5. COMPUTATIONAL RESULTS

In this chapter, we perform some experiments to observe the characteristics of PTSPTW model in this research. First we show the comparison between the proposed algorithm and the other algorithm proposed by Gendreau *et al.*[11] in Section 5.1. In Section 5.2, the simulation results of different parameter settings will be discussed, and the impacts of different proportions of immediate requests to all customers are discussed in Section 5.3. Finally, we will see the impacts of different widths of time windows and different requests probabilities in Section 5.4 and 5.5, respectively. According to the preliminary tests, we use the 1-shift and the 2-p-opt local search which p equals to 1, 2, 3, 4 and 5 as cores of the STM method and the improvement heuristic in Stage II. All algorithms are implemented in C++ and running on a Pentium IV machine with 480MB RAM.

5.1 Algorithms Comparisons

To our knowledge, no similar PTSPTW model with the ideas of double-horizon has been proposed. The proposed algorithm will be evaluated including the performance of solution quality and its computational time. Here, we choose GENIUS which was developed by Gendreau *et al.* [11] for comparison. GENIUS is an algorithm which can be used to solve many kinds of transportation routing problems such as TSP, VRP, TSPTW, etc. In the work of Gendreau *et al.* [11], a GENIUS for TSPTW was proposed and detailed computational results were listed. Remember that the objective function of proposed PTSPTW model is

$$\min_{k} \; Z(r_k) = E\left[\alpha \cdot q_k^S + (1-\alpha)\left((1-\beta)q_k^L - \beta h_k^L\right)\right]$$

In order to make the comparison, we considered only one time horizon which represents the whole planning horizon and let α be 1. All request probabilities of customers are set to 1. Therefore, the PTSPTW model is transformed into a TSPTW model. 95 instances from Dumas [8] are adopted for testing. These instances are divided into 19 sets by number of customers and average width of time windows. The results are shown in Table 5.1, where each problem set represents the average objective value of five instances. Table 5.1 indicates that the average objective values of our algorithm are worse than GENIUS by around 0.22% to 5%. However, we can plot the calculating times of both algorithms and observe the growth of times. From Fig. 5.1 we observe that as number of nodes and lengths of time windows increase, the calculating time of GENIUS almost increase exponentially. But the calculating time of our algorithm increase much more moderately. In PTSPTW problems, because every possible request combination must be considered and calculated, the complexity of problem increases sharply as number of regular customers increases. Therefore, our algorithm is suitable to solve such complicated problem.

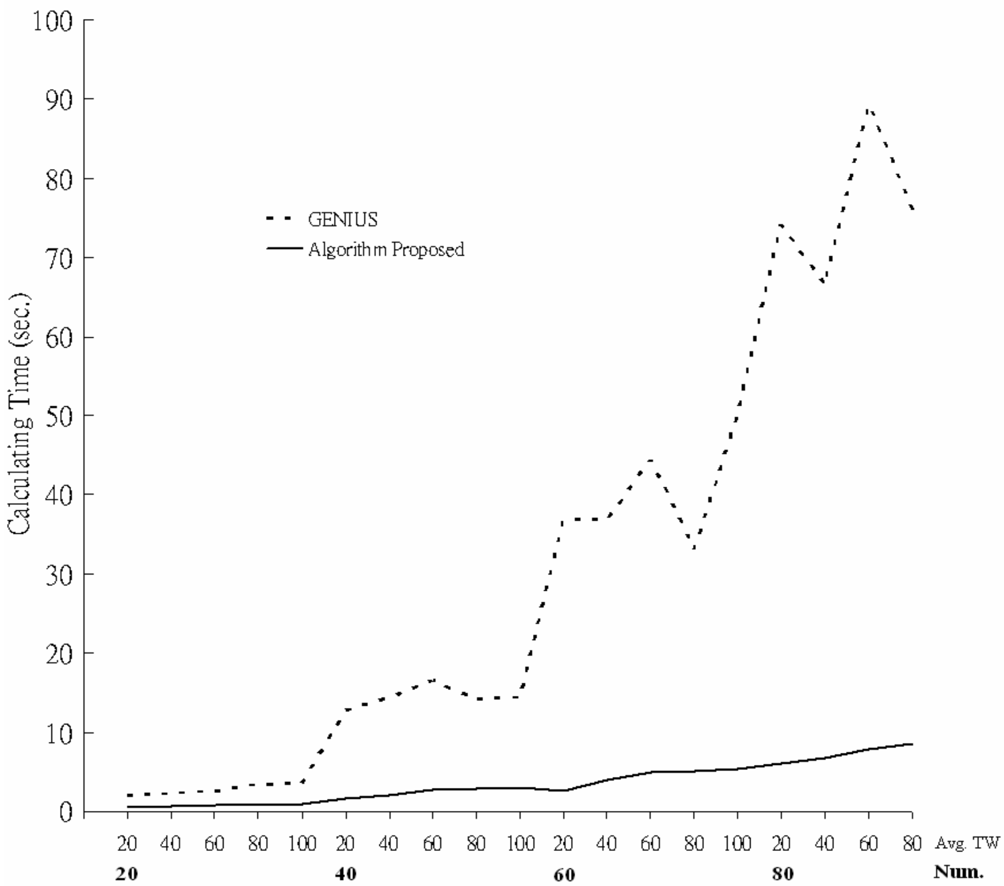
5.2 The Simulation Results of Different Parameter Settings

After the comparison on performances of algorithms, we will solve and discuss the problem described in Chapter 3. The customers can be divided into three categories: daily customers, regular customers and immediate customers. Information of daily and regular customers including their locations and time windows are known in advance. Daily customers request for service every day but regular ones do not. Whether a regular customer really requests for service is according to his request probability. Information of an immediate customer, including his location and time window is announced while the vehicle is *en* route. The proposed PTSPTW model is mainly constructing a predesigned (*a priori*) route for daily and regular customers. According to request situations of different days, the driver has to simply skip customers who do not really request for service. When the vehicle is *en* route,

Table 5.1 The Performance Comparison of GENIUS and the proposed algorithm

Computational Results

n	Time Window Width	Gendreau *et al.* [11] Average Objective Value	Gendreau *et al.* [11] Time (seconds)	Proposed Algorithm Average Objective Value	Proposed Algorithm Average Difference (%)	Proposed Algorithm Time
20	20	361.2	1.7	361.6	0.11	0.38
	40	316	2.1	322.0	1.90	0.44
	60	310.2	2.34	316.7	2.08	0.63
	80	314.2	3.15	319.6	1.71	0.62
	100	275.2	3.38	282.6	2.68	0.84
40	20	486.6	12.52	492.7	1.25	1.35
	40	461	14.16	483.4	4.87	1.92
	60	417	16.39	428.5	2.75	2.57
	80	399.8	13.95	413.6	3.46	2.65
	100	378.8	14.21	392.3	3.58	2.78
60	20	581.6	36.54	585.1	0.61	2.51
	40	590.2	36.79	602.1	2.02	3.91
	60	567	44.29	578.2	1.98	4.75
	80	517.2	32.93	533.4	3.13	4.91
	100	524	49.75	550.2	5.00	5.28
80	20	676.6	74.03	681.4	0.71	5.88
	40	630.4	66.32	650.3	3.16	6.53
	60	616.8	89.13	642.9	4.24	7.68
	80	601.4	75.75	616.5	2.51	8.45



Note: Avg. TW denotes average width of time windows. Num. denotes number of customers.

Fig. 5.1 The calculating time comparison of GENIUS and the proposed algorithm

however, the decision maker must still deal with immediate requests if it is possible. In the simulation, 20 immediate requests are randomly generated. We simulate the request situation of 500 days and try to insert the 20 immediate requests into each daily route. There are two rules for insertion:

1. Every immediate request has an announce time which represents the information disclosure time of this request. This request cannot be inserted into the part which is before the announce time of each daily route.
2. When an immediate request is known, try to insert it into the position which causes the least additional traveling time.

The average total traveling time and number of accepted immediate requests are calculated after all insertions in 500 cases. Instances from Dumas [8] are used for data of daily and regular customers. We use only the instance with 80 customers, 10 among these customers are designed as regular customers. Request probabilities are set randomly. All instances can be divided into three groups according to their average widths of time windows, 20, 40 and 60. There are five instances in each group. As the objective function proposed in Chapter 3, we consider 14 different settings by α and β, where α represents the weight of short-term horizon and β represents the weight of accumulated slack time in the long-term horizon. Since we only consider traveling time in the short-term horizon, higher α represents higher consideration of traveling time in *a priori* route construction. On the other hand, higher β can be viewed as higher consideration of slack time in the long term-horizon. Take two extreme cases $\alpha = 1$, $\beta = 0$ and $\alpha = 0$, $\beta = 1$ for example. By the first setting, there is only short-term horizon to be considered, which represents the whole planning horizon. The objective of this setting is to minimize the traveling time of the *a priori* route without any slack time consideration. Conversely, the long-term horizon and slack time are only considered by the second setting and the objective is to maximize the average slack time in the *a priori* route. The average numbers of accepted immediate requests and average total traveling times are shown in Table 5.2, where each data is the average value of five instances in each group. From Table 5.2, we can see the following phenomena:

1. By the first parameters setting ($\alpha = 1$, $\beta = 0$), not only the average accepted immediate request is the least but also the total traveling time is the largest.
2. In each average width of time windows and each α, the average number accepted immediate requests increases as β increases.
3. The average number of accepted immediate requests decreases as α increases.
4. There are no obvious differences between the total traveling times of different parameter settings except the first setting ($\alpha = 1$, $\beta = 0$).

Table 5.2 Simulation results by 14 different parameter settings

		Computational Results					
		TWW = 20		TWW = 40		TWW = 60	
β	α	# of Accepted Requests	Total Traveling Time	# of Accepted Requests	Total Traveling Time	# of Accepted Requests	Total Traveling Time
0	1	7.898	540.47	9.818	530.34	12.433	475.57
0.25	0.25	8.207	536.34	11.525	502.54	14.127	447.05
	0.5	8.150	536.75	11.487	507.15	13.937	446.32
	0.75	8.016	537.29	11.504	499.98	13.526	449.24
0.5	0.25	8.209	536.09	11.625	502.22	14.339	458.93
	0.5	8.152	535.98	11.520	508.54	14.127	452.08
	0.75	8.030	538.20	11.510	498.96	14.089	460.44
0.75	0.25	8.211	536.06	11.639	503.57	14.493	457.16
	0.5	8.198	535.62	11.561	504.12	14.378	454.07
	0.75	8.055	535.95	11.517	505.12	14.326	450.89
1	0	8.216	536.65	11.824	528.55	14.720	470.84
	0.25	8.212	536.23	11.716	512.50	14.571	468.27
	0.5	8.206	536.71	11.673	512.46	14.449	465.04
	0.75	8.183	536.54	11.553	510.38	14.341	473.82

Note: # of Accepted Requests denotes average number of accepted immediate requests of five instances in each data set, and Total Traveling Time denotes average total traveling time after immediate request insertion.

By the first phenomenon, we can clearly observe the differences on average numbers of accepted immediate customers between the *a priori* routes with and without slack time consideration. We also find an interesting point, however, the total traveling time of the setting α = 1, β = 0 contrarily cause larger average total traveling time after immediate customers insertion. We believe that is because if we only consider traveling time in *a priori* route construction, this *a priori* route does not have enough flexibility for immediate requests to be inserted into. Even though an immediate request can be inserted into, we hardly have cheaper choices than *a priori* routes with slack time consideration.

The second and third phenomena show that when the weight of slack time in the objective function is larger, the average number of accepted immediate requests should be larger, although it is not very apparent. It meets the assumption and goal of the proposed model. Finally, we also found that the average total traveling time does not always increase as the weight of slack time in the objective function increases.

5.3 The Impacts of Different Proportions of Immediate Requests to All Customers

The proportions of immediate customers to all customers are different in different local logistics problems. To discuss the impacts on total traveling time from numbers of immediate requests occurred when the vehicle is *en* route, we must first define the degree of dynamism (*dod*) as follows.

$$dod\,(\%) = \frac{\text{number of immediate customers}}{\text{total customers}} \times 100\%$$

Here we design an experiment. Given five instances with 100 nodes from Dumas [8]. 20 customers are deleted to retain lager inserting space for displaying the results remarkably. In other words, there are 80 customers in all five instances. 70 of these customers are daily and 10 are regular. The average width of time windows is 20. Four groups of immediate customers with 9, 20, 34 and 53 requests are generated corresponding to *dod* around 10%, 20%, 30% and 40%, respectively. An *a priori* route of daily and regular customers is constructed first and these four groups of immediate requests are tried to insert into the route respectively. For simplicity, we choose four representative parameters settings, (α, β) = (0, 1), (1, 0), (0.5, 0.5) and (0.5, 1), for experiments in this and following sections. After 500 days simulation, we obtain average total traveling times of the four different inputs as shown in Table 5.3 and Fig. 5.2.

Table 5.3 Average total traveling times under different degree of dynamisms

		Degree of Dynamism			
		10%	20%	30%	40%
B	*α*	Avg.	Avg.	Avg.	Avg.
0	1	518.025	568.04	608.752	643.375
1	0	546.298	579.89	604.483	634.634
0.5	0.5	529.067	574.68	598.673	632.748
1	0.5	535.182	575.44	600.533	635.555

Note: Avg. denotes average total traveling times.

From Fig. 5.2 we can clearly see that when *dod* is low, the *a priori* route without slack time consideration (α = 1, β = 0) performs better on average total traveling time than others. Average total traveling times of the routes with higher weight on traveling time (α), however, grow faster than those with higher weights on slack time (β). In the case with 40% *dod*, we observe that the average total traveling time of the route without slack time consideration is larger than others and there exists apparent difference. The most likely explanation of this phenomenon is that the *a priori* route with α = 1 and β = 0 only consider daily and regular customers but not future requests which occur real-time. The higher the consideration of slack time introduced into when the route is being constructed, the more flexibility for future immediate demands it retains. Therefore, when we have known that there will be lots of immediate requests based on past experience, the higher weight of slack time should be considered when we construct the *a priori* route.

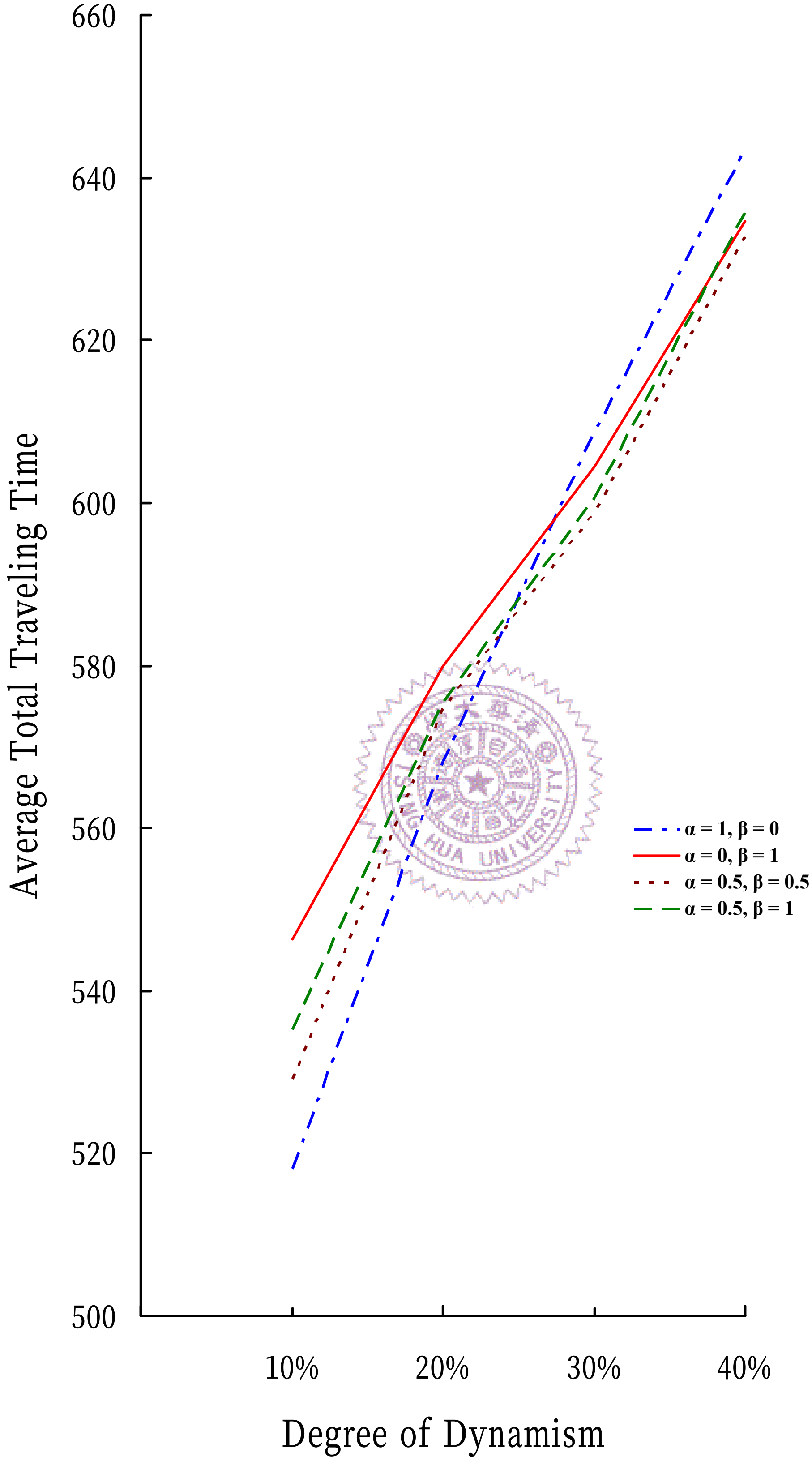


Fig. 5.2 Average total traveling time under different degree of dynamisms

5.4 The Impacts of Different Widths of Time Windows

To investigate the impact of time windows, we must design another experiments. Instances from Dumas [8] with 80 customers are also used here. To reduce the impact from different locations of customers, we only used the five instances which average width of time windows are 20, and generate other four groups of data by simply widen average width of time windows to 30, 40, 50 and 60. All request probabilities of regular customers are set as 0.5. Under four different parameter settings, the result of simulation is shown in Table 5.4.

We have shown that the least immediate requests can be inserted under the parameter combination $\alpha = 1$ and $\beta = 0$. Here we also find that the average number of accepted immediate request increases as the weight of slack time in the objective

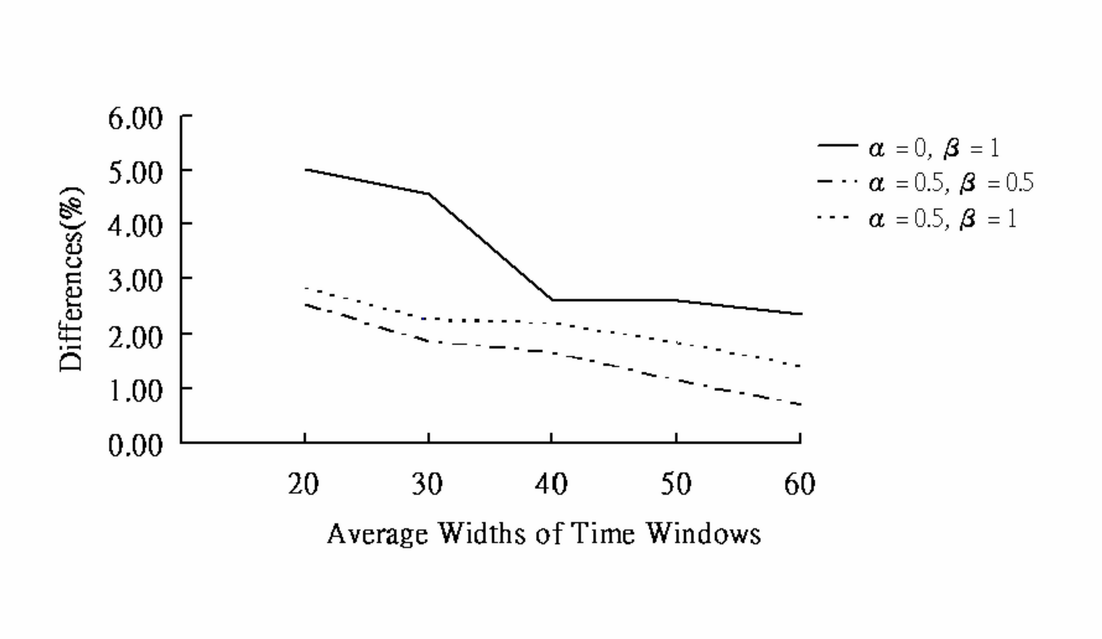
Table 5.4 Average number of accepted immediate requests under different average widths of time windows

		Average Widths of Time Windows									
		20		30		40		50		60	
β	α	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)
0	1	8.682	-	10.33	-	11.17	-	11.8	-	11.85	-
1	0	9.117	5.01	10.8	4.57	11.46	2.59	12.1	2.59	12.13	2.34
0.5	0.5	8.901	2.53	10.52	1.87	11.35	1.66	11.93	1.16	11.94	0.70
1	0.5	8.927	2.83	10.56	2.26	11.41	2.19	12.01	1.84	12.02	1.41

Note: Avg. denotes average numbers of accepted immediate requests and Dif.(%) denotes the differences in percentage between Avg. of the first parameter setting and other threes.

function increases. In addition, we also demonstrated that the differences on average numbers of accepted customers between the first parameter setting and other threes all decrease as the width of time windows increases, as shown in Fig 5.3. When widths of time windows becomes larger, the flexibility of the *a priori* route under $\alpha = 1$ and $\beta = 0$ should increases faster than the *a priori* routes under the other three parameter settings.

With regards to the total traveling times, as shown in Table 5.5 and Fig. 5.4, we can see the total traveling time decrease as the average width of time windows increase under all four parameter settings. That is an intuitive result. But there does not exit obvious trends of differences of the first parameter setting and the other threes while the average width of time windows increases.



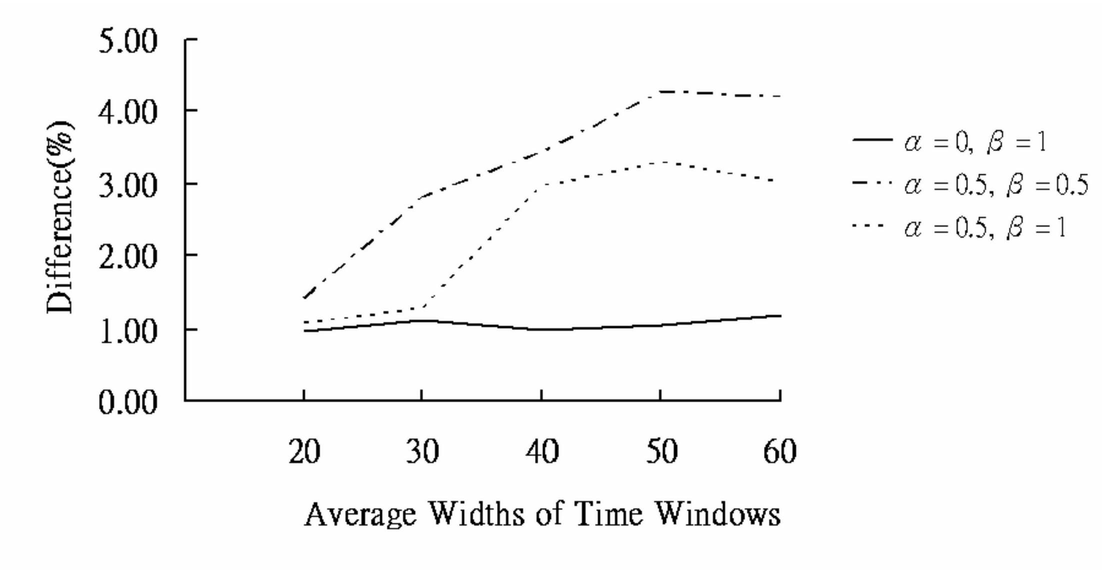
Note: Each broken-line represents the difference in percentage between average numbers of immediate accepted requests of the parameter setting and $\alpha = 1$, $\beta = 0$

Fig. 5.3 Differences between average numbers of accepted immediate requests under different average widths of time windows

Table 5.5 Average total traveling times under different average widths of time windows

		Average Widths of Time Windows									
		20		30		40		50		60	
β	α	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)
0	1	578.6	-	567.6	-	563.4	-	562.9	-	562.3	-
1	0	573	0.96	561.2	1.12	557.9	0.99	556.9	1.06	555.6	1.19
0.5	0.5	570.4	1.42	551.6	2.82	544	3.44	538.8	4.28	538.7	4.20
1	0.5	572.3	1.09	560.3	1.28	546.7	2.96	544.2	3.31	545.3	3.03

Note: Avg. denotes average total traveling times and Dif.(%) denotes the differences in percentage between Avg. of the first parameter setting and other threes.



Note: Each broken-line represents the difference in percentage between average total traveling times of the parameter setting and $\alpha = 1$, $\beta = 0$

Fig. 5.4 Differences between average total traveling times under different average widths of time windows

5.5 The Impacts of Different Request Probabilities

In this section, another experiment is done for discussing the impacts of different request probabilities. Consider five instances with 80 customers from Dumas [8] which average widths of time windows are 20. Ten of these customers are regular. We create five groups of instances by set probabilities of all regular customers as 1, 0.8, 0.6, 0.4 and 0.2, respectively. Under four different parameter settings, the result of 500 days simulation is shown in Table 5.6, where we can see as the probability of regular customers decreases, the average numbers of accepted immediate customers increase by all four parameter settings. That is because when the probability that regular customers really ask for service is small, the service route in each day is often only with daily customers and is very flexible for new incoming requests. We can also see the same phenomenon as section 5.4, the differences between the average numbers of accepted immediate requests of the first parameter setting and other threes decrease as the request probability of regular customers decreases, as Fig. 5.5. When $\alpha = 1$ and $\beta = 0$, total traveling time is considered but slack time is not. Because of

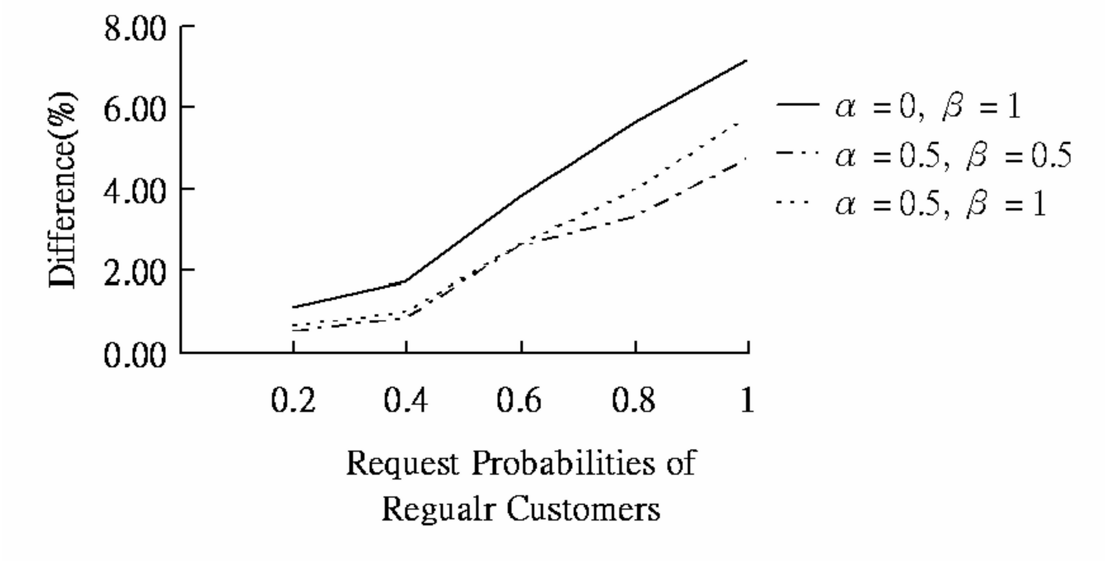
Table 5.6 Average number of accepted immediate requests under different request probabilities of regular customers

		Request Probability of Regular Customers									
		1		0.8		0.6		0.4		0.2	
β	α	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)
0	1	8.533	-	8.753	-	9.506	-	9.718	-	9.902	-
1	0	9.14	7.11	9.244	5.60	9.862	3.75	9.885	1.72	10.01	1.10
0.5	0.5	8.933	4.69	9.041	3.29	9.749	2.56	9.798	0.82	9.952	0.50
1	0.5	9.02	5.70	9.096	3.92	9.751	2.58	9.811	0.95	9.967	0.65

Note: Avg. denotes average numbers of accepted immediate requests and Dif.(%) denotes the differences in percentage between Avg. of the first parameter setting and other threes.

this concern, the flexibility of the *a priori* route under this parameter setting is always a little. However, when the probability of regular customers decreases, the flexibility of this *a priori* route will grow faster relatively to other *a priori* route under different parameter settings.

With regards to the total traveling times, as Table 5.7 and Fig. 5.6, it decreases as the probability of regular customers decreases under all four parameter settings. But we cannot find an obvious trend of the differences while the probability decreases.



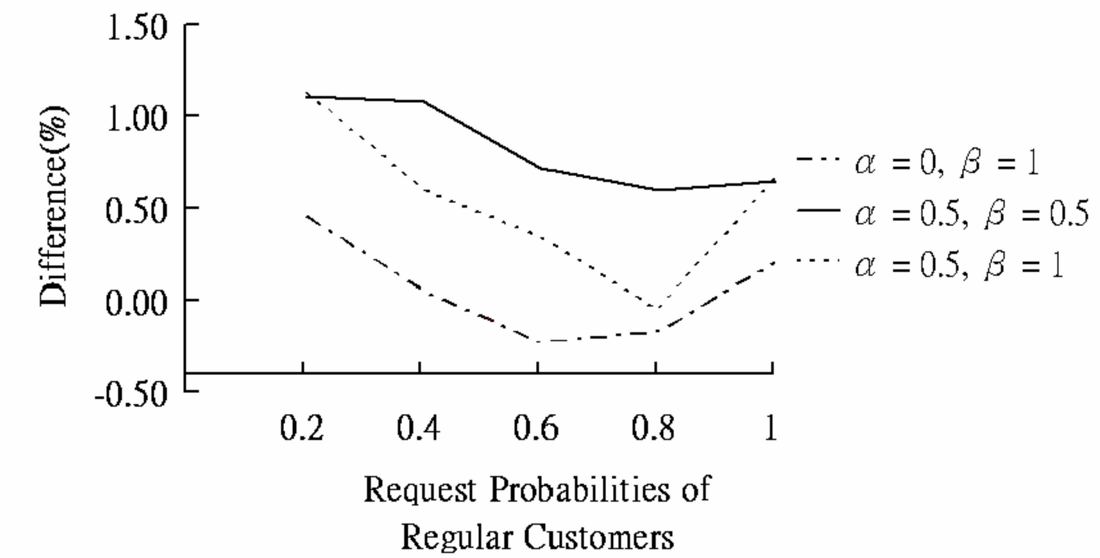
Note: Each broken-line represents the difference in percentage between average numbers of immediate accepted requests of the parameter setting and α = 1, β = 0

Fig. 5.5 Differences between average numbers of accepted immediate requests different request probability of regular customers

Table 5.7 Average total traveling times under different request probabilities of regular customers

		Request Probability of Regular Customers									
		1		0.8		0.6		0.4		0.2	
β	α	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)	Avg.	Dif.(%)
0	1	576.9	-	567	-	557.7	-	550	-	542.8	-
1	0	575.7	0.20	568	-0.17	559	-0.23	549.8	0.05	540.3	0.45
0.5	0.5	573.2	0.64	563.6	0.60	553.8	0.71	544	1.08	536.8	1.10
1	0.5	573.1	0.66	567.3	-0.05	555.9	0.34	546.7	0.60	536.6	1.13

Note: Avg. denotes average total traveling times and Dif.(%) denotes the differences in percentage between Avg. of the first parameter setting and other threes.



Note: Each broken-line represents the difference in percentage between average total traveling times of the parameter setting and α = 1, β = 0

Fig. 5.6 Differences between average total traveling times under different request probabilities of regular customers