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A hybrid system for facility layout by integrating simulation and ant colony optimization

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Abstract: In this paper, we integrated simulation and ant colony optimization for solving the facility layout problems in public service building. The optimization goal was to minimize the pedestrians' walking time between facilities in the building. By means of VISSIM, a microscopic simulation engine, the proposed system could simulate and calculate the change in the total walking time of the pedestrians as a result of locating the facility layout. The near-optimal layout can be derived by iterations and the pheromone update in the ant colony optimization. Locating the facilities in a public service building requires a lot of time, cost and human labor. Therefore, it is impossible to "try multiple layout portfolios" onsite. This paper applied and calibrated the simulation engine VISSIM to fit the real-life processes of pedestrian behaviors and facility operations in the space. This approach allows us to easily predict the operation situation of each layout portfolio at a very low cost. We further selected an airport terminal to evaluate the feasibility of the system. The results indicated that the proposed system could save pedestrians' walking time and improve the operation and service efficiency.

Keywords: Layout, Ant Colony Optimization, Simulation

1 Introduction

Facility layout is always one of the important issues for the manufacturing and service industries. As there are various ways to place facilities in a built environment, it is difficult to find an optimum solution of facility layout using general mathematic methods [1,2]. So far, a number of computer-aided approaches have been proposed. These approaches generally make use of the fast computing capability of computers to find the near-optimal solution for facility layout [3,4].

Ant colony optimization (ACO) is an application of warm intelligence initially introduced by Dorigo et al. [5]. It searches for the path with the highest density of pheromone left by ants through multiple iterations. This path is the near-optimal solution.

This paper applies ACO for selection of facility location and uses a simulation platform to estimate the objective value of each layout solution by ant's walking. ACO and the simulation platform are integrated as a hybrid system. In this system, the ants' path selection the evaluation of layout solutions are automatically and repetitively compared and analyzed, so facility layout planning can become a convenient, effective and automated process.

2 Framework of System

Prior research has demonstrated many successful models integrating simulation mechanisms and optimization algorithms [6]. In this paper, we propose a system for facility layout as shown in figure 1. One of the links between the two modules is that data and parameters required for the simulation must be prepared and delivered to the simulation platform during processing of ACO. The other link is that the simulation results need to be converted into the objective function value of ACO such that whether a solution satisfies the convergence conditions of ACO can be determined. Through the above links and iterative operations, the system can find the near-optimal solution of facility layout.

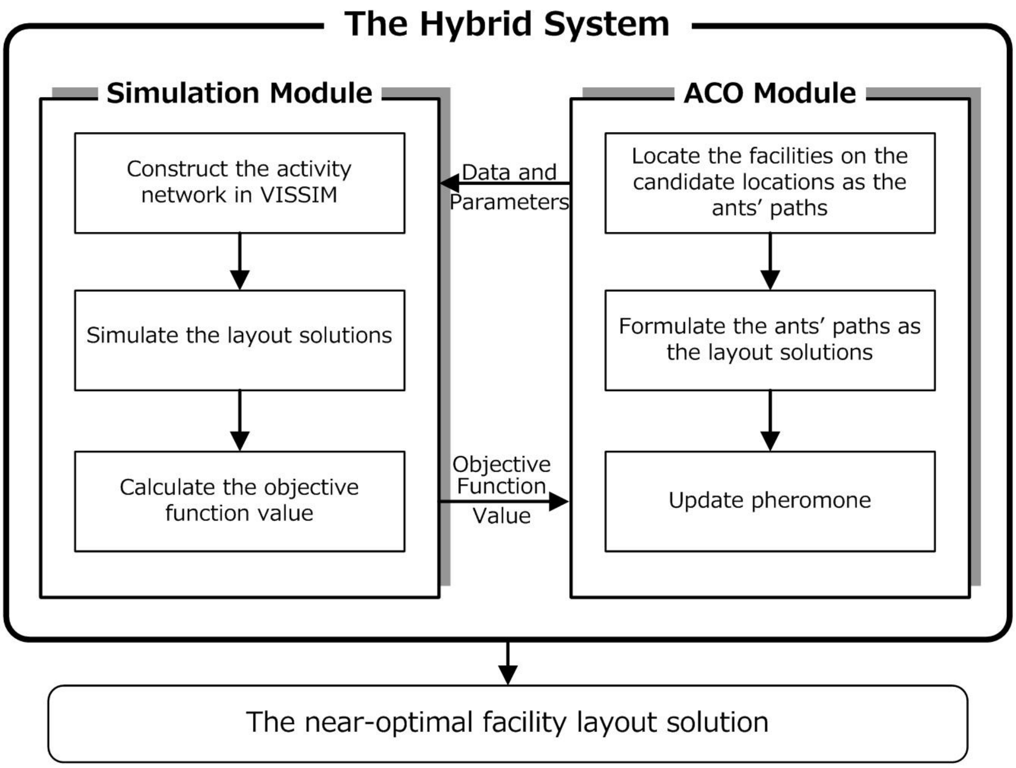

Figure 1: The Framework of the Proposed System

3 Simulation Module

3.1 Applied VISSIM Engine

Simulation mechanisms have been extensively applied to estimate the resources and tracks in dynamic environment [7,8,9]. For the facility layout problem, we also attempt to use simulation mechanisms to explore the interactions among objects in the floor, such as people, obstacles and facilities, that may be caused by each layout solution.

The applications of microscopic simulation engines to human behaviors are numerous, and VISSIM is one of them. VISSIM can estimate the walking time of pedestrians in built environments [10]. In VISSIM, the area combination data of activities' locations can be rewritten in a file, and the simulation can be controlled through the interface. Therefore, we use VISSIM as a simulation engine in the proposed system.

The walking behaviors of human were simulated on the basis of the Social Force Model [11,12]. The basic idea here is to model the elementary impetus for motion with forces analogously to Newtonian mechanics. From the social, psychological, and physical forces a total force results, which then sums up to the entirely physical parameter acceleration. The forces which influence a people's motion are caused by his/her intention to reach his/her destination as well as by other people and obstacles [10]. These forces are not directly exerted by the people's personal environment, but they are a measure for the internal motivations of the individuals to perform certain actions (movements). Computer simulations of crowds of interacting people show that the social force model is capable of very realistically describing the self-organization of several observed collective effects of human behavior [11,12].

3.2. Objective Function

For most facility layout problems, the goal of planning the facility layout is to improve the efficiency of facilities and spatial convenience for their users. In other words, minimizing the total pedestrian walking time (minimum *TPT*) to improve the efficiency of facilities and the built environment is the common goal of facility layout problems. The objective function can be represented as (3.1):

$$TPT = \sum_{t=1}^{n} PT_t \quad (3.1)$$

In the above equation, the total duration of the simulation is n hours, and PT_t denotes the pedestrian walking time of all users in the built environment on the t^{th} hour. The *TPT* and each PT_t are expressed in man-hr.

4 ACO Module

The Ant Colony Optimization (ACO) algorithm is part of the swarm intelligence theory. Communication between ants relies on a chemical substance called a pheromone. To search for food, ants follow pheromone paths made by other ants, and at the same time they themselves deposit pheromones along the path they take. More ants will habitually take the path on which more pheromones are deposited. The path taken by the majority of the ants will certainly have more pheromones deposited. Consequently, the effect of this positive feedback will lead ants to take the path with more pheromones deposited [13].

4.1 Selection Probability of Layout

For each facility in a built environment, there are multiple candidate locations into which it can be settled. In the ACO module, selections of location are expressed by ants' selections of paths. In the selection of a path (i.e., one location from candidate locations) to walk (i.e., settle a facility), an ant will refer to the amount of pheromone left on candidate paths. After the ant has selected a location for each facility (the number of candidate locations chosen equals to the number of facilities), the sequence of selected locations becomes a solution for facility layout.

ACO runs iteration after iteration. In each iteration, a set of solutions will be produced. These solutions are constituted by the ants' paths. When ant k has already assigned candidate location i and is moving to candidate location j, the selection probability used in ACO is as per (4.1) [14]:

$$p^k_{ij} = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \cdot \eta_j^{\beta}}{\sum_{l \in allowed_k} \tau_{il}^{\alpha} \cdot \eta_l^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases} \quad (4.1)$$

where $allowed_k$ is the list of candidate locations not yet selected; τ_{ij} is the pheromone trail between candidate location i and candidate location j; η_j, which is the heuristic value representing the desirability of selecting candidate location j, is the inverse of walking time by only locating this facility to candidate location j; α and β are the parameters that determine the relative influence of the pheromone trail and the heuristic value.

4.2 Pheromone Update

The selection probably of facility layout (p^k_{ij}) varies depending on the movement of ants in each iteration. This is because ants' movements will cause an update of pheromone (τ_{ij}) on the paths. When an ant moves from a selected location to a candidate location for the next facility, it will release pheromone on the path as a reference for other ants. This behavior is called pheromone update. There are two kinds of pheromone updates. One is the local update that all ants will perform, and the other is the global update that only the best ant will perform [14].

(1) The local update is performed each time by all ants after selecting a candidate location. The main goal of local update is to diversify the search performed by subsequent ants during each iteration [14]. Each ant applies it only when the last facility location's assignment is finished:

$$\tau_{ij} = (1-\rho) \cdot \tau_{ij} + \rho \cdot \tau_0 \quad (4.2)$$

where $\rho \in (0,1)$ is the pheromone decay coefficient, and τ_0 is the initial value of the pheromone.

(2) The global update is applied at the end of each iteration by only one ant (either the one that found the best solution in the iteration or the best-so-far) [14]. The update formula is slightly different from local update, and as follows:

$$\tau_{ij} \rightarrow \begin{cases} (1-\rho) \cdot \tau_{ij} + \rho \cdot \Delta\tau & \text{if candidate location } j \text{ belongs to the solution of the best ant} \\ \tau_{ij} & \text{otherwise} \end{cases} \quad (4.3)$$

where $\Delta\tau$ is the inverse of the minimum *TPT* of the iteration.

Through the above pheromone update methods, ants will deposit different amounts of pheromones according to the quality of the layout (the level of

TPT). With the increase in the number of iterations, lower-*TPT* solutions will gain more pheromones, and the near-optimal facility layout can be gradually discovered.

5 Flowchart of the System

The goal of the proposed hybrid system is to obtain a layout solution for the facilities in a building. Figure 2 illustrates the flowchart of the system.

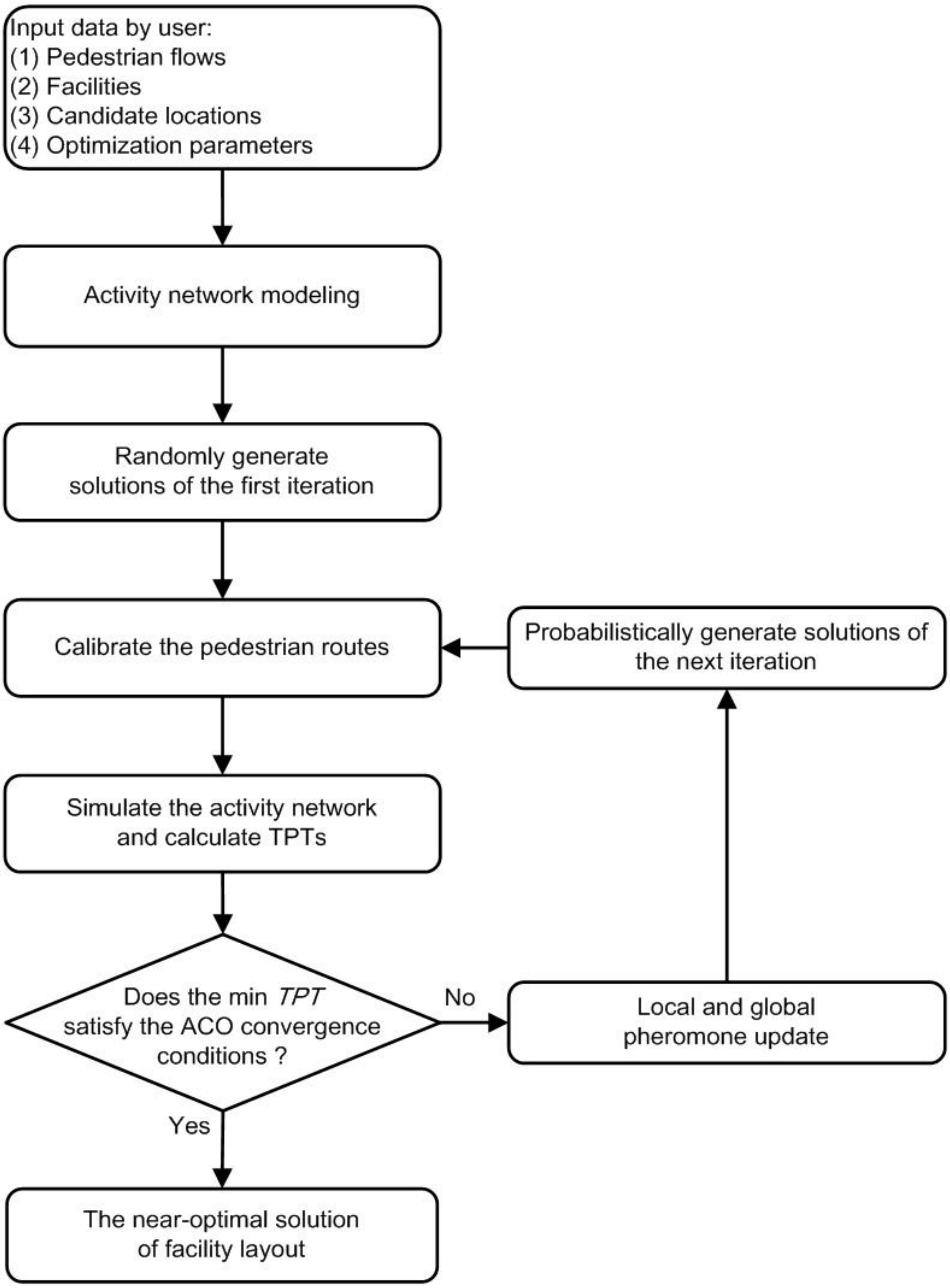

Figure 2: The Flowchart of the Proposed System

(1) The user inputs the data of the pedestrian flows, the movable facilities, the candidate locations, and the optimization parameters:
   - Pedestrian flows: The user inputs the pedestrian flows into VISSIM in the form of an activity network. This network covers the routes of all the pedestrian flows from one facility to another. It is based on two assumptions: (1) the activities of the pedestrians in the public building (e.g. using the washroom) remain constant; (2) the directions for the routes in the public building are clearly indicated, and the pedestrians know where they are going.
   - Movable facilities: A public building consists of numerous facilities, but not all of them can or need to be located. For instance, the stairs are the facilities for the exit and entry activities of pedestrians. As they are based on the overall structure of the building, they are immovable during the layout operation. The user can only input facilities that are allowed to be located. These facilities should be classified such that they can be assigned to the appropriate candidate locations. For example, the facilities can be classified by size into large, medium, and small facilities.
   - Candidate locations: The user has to select candidate locations for each type of the facilities. The user can propose several candidate locations for each facility.
   - Optimization parameters: The planner inputs the ACO parameters, including the number of ants and iterations, α and β, which determine the relative influence of the pheromone trail and the heuristic value, the pheromone decay coefficient ρ, and the initial pheromone value τ_0.

(2) Based on the data inputted by the user, the activity network can be modeled for simulation in VISSIM. Then the facility layout solutions of the first iteration of ACO are generated to be simulated. The ant will select an area for each facility according to its type and sequence as defined by the user. Because no pheromone update has been carried out yet, the probability of being selected by ants in the first iteration is the same for all paths between the candidate facilities.

(3) In a public building, there may be several facilities that can support the same kind of activities, such as the washroom. For each layout solution that is generated, the proposed pedestrian routes must be calibrated to ensure that pedestrians walk to the first available facility nearest to them for whatever activities they desire to do. For instance, among the washrooms in the floor, pedestrians will walk to the one that is available and nearest to them.

(4) The facility layout solutions will be simulated one by one in VISSIM. Each simulation in VISSIM spans the operation of the public building for an entire day, both continuously and microscopically. After the simulation of the layouts, the *TPT*s can be calculated by (3.1).

(5) Whether or not the best facility layout solution, which is quantified as the total pedestrian walking time (minimum *TPT*), of the iteration approaches a stable convergence will be verified. If a stable convergence does not appear, the iteration will continue.

(6) Prior to the next iteration, the local pheromone update and the global pheromone update will provide a new probability for the ants. When the ants finish their laying out of candidate locations, a new facility layout solution will be generated. The new facility layout solution is then used to repeat the simulation steps.

(7) The repetition does not terminate until the min *TPT* exhibits a stable and satisfactory convergence, and a near-optimal facility layout solution of the facilities for pedestrian flows is obtained.

The system operation yields a near-optimal facility layout solution that can help the designer enhance the operating efficiency of the public building. To implement the system operation, we compiled a program to automate both simulation and ant colony optimization. The program diverts human routing according to the facility layout solutions derived from the ant colony optimization.

6 Case Study: An Airport Terminal

In order to evaluate the performance of the proposed system, we used the facility layout of the first terminal of Taipei SongShan Airport as a case. The first terminal has been in service for several years. Due to the inauguration of the second terminal and changes of the passenger volume and trip types, the facility layout of the first terminal can no longer meet today's needs.

The administrator of the airport has constantly received complaints from passengers about the inconvenience of many service facilities in this terminal due to improper assignment of their locations. Hence, the administrator has decided to come up with a new layout solution for the service facilities to advance the service efficiency. The hybrid system proposed by this paper will provide decision support and a solution that can effectively shorten passengers' walking time.

6.1 Facility and Candidate Locations

A total of 32 service facilities needed to be relocated. For these service facilities, the administrator selected 41 candidate locations, as shown in figure 3. Based on the size and characteristics of each service facility, we broke down the service facilities and candidate locations into four categories, as shown in table 1. Each facility can be assigned only one of the candidate locations in the same category.

6.2 Walking Route Modeling

Because passengers' walking routes must be modeled in the system, we used video cameras to capture the walking behavior of passengers. It should be noted that passengers are not always on the move. They may sometimes stay at a location to wait for certain services or for other purposes. Therefore, we reviewed the video recordings to eliminate the waiting behavior before modeling the walking behavior of passengers. The modeling results were then input into VISSIM to form a walk activity network consisting of starting points, pass points and terminal points as shown in figure 4.

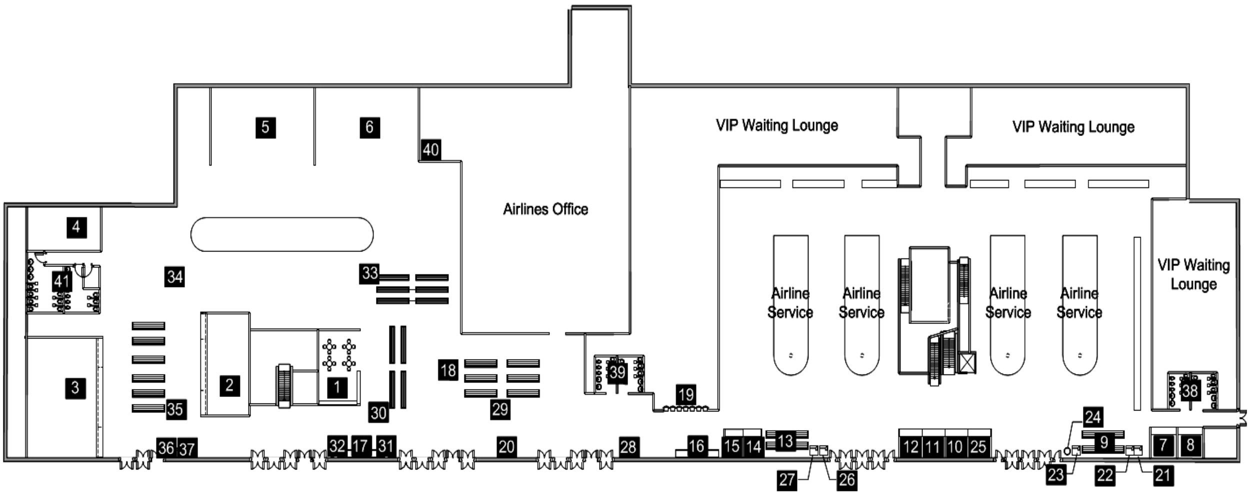

Figure 3: The Candidate Locations for the Facilities

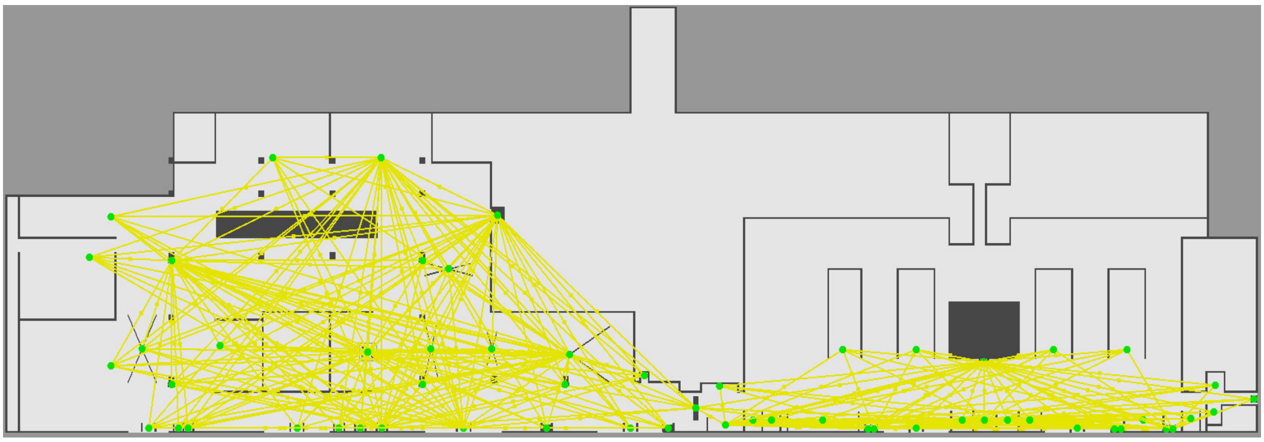

Figure 4: The Walking Route Network of a Layout Solution

Table 1: The Facilities and Candidate Locations Classified by Size

Service facilities	*Candidate locations (Location No.)*
Restaurant	Select the 3 locations from the 6 candidate locations (No. 1 - 6)
Post Office	
Bank	
Animal & Plant Quarantine	Select the 13 locations from the 14 candidate locations (No. 7 - 20)
Immigration Service	
Waiting Area A	
Waiting Area B	
Bank Service	
Duty Collection Counter	
Information Center	
Insurance Service	
Nursery Room	
Baggage Service A	
Baggage Service B	
Tourist Service	
Pay Phone	
Newspaper Machine A	Select the 14 locations from the 17 candidate areas (No. 21 - 37)
Newspaper Machine B	
Newspaper Machine C	
Newspaper Machine D	
Beverage Machine A	
Beverage Machine B	
Beverage Machine C	
Internet Service	
ATM	
Chargers for Mobile Phone	
Small Change Service	
Trash Can A	
Trash Can B	
Trash Can C	
Restroom A	Select the 3 locations from the 4 candidate areas (No. 38-41)
Restroom B	
Restroom C	

Another item that should be predefined in VISSIM is walking speed. If not hindered by other pedestrians, a pedestrian will walk at his desired speed with a small stochastic variation called oscillation [10]. Based on the VISSIM predefined parameters, the regular desired speed is set as two random distributions. One ranges from 3.5 to 5.8 km/hr for adult male and the other from 2.6 to 4.3 km/hr for adult female [10].

6.3 Solution and Analysis

The parameters for the ACO module had to be properly configured so that a near-optimal solution for facility layout could be obtained. In this case, the number of ants, corresponding to the number of solutions in each iteration, was 100. To avoid loss of good solutions, the best solution of each iteration was reserved for the next iteration. In other words, in the second iteration, only 99 teams were new searched solutions. Besides, many values in the simulation (such as the speed of pedestrians) were characterized by a certain statistic distribution. To avoid deviation, each simulation was run 30 times to get the mean *TPT*. The model was run a total of 1000 iterations. Figure 5 shows the near-optimal solution for the service facility layout of the first terminal. Figure 6 is the VISSIM 3D simulation of the layout solution.

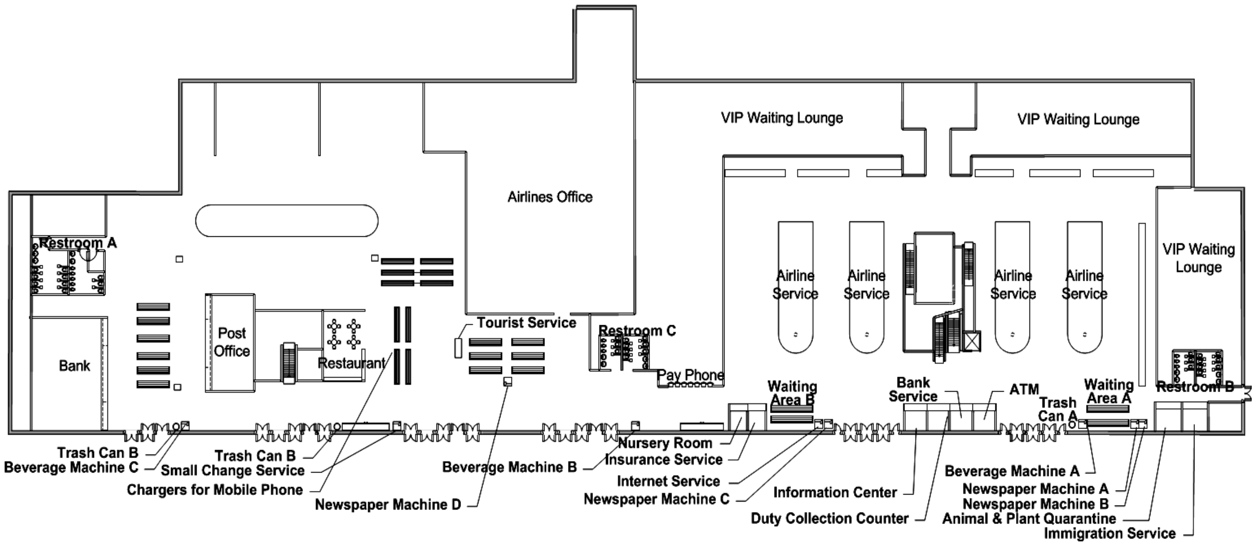

Figure 5: The Proposed Near-optimal Solution for the Airport Terminal Layout

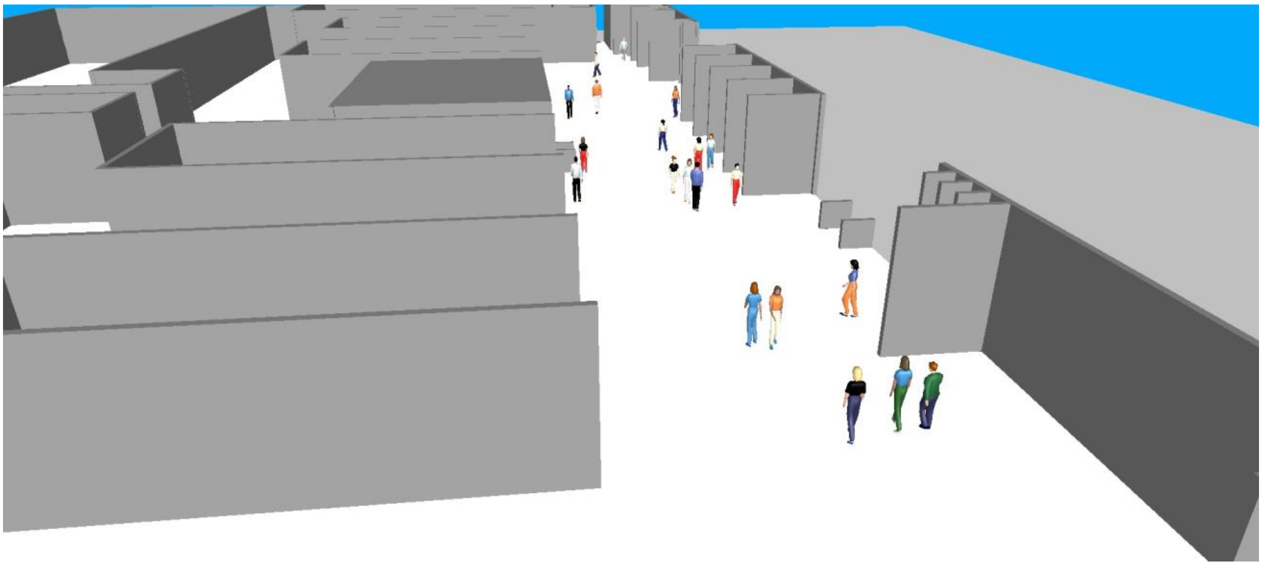

Figure 6: The VISSIM 3D Simulation of the Layout Solution

The ACO parameters, ρ, α and β, significantly impact upon the search for a global optimal solution and the convergence speed. Previous studies have shown that the proper parameter settings vary from one problem to another. To search for an optimal parameter setting for our problem, nine sets of parameters (α =1, β =1 or α =2, β =1 or α =1, β =2 with ρ =0.5; α =1, β =1 or α =2, β =1 or α =1, β =2 with ρ =0.7; α =1, β =1 or α

=2, β =1 or α =1, β =2 with ρ =0.9) were employed in the optimization process.

Table 2 presents the optimal results. No matter ρ =0.5, 0.7 or 0.9, the sets with α =2 and β =1 reached convergence faster than the other sets, but they also derived the worst solutions among those derived with the same ρ. Besides, no matter ρ =0.5, 0.7 or 0.9, the set with α =1 and β =2 derived good solutions but did not satisfy the stable convergence standard that the number of iterations in which minimum *TPT* is not updated within the range observed (1000 iterations) > 200. Generally speaking, the ratio of α to β affects the efficiency and quality of solutions, and ρ is of less significance. For the example problem, α =1, β =1 with ρ = 0.9 is a better parameter setting.

Table 2: The Optimal Results of the Three Sets of Parameters

Parameters Setting		*Iteration of minimum TPT*	*Number of iterations with no better solution in the observation range*	*Minimum TPT in the observation range (man-hr/day)*
ρ=0.5	α= 1, β= 1	316	319	1,688.17
	α= 2, β= 1	118 (Fastest)	615	1,767.81
	α= 1, β= 2	561	134 (<200)	1,701.92
ρ=0.7	α= 1, β= 1	367	365	1,732.56
	α= 2, β= 1	240	478	1,786.96
	α= 1, β= 2	631	126 (<200)	1,722.63
ρ=0.9	α= 1, β= 1	416	332	1,630.99 (Min)
	α= 2, β= 1	377	397	1,824.61 (Max)
	α= 1, β= 2	702 (Slowest)	86 (<200)	1,806.75

7 Conclusion

This paper proposed a hybrid system integrating VISSIM and an ACO module for solving the layout problems of built environments. VISSIM, a microscopic simulation engine, was used to simulate and calculate the total pedestrian walking time of each layout solution. The ACO module was used to find a near-optimal solution based on pheromone update through iterations.

To evaluate the performance of the system, the service facility layout of an airport terminal was used as a case. The results indicated that the proposed system could significantly advance the operation efficiency of the facility layout. Compared with other mathematic approaches, microscopic simulation may require a longer period of time to compute a solution, but it is closer to practical conditions and can produce more reliable estimations and predictions. Because the complex simulations and calculations are carried out by the system rather than by human, facility layout planning can be done in a substantially faster and easier manner.

ρ, α, and β are the parameters for the algorithm of ACO. Future researcher can use different values of these three parameters to further improve the performance of ACO for the proposed system.

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