queuing Time.* When passengers leave the airport via subway, average queuing time involves waiting in front of and walking through the fare gates. Queue time derived from the differences between the passenger arrival rate and the LOS of the fare gate. We assume that the queuing system is an M/M/S system [40], which is characterized by the following: (i) the passenger arrival rate follows a Poisson distribution; (ii) the service duration of fare gates follows an exponential distribution; (iii) the number of fare gates in service is  $S$ ; and (iv) space in the ticket hall is considered to be infinite. In addition, we include the service time of fare gates in the queuing time. Therefore, the average queuing time is computed using

$$T_{q,i} = \frac{1}{\mu} + \frac{(S\rho)^S}{(S\mu) S! (1-\rho)^2} P_0, \quad (4)$$

where  $\rho = \lambda/S\mu$ ,  $P_0 = (\sum_{i=0}^{S-1} ((S\rho)^i / i!) + (S\rho)^S / S!(1-\rho))^{-1}$ ;

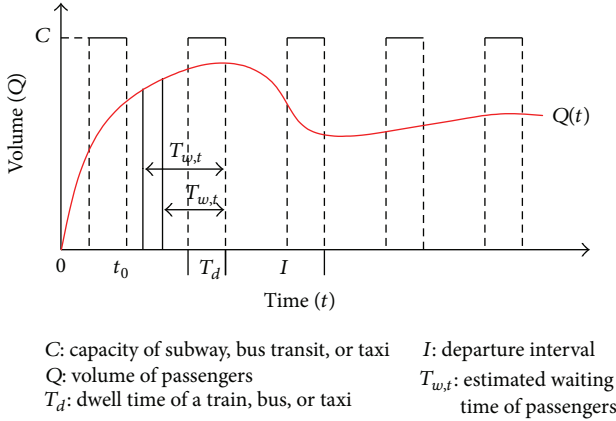


FIGURE 2: Analysis of the estimated passenger waiting time.

$T_{q,i}$  = the average queuing time for passengers selecting transit mode  $i$  (s);

$\mu$  = the average service rate of fare gates (ped/s);

$\lambda$  = the average arrival rate of passengers (ped/s), which can be estimated as  $Q/3600$ .

**Average Waiting Time.** Average waiting time arises because of the difference between the capacity of a transit mode and the volume of passengers arriving in the waiting area. Specifically, a queue forms when passengers arrive in the waiting area and no train (bus or taxi) is present. In addition, when the volume of arriving passengers exceeds the capacity of a train (bus or taxi), a second-term queue forms and remaining passengers have to wait until the next vehicle arrives. The capacity also differs between the terminal and stops because of the load rate of vehicles.

We assume that the subway station, bus station, and taxi stop in the airport are all terminal stations. In addition, we assume that, over a long period, such as one hour, second-term queues can be ignored. Therefore, based on the model described in Figure 2, the average waiting time is computed using

$$T_{wt,i} = \frac{\sum_{n=0}^m \int_{t_0+nI}^{t_0+(n+1)I} Q_i(t) (t_0 + (n+1)I - t) dt}{\sum_{n=0}^m \int_{t_0+nI}^{t_0+(n+1)I} Q_i(t) dt}, \quad (5)$$

where

$T_{wt,i}$  = the average waiting time for passengers selecting transit mode  $i$  (s);

$Q_i(t)$  = the volume fluctuation function for passengers selecting transit mode  $i$  (ped/s);

$I$  = the departure interval for vehicles (s).

To simplify the computational process, we assume that fluctuation function for passenger volume is uniform. Under these conditions, the average waiting time is computed using

$$T_{wt,i} = 0.5I. \quad (6)$$

However, the low capacity of cars means that the second- or even higher-term queues occur more frequently for taxi. Therefore, neither (5) nor (6) is sufficient. We recommend using an M/M/S queue model to compute the average waiting time for taxis platform, which is similar to (4).

**(2) Percentage of Passengers in Each Transit Mode.** Given the original percentage of passengers in transit mode  $i$  as  $\beta_i$  ( $i = 1, 2, 3, 4$ ), we obtain the volumes of rigid and elastic passengers in mode as  $\alpha_i \beta_i \times Q$  and  $(1 - \alpha_i) \beta_i \times Q$ .

In addition, we define the total volume of passengers transferring from mode  $i$  to others as  $Q_{t,i}$ , so (i)  $0 \leq Q_{t,i} \leq (1 - \alpha_i) \beta_i \times Q$  and (ii)  $Q_{t,4} = 0$  (private car drivers are all considered as rigid passengers).

To reflect differences in the inclination of elastic passengers to choose transit modes, we suppose that passengers whose first choice is mode  $i$  changing to mode  $j$  ( $j \neq i$ ) are in different proportions  $\gamma_{j,i}$  ( $j \neq i$ ), according to  $\sum_{j \neq i} \gamma_{j,i} = 1$  and  $\gamma_{4,j} = \gamma_{i,4} = 0$ . Therefore, the adjusted volume of passengers selecting mode  $i$  is computed using

$$Q_i = \beta_i \times Q - Q_{t,i} + \sum_{j \neq i} \gamma_{j,i} \times Q_{t,j}, \quad (7)$$

where

$\beta_i$  = the original percentage of passengers in mode  $i$ ;

$Q_{t,i}$  = the total volume of passengers transferring from mode  $i$  to other modes (ped/min);

$\gamma_{j,i}$  = the transfer proportion of passengers transferring from  $j$  to mode  $i$ .

Other variables are as previously defined. In addition, we describe the total passenger volume for each transit mode in matrix form, as

$$\begin{bmatrix} Q_1 \\ Q_2 \\ Q_3 \\ Q_4 \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} \times Q + \begin{bmatrix} -1 & \gamma_{2,1} & \gamma_{3,1} \\ \gamma_{1,2} & -1 & \gamma_{3,2} \\ \gamma_{1,3} & \gamma_{2,3} & -1 \end{bmatrix} \begin{bmatrix} Q_{t,1} \\ Q_{t,2} \\ Q_{t,3} \end{bmatrix}. \quad (8)$$

As discussed above, the volume of passenger in each mode will have a great impact on the average departure time. As a result, owing to the uncertainty of the transfer volume  $Q_{t,i}$ , the hub between airport and transit stations has great potential to appropriately organize passenger departures to improve the average departure time.

The percentage of passengers taking transit mode  $i$  among total passengers is computed using

$$\eta_i = \frac{Q_i}{\sum_{i=1}^4 Q_i}. \quad (9)$$

**2.3.2. Constraint Condition.** Constraint conditions are derived from the capacity of the transfer routes, platforms (or waiting rooms), and transit modes (subway, bus, and taxi). The constraint condition for the departure route is given by

$$Q_i \leq C_{r,i}, \quad (10)$$

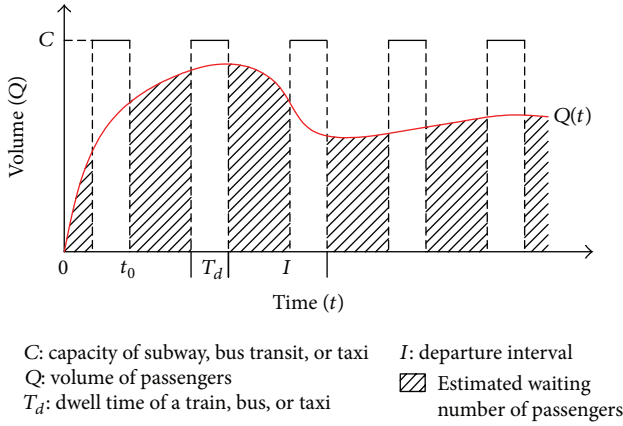


FIGURE 3: Analysis of the estimated number of waiting passengers.

where  $C_{r,i}$  is the capacity of departure route (ped/m/min). The constraint condition for the platform or waiting room is

$$N_{w,i} \leq C_{p,i}, \quad C_{p,i} = \frac{A_{\text{platform}}}{A_{\text{ped}}}, \quad (11)$$

where

$N_{w,i}$  = the number of passengers waiting on the platform (in the waiting room);

$C_{p,i}$  = the capacity of the platform or waiting room (ped);

$A_{\text{platform}}$  = the platform or waiting room area ( $\text{m}^2$ );

$A_{\text{ped}}$  = average area taken up by a single pedestrian,  $0.197 \text{ m}^2/\text{ped}$ .

The number of waiting passengers is derived from the model described in Figure 3. We assume that, during a long period, such as an hour, the second-term queue can be ignored. Therefore, based on the model described in Figure 3, the number of waiting passengers is computed using

$$N_{w,i} = \int_{t_0+nI}^{t_0+(n+1)I-T_d} Q_i(t) dt, \quad (12)$$

where  $T_d$  = the vehicle dwell time.

Other variables are as previously defined. To simplify the computation, we assume that fluctuation of the passenger volume is uniform, so the number of waiting passengers is computed using

$$N_{w,i} = Q_i(I - T_d). \quad (13)$$

The constraint condition for the transit mode is

$$Q_i \leq C_{t,i}, \quad (14)$$

where  $C_{t,i}$  = the capacity of transit mode  $i$  (ped/h).

For the subway,  $C_{t,1} = 60 \sum_{i=1}^N (P_{si} J_{si} \alpha_{si} / I_{si})$ , where  $N$  = the number of metro lines;  $J_{si}$  = the number of carriages in a train;  $P_{si}$  = the carriage capacity (ped);  $\alpha_{si}$  = the load rate (%); and  $I_{si}$  = the minimum departure interval for the line (min).

For bus transit,  $C_{t,2} = 60 \sum_{i=1}^N (P_{bi} \alpha_{bi} / I_{bi})$ , where  $N$  = the number of bus transit routes;  $P_{bi}$  = the bus capacity (ped);  $\alpha_{bi}$  = the load rate (%);  $I_{bi}$  = the minimum departure interval for the route (min).

For taxi transit,  $C_{t,3} = 60(P_t \alpha_t / I_t)$ , where  $P_t$  = the capacity of a taxi (ped);  $\alpha_t$  = the load rate (%);  $I_t$  = the minimum departure interval for taxis (min).

From the discussion above, the other constraint conditions are given by

$$Q_{t,i} \leq (1 - \alpha_i) \beta_i \times Q, \quad \sum_{j=i} \gamma_{i,j} = 1. \quad (15)$$

## 2.4. Model Solution

**2.4.1. Survey in Shanghai Hongqiao International Airport.** We conducted a case study of Shanghai Hongqiao International Airport, China, to provide a model solution. The result was expected to guide more efficient operation of the airport.

We selected a peak hour (19:00-20:00 h) in July 2013, when the total passenger volume was  $Q \approx 6000$  ped/h. As state preference survey revealed, the current percentage of passengers in each mode is  $\vec{\beta} = [47, 18, 25]\%$  and the proportion of rigid passengers to total passengers using each mode is  $\vec{\alpha} = [52, 43, 50]\%$ , for subway, bus, and taxi modes, respectively. In addition, the proportion of passengers transferring is  $\gamma_{1,2} = 0.04$  from subway to bus,  $\gamma_{1,3} = 0.96$  from subway to taxi,  $\gamma_{2,1} = 0.72$  from bus to subway,  $\gamma_{2,3} = 0.28$  from bus to taxi,  $\gamma_{3,1} = 0.91$  from taxi to subway, and  $\gamma_{3,2} = 0.09$  from taxi to bus.

According to the geographic information for Hongqiao Airport, apart from the route to the parking garage, the distance from the luggage area to the platform (or waiting room) of each is  $\vec{L} = [170, 230, 130]$  (m) for subway, bus, and taxi transit, respectively; the average width of the route is  $\vec{L} = [10, 10, 10]$  (m).

The metro station in Hongqiao Airport is the terminal for metro lines 2 and 10. There are 13 fare gates in the ticket hall with half in service and a capacity of 2.3 s/ped per gate. The platform area for each line is  $1200 \text{ m}^2$ . Line 2 operates on a 3.5-minute departure interval, with eight carriages per train and a maximum of 310 passengers per carriage. Line 10 operates on a 5-minute departure interval, with six carriages per train and a maximum of 310 passengers per carriage.

The bus transit station has a waiting room of  $1500 \text{ m}^2$ . There are 13 transit routes operating on a 30-minute departure interval and each bus holds a maximum of 50 passengers. The taxi stop has a platform of  $500 \text{ m}^2$ , at which nearly 10 taxis can arrive simultaneously, with an average 20-second departure interval and an average 2 passengers per taxi.

**2.4.2. Model Solution for Hongqiao Airport.** We choose Genetic Algorithm (GA) to solve this distribution optimization problem, because it has excellent capability to solve problems with complex objective functions and large solution search space.

The search space was calculated according to the combination of transferred elastic passenger proportions in

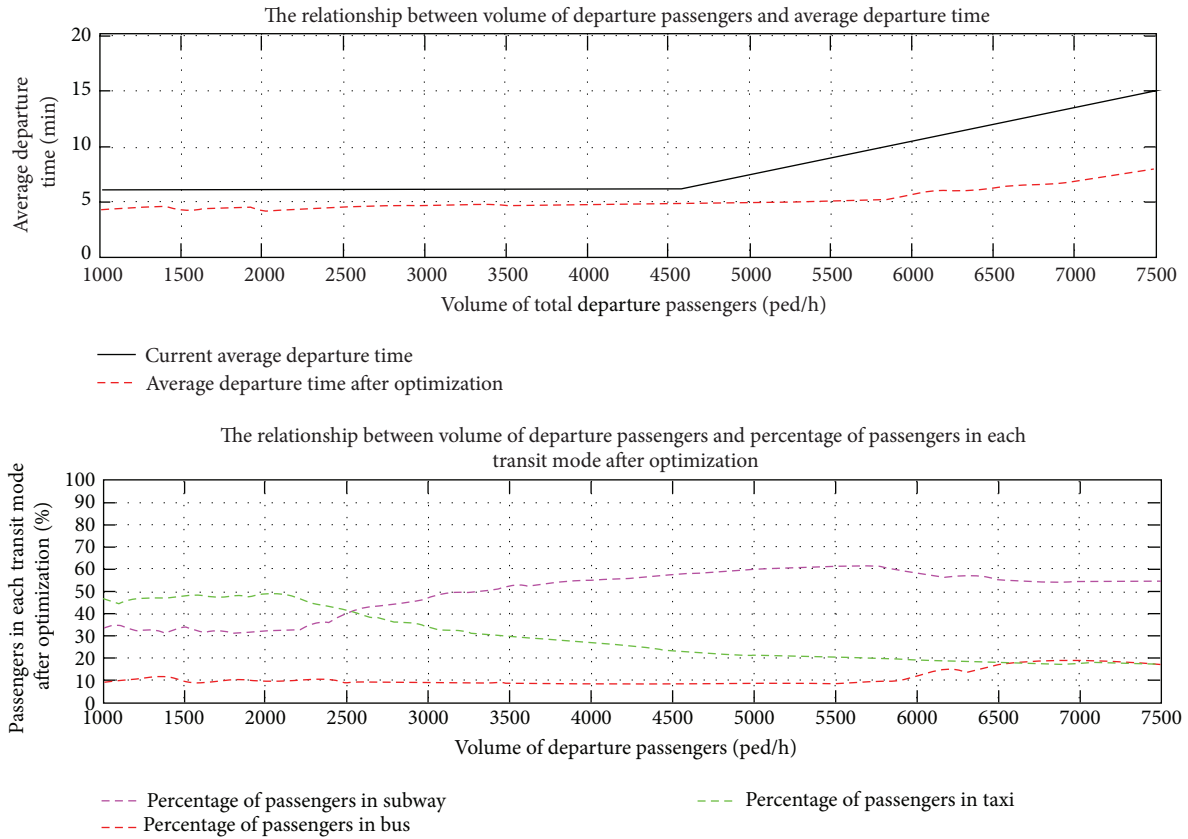


FIGURE 4: Relationship between passenger volume and the average departure time and the percentage of passengers in each transit mode after optimization.

each transit mode. Also, we select percentage unit as 0.1%. Therefore, the total probable solutions in the searching = (number of transferred elastic subway passenger proportion)  $\times$  (number of transferred elastic bus passenger proportion)  $\times$  (number of transferred elastic taxi passenger proportion) =  $(48 \times 10) \times (57 \times 10) \times (50 \times 10) = 136,800,000$ .

Each proportion combination is considered as an “individual” in the GA. The basic variables of the combination are encoded into a chromosome that represents the individual. The whole group of individuals is considered as a “population.” For high computation speed is not demanded in our research, we found that 100 generations are sufficient for this distribution optimization. The GA selects 80 out of 100 chromosome and then conducts operators of pairwise replacement, single point crossover and mutation. The “winner” of each “tournament,” the individual with lower departure time, is selected for the crossover and mutation proceeding. Since the tournament selection is pairwise, the crossover probability is 50%. The crossover and mutation operators are applied to generate the population of the next generation from the individuals selected earlier in the “tournaments.”

Based on the above defined parameters, GA optimization procedure result would be the proportion combination proposed by the individual with the minimum departure time in the final generation population.

Under the conditions given for Hongqiao Airport, the current average departure time within the hub is 10.4 minutes, with 4.7 minutes for the subway, 17.9 minutes for bus, and 19.9 minutes for taxi. After optimization, the minimum average departure time is 5.6 minutes, with 4.7 minutes for the subway, 17.9 minutes for bus, and 3.5 minutes for taxi. The percentage of passengers is  $\vec{\beta}_0 = [58.6, 12.0, 19.4]\%$  in subway, bus, and taxi transit modes, respectively.

**2.5. Result Analysis.** According to the computational results, the average departure time within the hub is improved by 46% by transferring passengers whose first choice is taxi or bus to subway. The reasons for these transfers are as follows: (i) the taxi capacity of Hongqiao Airport is low which causes an exceptionally long queue at peak hour; (ii) there is a long departure interval for bus transit; and (iii) the subway capacity is high and can bear high passenger volume. In addition, hub managers can partly balance the distribution of passengers in each mode, owing to the presence of rigid passengers.

We also performed simulations to reveal how the optimized average departure time and the percentage of passengers in each transit mode fluctuate as the total passenger volume changes. The results are shown in Figures 4 and 5.

The results show that, as the total passenger volume increases, the current average departure time increases only

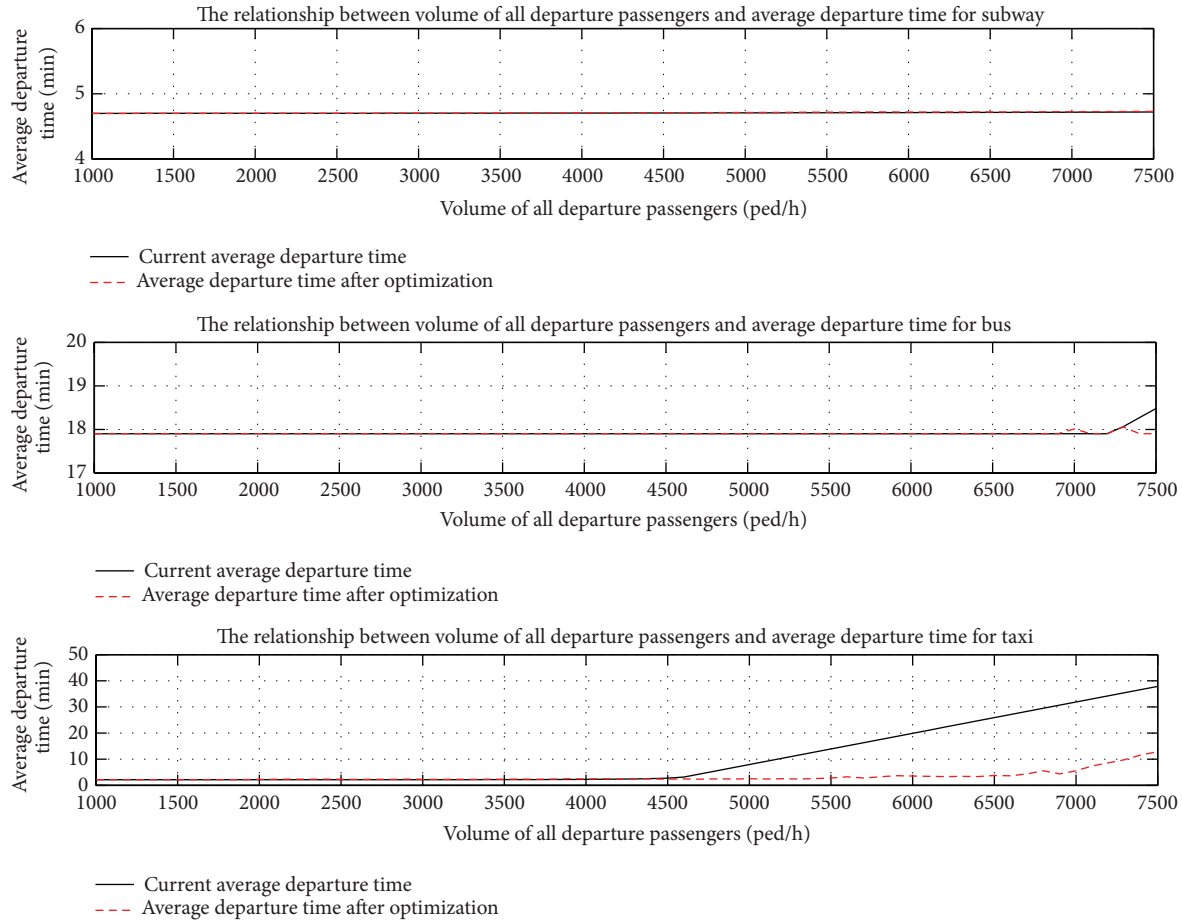


FIGURE 5: Relationship between passenger volume and the average departure time for each transit mode.

slightly, by several seconds. However, when the volume exceeds 4500 ped/h, the average departure time strongly rises and the optimization model improves the departure time more significantly. Under these conditions, additional queues occur at the platform of taxi stop and the average departure delay of taxi passengers increases. When the volume exceeds 7000 ped/h, the average departure time for bus riders increases, because the second-term waiting occurs. However, with the total passenger volume increasing, the optimized average departure time increases slightly, owing to the distribution balance of the optimization model.

In addition, after optimization, the elastic passengers whose first choice is taxi or bus are transferred to subway, and therefore the waiting time of taxi passengers markedly decreases. However, when the total departure volume (subway plus bus plus taxi) is not high, the average departure times in subway and bus transit hardly change. That is because both before and after optimization the second-term waiting does not occur in the subway platform and bus waiting room. Under this circumstance, the departure time is mainly determined by the subway and bus departure interval that is fixed. The improvement can only be derived from shortening subway and bus departure interval, which hub managers are not privileged to change.

Furthermore, as the total passenger volume increases, the percentage of passengers in subway grows while that in taxi decreases. In particular, when the volume exceeds 6000 ped/h, the percentage of passengers in bus starts to increase and the bus transit begins to help the subway bear the passenger flows transferring from the taxi.

### 3. Conclusions and Recommendations

To help hub managers alleviate congestion in transit stations and reduce the delays in passenger departure from the airport, we developed a distribution optimization model for passenger departure that minimizes the average passenger departure time for all transit modes and is solved by Genetic Algorithm.

To describe the differences in passenger transit choices and emphasize the impact of departure time within the hub, we introduced the concept of rigid and elastic passengers. Rigid passengers are not inclined to change their choice of transit mode for departure from the airport, regardless of waiting and walking time in the hub. Apart from individual preferences, their rigidity is determined by travel cost, travel time, and accessibility outside the air terminal. In contrast, elastic passengers tend to change their choice, after



comparing departure times among various transit modes, and their choice is primarily affected by the departure time within the hub. We also assumed that the percentage of rigid passengers does not change, regardless of fluctuations in passenger volume.

In addition, to reflect variation in the inclination of elastic passengers to choose different transit modes, we supposed that passengers change to other modes in different proportions. Using this assumption, we applied a transfer matrix to describe the choice characteristics of elastic passengers. We also assumed that the transfer matrix is constant although the passenger volume fluctuates.

A case study of Shanghai Hongqiao International Airport, China, revealed the following. (i) Although hub managers and operators cannot change the operating plans of airports or transit stations, our model simulation results show that they can partly balance the distribution of departure passengers in each transit mode and improve the average departure time. (ii) As the total passenger volume increases, the current average departure time increases only slightly, by several seconds. However, when the volume exceeds a critical level, the average departure time strongly rises and the optimization model improves the departure time more significantly. (iii) After optimization, the elastic passengers whose first choice is taxi are transferred to subway, and therefore the waiting time of taxi passengers markedly decreases. (iv) As the total passenger volume increases, the percentage of passengers in subway grows while that in taxi decreases. In particular, when the volume exceeds a critical level, the percentage of passengers in bus starts to increase and the bus transit begins to help the subway bear the passenger flows transferring from the taxi.

Future research can address a number of issues. For example, instead of assuming that both the elastic percentage and transfer matrix are constant, a more accurate model could be developed if a mathematical relationship between the elastic percentage, transfer matrix, and total passenger volume was obtained. In addition, estimation of the departure time including walking, queuing, and waiting times could be improved by a more accurate description of the motion characteristics of passenger flows.

## Disclaimer

The authors take sole responsibility for all views and opinions expressed in this paper.

## Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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