Chapter 7: Numerical Analysis

7.1. Introduction

In the previous chapters, the Insertion Algorithm (IA) and Two-stage Heuristic (TSH) were shown to be effective and efficient in solving the manpower-scheduling problem as demonstrated through the use of real data from the company. Both heuristics also generated solutions quickly. In this study, IA is developed to solve the problem without considering workforce synchronisation; meanwhile TSH includes this constraint. Since TSH can actually be used to solve both versions of model, it will be interesting to know the best algorithm under different settings.

In this chapter, both heuristic solutions, the IA and the TSH, are evaluated further and compared with a range of data sets with different factors. (CPLEX is not included in this comparison analysis because of its limitation in solving the scheduling problem within a reasonable computing time.) All experiments were carried out on a Dell Pentium IV 1.8GHz computer.

7.2. Case study

The same set of real data described in previous chapters was used to compare the performance of proposed heuristic solutions. On average, there were 140 to 160 flights (230-280 split aircraft maintenance tasks) each day. The company assigned 75 to 79 maintenance teams to load all aircraft on any given day, as shown in Figure 7.1.

From Figure 7.1, both heuristic solutions outperform the manual solution developed by the company's expert planner. All test data can be executed in less than 3 seconds. The IA reduces the required manpower by 10.39% (40 teams in total) on average. On the other hand, two different assumptions are considered by the TSH. Heuristic B takes into account the synchronisation of loading teams, while heuristic A allows different teams to carry out the operation any time in a given time window. In total, heuristic A manages to reduce the manpower by as many as 75 teams (19.59%) over the 5 day period. Even though synchronisation of teams is applied, heuristic B performs better than the IA (3.2% or 11 teams) and the real roster (13.33% or 51 teams).

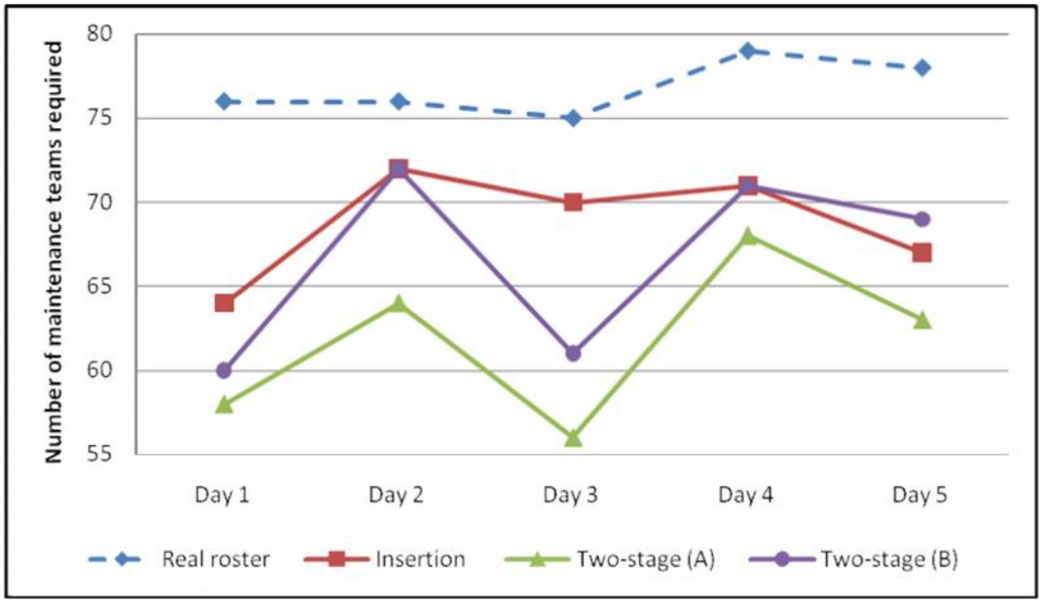

Figure 7.1: Comparison of number of teams required by real roster and heuristic methods

This comparative results shows that both heuristic solutions are able to solve the problem effectively and efficiently, even in instances with large problems.

In the meal break sensivity analysis, loading teams are not given one hour meal break. The teams not only perfrom an extra hour of work but also save the travelling time to and from the service centre for the break. Indirectly, manpower productivity can also be increased due to time saved, including the unaviodable idle time caused by its time window constraint.

The meal break sensivity results of both heuristic solutions are shown in Figure 7.2. On average, the differences are 6.69% (23 teams) for the IA, compared to over 8.41% (26 teams) and 8.7% (29 teams) for the TSH under different settings. The maximum difference is 13.24% (9 teams) on Day 4 by the TSH (A). This sensitivity analysis shows that both heuristic methods are capable of assigning and scheduling the aircraft efficiently, regardless of whether or not the meal break allocation is applied.

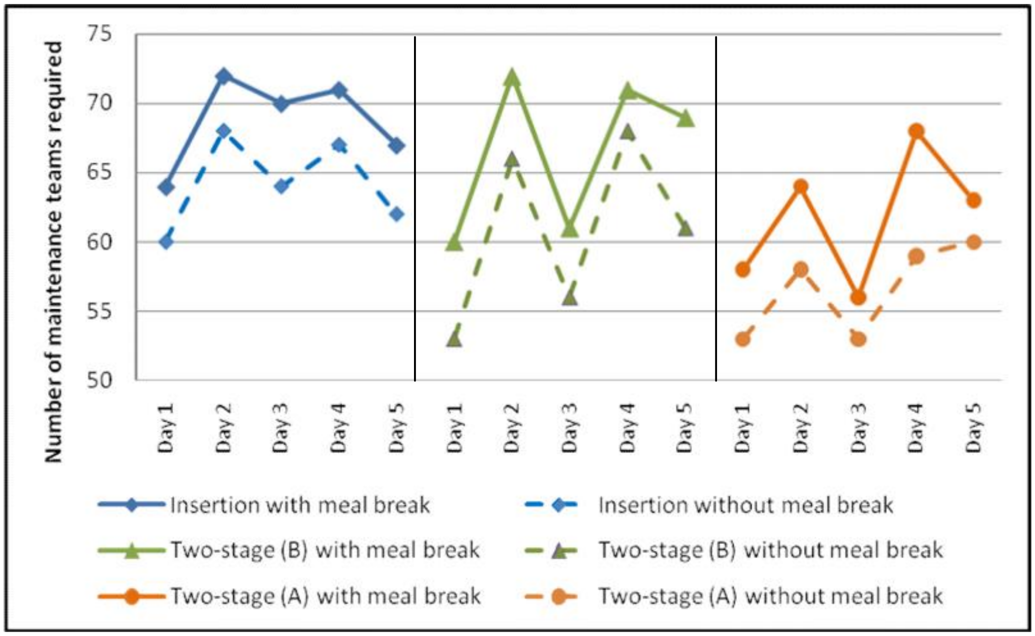

Figure 7.2: Meal break sensitivity analysis

In conclusion, both heuristic solutions perform significantly better than the existing manpower planning practice. Furthermore, they can generate a solution in a few seconds. The company could consider the possibility of real-time changes and update the work assignment to cope with contingency. The comparison results demonstrate that the TSH dominates the real roster as well as the IA, even when synchronisation of teams is applied. In addition, meal break sensitivity analysis tests were conducted to show the efficiency and effectiveness of both heuristic solutions. The results show that both heuristics yield efficient solutions for the problem and can accommodate difficult operational requirements.

7.3. Computational Experiments

In order to further evaluate the computational capabilities of the proposed heuristics, we developed a set of test problems. Comparison between the two heuristics under different conditions is done in order to identify the best heuristics for different scenario. Due to the fact that IA is developed for the case without workforce synchronisation, the constraint is not applied in all simulation settings.

7.3.1 Description of the Test Problems

We generated sixteen sets of problems, each consisting of ten test problems. These test problems were designed to highlight several demand factors that can affect the behaviour of routing and scheduling heuristics. These factors include demand distribution, demand size and the tightness of time windows.

- Demand distribution

Two types of demand distributions were generated for performance analysis: demand with peak demand (P) and demand without significant peak (N). These reflect the norm of peak and off-peak seasons in real life situation. The aircraft arrival and loading times are randomly generated. Arrival times fall within a daytime period, while loading times vary, in range 1 to 5 units of time, as in the case study.

- Tightness of time windows

In the case study, time windows are defined as aircraft arrival and departure times. Tightness of time window is defined as the ratio of the time window width to the processing time. Again, two types of time window tightness are included in the test problems: tight-width time windows (A) and a mixture of tight- and wide-width time windows (B). In test problem type A, the ratio of an aircraft's time window width to its processing time is set to be 1 to 3. Meanwhile, in test problem type B, the ratio is 1 to 10. We randomly generate a time window's ratio over a predefined interval. Given the aircraft's arrival time, we then generate departure time by adding the time window width to the arrival time.

- Demand size

Test problems that evaluate each demand distribution and time window are prepared in four different sizes: 100 aircraft, 250 aircraft, 500 aircraft and 750 aircraft. This is to test the robustness and efficiency of the proposed heuristic solutions.

7.3.2. Managerial Settings

Each test problem generated is tested with different managerial settings, such as meal-break duration, length of working-shift and trip travelling limit. The managerial settings are:

- Meal-break duration: one-hour meal break, thirty-minute meal break, fifteen-minute meal break or no meal break
- Length of working-shift: four-hour shift, six-hour shift or eight-hour shift.

- Trip-travelling limit: tight trip-travelling limit (loading, at most, three aircraft and two hours' travelling duration) or loose trip-travelling limit (loading, at most, four aircraft and three hours' travelling duration).

7.4. Computational Results

To analyse the performance of the IA and TSH, we programmed them in C# and performed computational tests on the problem classes described in section 3.1. Solution quality is measured in terms of the minimum number of servicing teams and the computational time required to produce this solution.

Table 7.1: Comparison of heuristic solutions to test problems

Shift	**4 hours**				**6 hours**						**8 hours**							
Meal break	**Nil**		**15 mins**		**Nil**		**15 mins**		**30 mins**		**Nil**		**15 mins**		**30 mins**		**1 hour**	
Trip constraint	**T**	**L**	**T**	**L**	**T**	**L**	**T**	**L**	**T**	**L**	**T**	**L**	**T**	**L**	**T**	**L**	**T**	**L**
AP_100	I	-	I	2	-	I	-	I	-	I	-	2	I	-	I	-	I	I
AN_100	I	-	I	2	I	I	I	I	I	I	-	2	I	-	I	-	I	I
BP_100	I	-	I	2	-	I	I	I	I	I	-	-	I	I	I	I	I	I
BN_100	I	-	I	2	-	I	I	I	I	I	-	2	I	-	I	I	I	I
AP_250	I	I	I	2	I	I	I	I	I	I	-	-	I	I	I	I	I	I
AN_250	I	-	I	2	-	I	-	I	-	I	-	2	I	-	I	-	I	-
BP_250	I	I	I	2	2	I	I	I	I	I	-	2	I	I	I	I	I	I
BN_250	I	-	I	2	2	I	-	I	2	I	2	2	I	I	I	I	I	I
AP_500	I	2	I	2	I	I	I	I	I	I	-	-	I	I	I	I	I	I
AN_500	I	2	I	2	I	I	I	I	2	I	-	-	I	I	I	I	I	I
BP_500	I	I	I	2	2	I	I	I	-	I	2	2	I	I	I	I	I	I
BN_500	I	I	I	2	2	I	-	I	2	I	2	2	I	I	I	I	I	-
AP_750	I	I	I	I	I	-	I	I	I	I	-	-	I	I	I	I	I	I
AN_750	I	I	I	I	-	I	I	I	I	I	-	-	I	I	I	I	I	I
BP_750	I	I	I	2	2	I	I	I	-	I	2	2	I	I	I	I	I	I
BN_750	I	I	I	2	2	I	2	I	2	I	2	2	I	I	I	I	I	-

* I – Insertion Algorithm; 2 – Two-stage Scheduling heuristic

The overall performance of the TSH compared to the IA is illustrated in Table 1. The first row of the table shows the working-shift hours, and the second row is the meal-break duration, which must be allocated within given time windows. Each unit of meal break in the row represents fifteen minutes. Tight (T) and loose (L) travelling constraints are also carried out in the test problems, shown in the third row of the table. The left-hand side column shows the sixteen problem sets: for example, BP_100 is the 100 aircraft test problem with peak-demand distribution characteristics and a mixture of tight and wide time windows.

In Table 1, the column labelled "I" reports when the IA dominates the TSH in this particular set of ten test problems; meanwhile, "2" represents when the TSH dominates the IA. The column labelled neither "I" nor "2" shows when both heuristics have similar performance, or when neither has significant domination performance over the other.

Table 7.1 demonstrates that the IA performs better than the TSH in most of the test problems. This result is expected because the IA is a more complicated algorithm, compared to the TSH, for evaluating and choosing the best aircraft to be inserted.

In terms of computational time, Table 7.2 shows the average computing time for generating a solution using each heuristic. The computational time is rather static in all test problems for each sample size, regardless of the scenario settings. The result demonstrates that both heuristics are efficient when it comes to handling large problem instances. However, the TSH requires slightly less computational effort than the IA, which is explained by the more complicated algorithm procedure of the IA.

Table 7.2: Computational time for heuristics

Problem Size	**Insertion Algorithm**	**Two-stage heuristic**
100 aircrafts	250 - 850 milliseconds	250 - 850 milliseconds
250 aircrafts	2.5 - 3.5 seconds	1 - 2.5 seconds
500 aircrafts	18 - 25 seconds	9 - 15 seconds
750 aircrafts	1 - 1.75 minutes	0.9 - 1.1 minutes

7.4.1. Analysis on Demand Size

The number of test problem for which each heuristic obtains the best solution is plotted in Figures 7.3 and 7.4. In the case of demand size, the IA dominates the TSH in 14 out of 18 settings as shown in Figures 7.3 and 7.4. Overall, there is no general trend related to demand size for both heuristics.

For the tight trip travelling settings, described in Figure 3, IA performs better than TSH in 7 out of the 9 settings. IA produces better solution than TSH in all four-hour working shift test problem. Similarly, IA performs better in both six-hour and eight-hour working shift when meal break allocation is applied.

For TSH, there is no identified trend across different demand sizes, with respect to the number of superior solutions provided. However, IA shows a slight drop in number of test problems when the demand size increases.

Similarly to the case of tight trip travelling settings, IA performs better than TSH in 7 out of 9 settings under loose trip travelling settings. However, the two settings for which TSH performs better are not the same settings as in tight trip travelling. IA produces better solution in all test problems in six-hour working shift and eight-working shift (when the meal break is considered).

In summary, TSH performs better when six-hour or eight-hour working shifts are considered, no meal break is given, and under a tight travelling assumption. Furthermore, it is also performs better, in a loose travelling setting, with a four-hour working shift with a 15 minute meal break and eight-hour working shift with no meal break.

7.4.2. Analysis on Demand Distribution

Next, we focus on the pattern of demand: demand with peak periods (P) and without peak periods (N) as shown in Figure 7.5. The number of test problems for which the different heuristics dominate is reported. IA dominates the TSH in 29 out of 36 settings, 16 times under a setting with peak demand and 13 times where there is no peak demand. Furthermore, IA performs betters than TSH in all test problems, where tight trip travelling is set in peak demand distribution.

When considering IA on its own, it performs better in the first setting (15 out of 18 settings) compared to latter setting (8 out of 18 settings), regardless of whether one considers tight or loose travelling settings. TSH appears to perform better in demand without peak.

7.4.3. Analysis on Demand Time Windows

The results of the analysis of the effect of the time window size on the efficiency of the heuristics are similar to those obtained in the previous subsection. IA outperforms TSH under most of the settings (29 out of 36 settings) and has a better performance with tight time windows (14 out of 18 settings).

To conclude, we can summarise the performance of both heuristics under different demand patterns, as shown in Table 7.3 below.

Table 7.3: Performance analysis of IA and TSH

	IA	**TSH**
Data distribution	Performs better with data distributions with peaks (P)	Performs better with data distributions without peaks (N)
Tightness of time windows	Performs better with tight time windows (A)	Almost similar performance in both tight (A) and mixture of tight and wide time windows (B)
Sample sizes	Almost similar performance in all sample sizes	Almost similar performance in all sample sizes

7.4.4. Analysis on Travelling Trip Setting

A scenario based on the case study is simulated by setting the following parameters: an eight-hour working shift, a one hour meal break between the 3^{rd} and 5^{th} hour of working and tight trip travelling limit. The average efficiency gap of both heuristics is shown in Table 7.4 (under column of tight trip travelling), by (TSH - IA)*100/IA.

In the tight trip travelling setting, TSH requires more servicing teams than the IA to complete the workload, especially in BP and BN test problems. On the other hand, the TSH performs slightly better with a sample size of 750 aircraft in all data sets. The gap in both AP-750 and AN-750 test problems are not only small in percentage but also two or more times less than the other smaller sample size test problems.

Figure 7.3: Demand size analysis on tight trip traveling setting

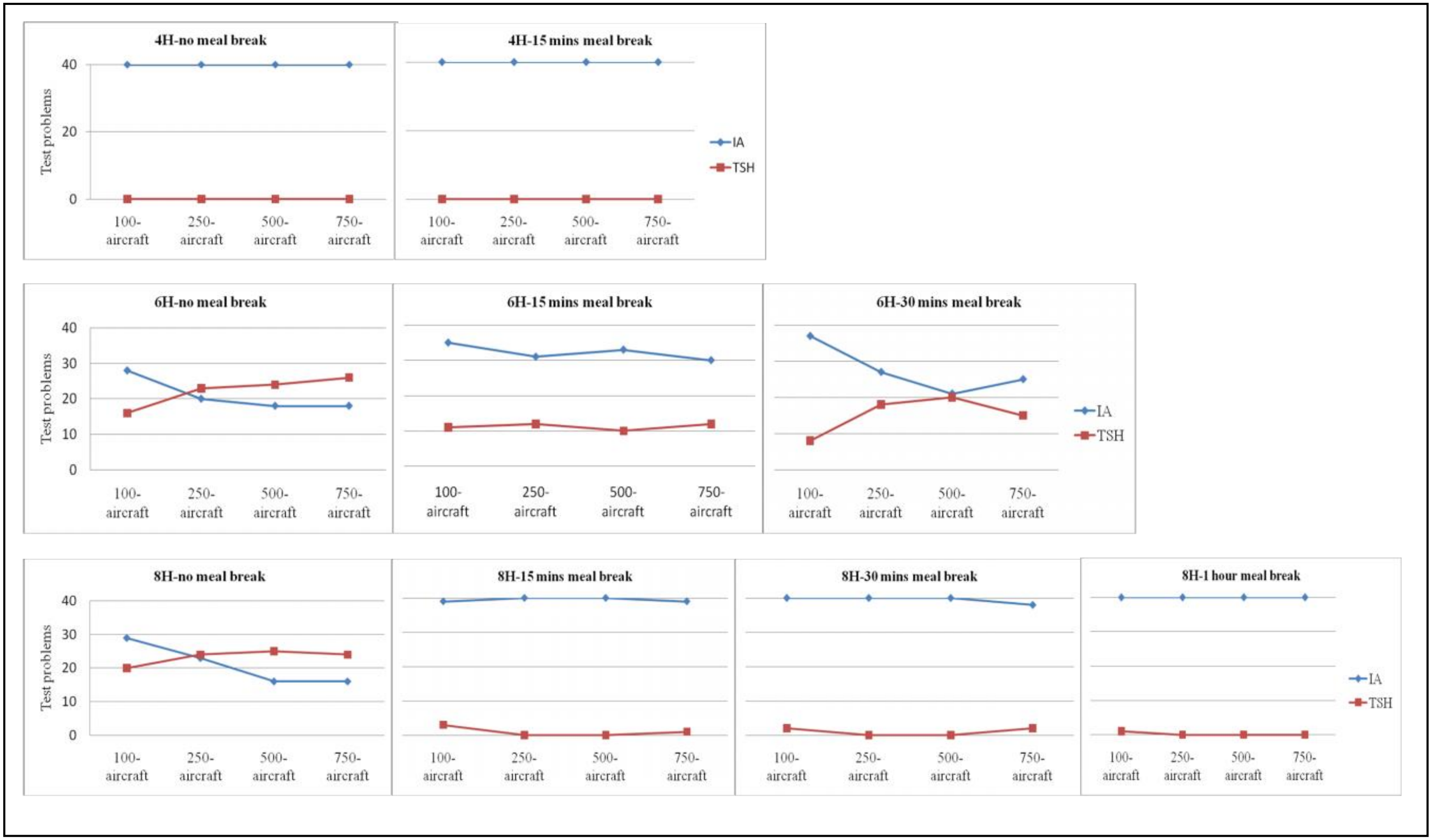

Figure 7.4: Demand size analysis on loose trip travelling setting

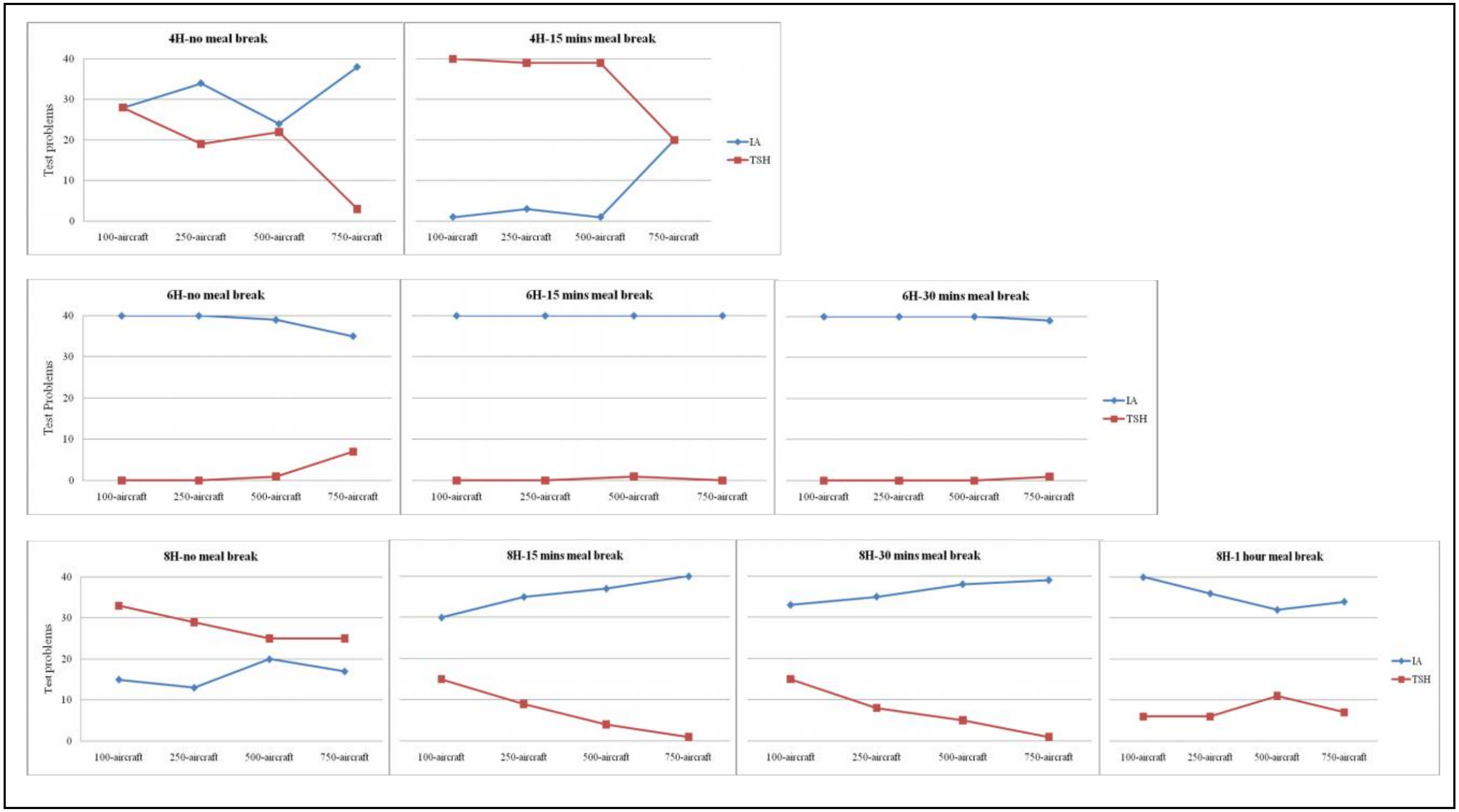

Figure 7.5: Time windows analysis

Demand distribution with peak (P)

	Tight trip travelling									Loose trip travelling								
	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4
IA	80	80	45	73	68	50	78	78	80	64	14	77	80	79	43	75	74	74
TSH	0	0	41	11	16	38	2	2	0	35	69	4	0	1	48	7	12	11

Demand distribution without peak (N)

	Tight trip travelling									Loose trip travelling								
	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4
IA	80	80	39	56	42	34	80	80	80	60	11	77	80	80	22	67	71	68
TSH	0	0	48	34	45	55	2	2	1	37	69	4	1	0	64	22	17	19

Insertion Algorithm

	Tight trip travelling									Loose trip travelling								
	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4
P	80	80	45	73	68	50	78	78	80	64	14	77	80	79	43	75	74	74
N	80	80	39	56	42	34	80	80	80	60	11	77	80	80	22	67	71	68

Two-stage Scheduling Heuristic

	Tight trip travelling									Loose trip travelling								
	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4	4H_0	4H_1	6H_0	6H_1	6H_2	8H_0	8H_1	8H_2	8H_4
P	0	0	41	11	16	38	2	2	0	35	69	4	0	1	48	7	12	11
N	0	0	48	34	45	55	2	2	1	37	69	4	1	0	64	22	17	19

When the travelling trip constraints are looser, the performance of the TSH is competitive with that of the IA, as presented in the computational results in Table 7.4 under column loose trip travelling. For example, there is a difference of less than 2 loading teams (1.67%) in BN-750 as shown in graph analysis in Figure 7.6. With the mixture of wide and tight time windows test problems, the TSH performs better when the number of aircraft increases.

Table 7.4: Comparison result of case study simulation

	Tight trip travelling				**Loose trip travelling**			
No. of aircraft	**100**	**250**	**500**	**750**	**100**	**250**	**500**	**750**
AP	13.27	16.31	20.27	7.97	9.60	10.65	2.88	9.30
AN	12.60	13.04	15.32	6.75	7.79	1.65	3.43	8.77
BP	26.34	28.74	22.98	22.82	19.56	18.39	10.80	6.39
BN	22.55	22.02	16.41	15.57	11.19	7.18	2.34	1.67

From the numerical results, and by using the IA as lower bound, it is shown that the TSH performs better in tight trip settings with tight time windows (A) or loose trip settings with a mixture of tight and wide time windows (B), even in a large sample size of test problems.

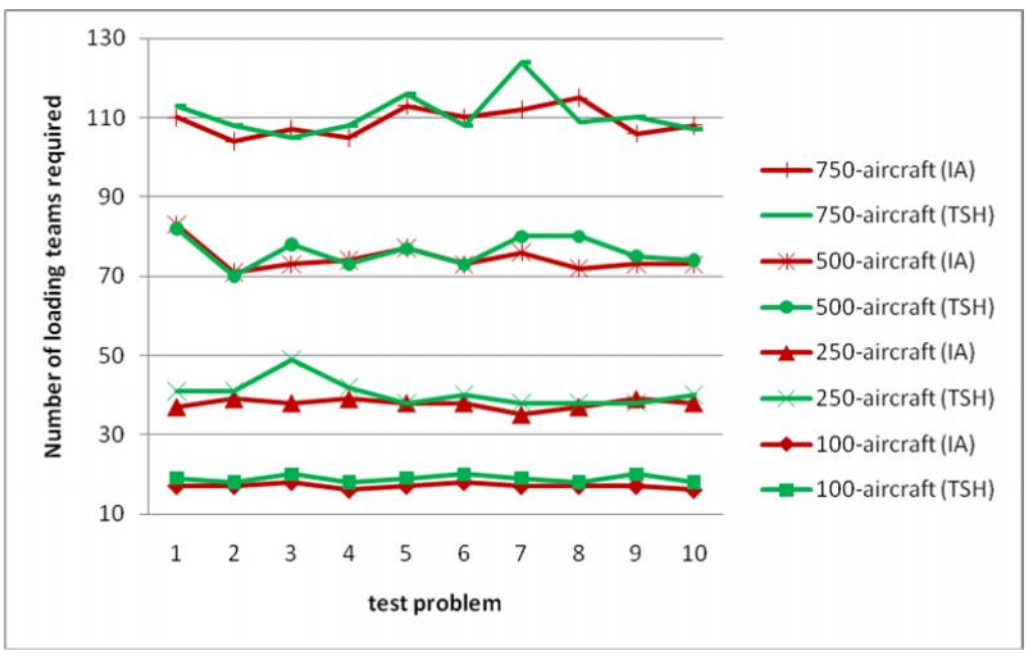

Figure 7.6: The comparison result of the TSH and IA on BN test problems

7.4.5. Analysis on Meal Break Allocation

We assume a similar setting to that considered in previous sections except for the fact that a meal break is not given to the loading team. In this sensitivity study, we focus on the scenario with the eight-hour working shift. Most of the computational results show the reduction statistic is similar in pattern to that obtained for the analysis which considers the meal break. This is demonstrated in Figure 7.7 and Figure 7.8. As expected, the number of loading teams required is less than that required under the scenario where the meal break is an must be scheduled during the working shift, regardless of the sample size. This is due to the fact that the loading teams have extra time from not having a meal break and the resulting unavoidable idle time.

The comparative results for percentage reduction are given in Table 7.5. The improvement for the TSHs is significantly larger than that of the IAs. Furthermore, the manpower reduction is also greater than expected in the TSH, when the saved hours (missing the meal break) are divided by the working shift hours, for example a 28.24% (40 teams) reduction on the BN-tight trip for 750 aircraft compared to the expected 12.5% (18 teams). It shows that the TSH is able to solve the scheduling problem effectively even when the meal break is not applied.

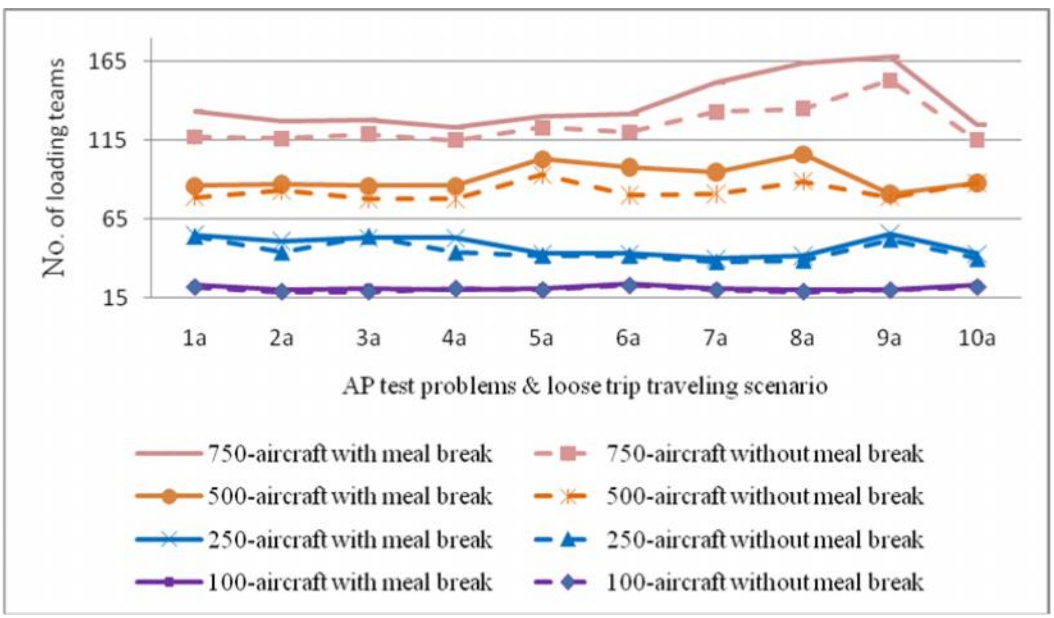

Figure 7.7: Computational result of the IA on AP test problems

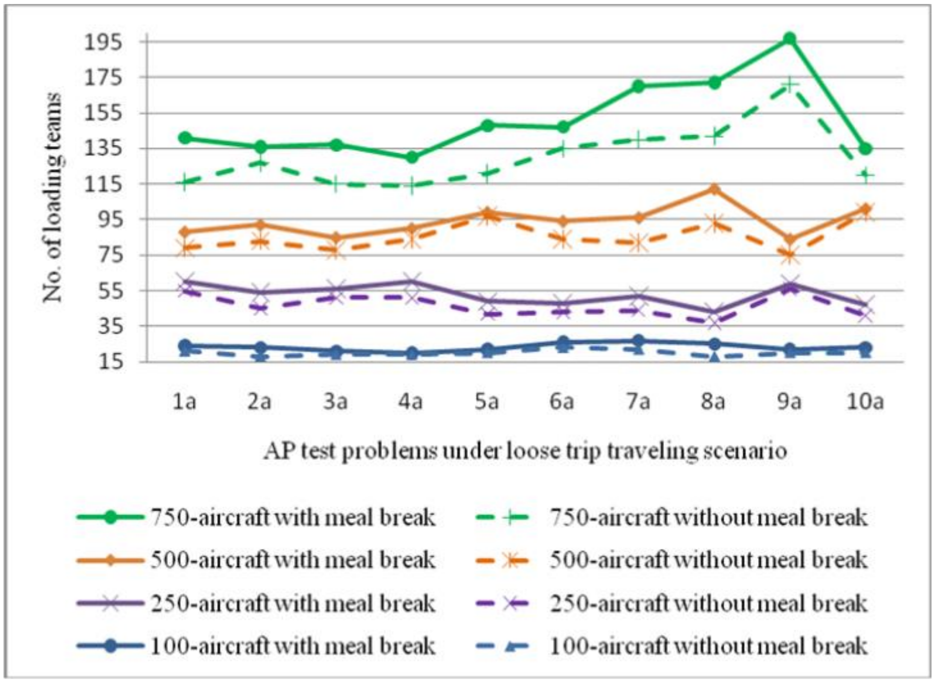

Figure 7.8: Computational result of TSH on AP test problems

On the other hand, the IA has the opposite computational result in the BN and BP test problems. The number of loading teams required is similar, regardless of whether a meal break is allocated within the working shift. Furthermore, more than half of the results show that even more loading teams are required when the meal break is not considered. This explains the time window cost evaluation component (as in equation (1) in Chapter 5) in the IA, where it tends to opt for the aircraft with the widest time window in order to insert more aircraft in the following iteration. By solving the BN and BP test problems, this evaluation component performs very well at the beginning. Later, though, the scheduling process is restricted with most of the aircraft with tight time windows. As the meal break functions as a divider of a shift, the situation worsens if the meal break is not applied. This happens especially in a large sample size with a short planning horizon. However, a time window cost evaluation component suits the following scenarios:

- tight trip travelling
- aircraft with tight time windows
- smaller sample sizes with a mixture of tight and wide time windows

Table 7.5: Computational result on manpower reduction (%)

	IA				TSH			
No. of aircraft	**100**	**250**	**500**	**750**	**100**	**250**	**500**	**750**
AP-tight trip	10.78	10.66	9.54	10.74	16.95	19.96	24.41	13.75
AP-loose trip	3.69	6.16	9.27	9.58	13.80	12.08	9.18	13.85
AN-tight trip	12.70	12.23	12.99	14.96	21.01	22.65	24.90	20.60
AN-loose trip	6.23	8.96	9.72	11.01	18.35	14.66	12.16	16.57
BP-tight trip	2.97	3.94	*-0.18*	0.88	18.98	22.72	23.06	24.82
BP-loose trip	*-1.87*	*-2.12*	*-0.18*	*-1.14*	13.96	13.56	12.12	9.95
BN-tight trip	4.80	1.63	1.55	*-2.43*	21.20	26.83	26.09	28.24
BN-loose trip	1.04	*-5.60*	*-2.75*	*-6.75*	16.87	13.65	8.35	9.18

7.4.6. Analysis on Working Shift

We analyse further the effectiveness of different working shifts in both heuristic solutions. It is unfair to compare the number of loading teams directly among three working shifts. Therefore, we split the eight-hour shift with fifteen minutes meal break as twice the workload of the four-hour shift, with seven and a half minutes of meal break allocation for each. The 6-hour shift with fifteen minutes meal break is split as one and a half times the workload of a four-hour shift, with 10 minutes of meal break allocation for each complete shift.

In the computational result, we use the four-hour shift (4H) as the comparison ratio base for the split eight-hour (8H') and six-hour (6H') shift. The four-hour shift is chosen as the ratio base because fewer teams are expected from this shift pattern than others due to its increased flexibility. The teams can have more shift starting time choices due to its working hours being the shortest.

On average, the numerical results based on the number of loading teams required of three working shifts are shown in Table 7.6. The "**" sign represents a shift in manpower reduction more than 10% compared to 4H, and the "##" a shift of more than 10% manpower increase compared to 4H.

Table 7.6: Working shifts analysis with meal break allocation

(Four-hour shift ratio base)

	Tight trip travelling		**Loose trip travelling**	
	IA	**TSH**	**IA**	**TSH**
AP- 100 & 250	4H < 6H’ < 8H’	6H’ < 4H < 8H’	6H’ < 4H < 8H’	4H < 8H’ < 6H’ ## ##
AP- 500 & 750	4H < 6H’ < 8H’	6H’ < 4H < 8H’ **	6H’ < 4H < 8H’	4H < 6H’ < 8H’
AN- 100 & 250	4H < 6H’ < 8H’	6H’ < 4H < 8H’	6H’ < 4H < 8H’	4H < 8H’ < 6H’ ##
AN- 500 & 750	6H’ < 4H < 8H’	6H’ < 8H’ < 4H **	6H’ < 8H’ < 4H	6H’ < 8H’ < 4H
BP- 100 & 250	4H < 6H’ < 8H’	8H’ < 4H < 6H’	6H’ < 8H’ < 4H **	4H < 8H’ < 6H’ ##
BP- 500 & 750	6H’ < 8H’ < 4H	6H’ < 8H’ < 4H **	6H’ < 8H’ < 4H **	4H < 8H’ < 6H’
BN- 100 & 250	6H’ < 8H’ < 4H	6H’ < 8H’ < 4H **	6H’ < 8H’ < 4H **	4H < 8H’ < 6H’ ##
BN- 500 & 750	8H’ < 6H’ < 4H	6H’ < 8H’ < 4H	6H’ < 8H’ < 4H **	4H < 8H’ < 6H’

Table 7.6 demonstrates that 6H’ dominates 4H as well as 8H’ in 19 out of 32 settings. Furthermore, 8 out of 19 leading results of 6H’ achieve manpower reduction more than 10% of the teams’ ration of 4H. Most of these excellent results are found in the loose trip travelling scenario for the IA (especially BN and BP data sets) and the tight trip travelling scenario for the TSH (especially large problem sets). However, 6H’ requires more loading teams in the loose trip travelling scenario for the TSH in small problem sets, where the team ratio can be as much as 1.37 - 1.41 of 4H. Even though 6H’ has the highest ratio of teams in certain scenarios, it has the lowest frequency (21.88%) compared to 4H (40.63%).

We also ran the same data set as in Table 7.6, regardless of the meal break allocation, and the numerical results are shown in Table 7.7. Again, 6H’ shows a very contradictory result in this sensitivity result. It generates the lowest team ratio 0.78 -

0.87 in the tight trip travelling scenario; meanwhile, the highest team ratio is the 1.31 - 1.35 loose trip travelling scenario with small sample sizes. Both these lowest and highest ratios are found by applying the TSH.

Table 7.7: Working shifts without meal break analysis (4-hour shift ratio base)

	Tight trip travelling		Loose trip travelling	
	IA	TSH	IA	TSH
AP- 100 & 250	4H < 6H’ < 8H’	6H’ < 4H < 8H’	4H < 6H’ < 8H’	4H < 8H’ < 6H’ ##
AP- 500 & 750	4H < 6H’ < 8H’	6H’ < 4H < 8H’ **	4H < 6H’ < 8H’	6H’ < 4H < 8H’
AN- 100 & 250	4H < 6H’ < 8H’	6H’ < 8H’ < 4H ** **	4H < 6H’ < 8H’	4H < 8H’ < 6H’ ##
AN- 500 & 750	4H < 6H’ < 8H’	6H’ < 8H’ < 4H	6H’ < 4H < 8H’	6H’ < 8H’ < 4H
BP- 100 & 250	4H < 6H’ < 8H’	6H’ < 8H’ < 4H **	4H < 6H’ < 8H’	4H < 8H’ < 6H’ ##
BP- 500 & 750	4H < 8H’ < 6H’	6H’ < 8H’ < 4H ** **	4H < 6H’ < 8H’	4H < 8H’ < 6H’
BN- 100 & 250	4H < 8H’ < 6H’	6H’ < 8H’ < 4H **	4H < 6H’ < 8H’	4H < 8H’ < 6H’ ##
BN- 500 & 750	4H < 8H’ < 6H’	6H’ < 8H’ < 4H **	4H < 6H’ < 8H’	4H < 8H’ < 6H’

In 21 out of 32 settings the least loading teams are obtained by applying 4H, followed by 6H’ (11 out of 32 settings). It is worth to mention that, 6H’ provides the best solution in all tight travelling settings, regardless the demand sizes. On the other hand, 8H’ requires the most teams in half of the settings.

The findings presented in Tables 7.6 and 7.7 demonstrate that a four-hour shift requires significantly less manpower than both longer working shifts in 32 out of 64 settings. This result makes sense as shorter working shifts have greater flexibility in accommodating complicated multi-trip travelling requirements. The company could consider implementing a four-hour working shift, as it performs much better than the eight-hour shift with a meal break (only 6.25% of the settings achieve smallest number of teams). Moreover, the four-hour shift is the top performer in the working shift analysis when the meal break is not considered. Since a four-hour shift is a short working period, it is reasonable not to have a meal break during the working shift.

Even though the four-hour shift proves to be the more effective managerial setting in general, it does not seem practical to be implemented in industries. It would greatly affect the welfare of workers as well as on the efficiency of the entire operations process due to the high interchange of workers during the day. Therefore, a longer working shift with an appropriate break time is recommended. The computational results show that six-hour working shift is a significantly better managerial setting when meal break is considered, compared to a longer working shift (eight-hour) and short (four-hour) shifts, except for the case where the loose trip travelling are considered, and the TSH performs better. Therefore, the company could consider shortening the current 8-hour shift practice to a 6-hour shift.

7.4.7. Analysis on Meal Break Duration

We also conducted the sensitivity study on the meal break duration with three different shift types, as shown in Table 7.8. Each unit of meal break duration represents a 15-minute meal break.

After calculating the mean number of teams required for each test problem set, we generated the performance gap of each meal break duration. To ease the comparison, we calculated the difference in terms of the number of loading teams between every two sets of meal break durations by using a longer duration minus the smaller duration. All the calculations were conducted within the same working shift, for example calculating the difference between a 1 hour (4 units) and a 30-minute meal break (2 units) for an eight-hour shift. Then, this was followed by the difference between the 30-minute (2 units) and a 15-minute (1 unit) meal break.

Table 7.8: Meal break duration type

Shift	**4-hour shift**		**6-hour shift**			**8-hour shift**			
Meal break duration	0	1	0	1	2	0	1	2	4

The summary of the comparative results as a function of the sample size is presented in Table 7.9. The second row shows the difference of the number of teams required based on the mean value from each set of test problems. The third and fourth rows report the minimum and maximum gap in the differences. In the following two rows, the scenarios where the smallest and biggest differences found are presented. The reported criteria are: the scenario, the heuristic methodology applied, the working shift type, the comparison meal break duration types and the difference interval. The meal break types where the overall smallest and biggest differences in terms of number of loading teams are in seventh and eighth rows. The details are: working shift type, the comparison meal break duration types and the differences interval. There are some negative values of differences found in the numerical results, which means that the number of teams required is less with the longer meal break duration. The last row shows the scenarios, heuristics and data types where the negative values of difference occur.

From the table, it can be seen that the smallest difference in terms of the number of teams required is between the 30-minute and the 15-minute meal break in the 8-hour shift, while the largest is in the four-hour shift, without a meal break and with a 15-minute meal break. These results occur in all types of sample sizes. The numerical results also show that there is a huge increase of manpower required from a no meal break allocation to any type of meal break duration, especially when the IA is applied.

It is interesting to note the performance analysis performed on the different meal break durations in the six-hour shift. The difference between the 30-minute and the 15-minute meal break in the six-hour shift is the second smallest in comparison. However, the gap in difference greatly increases in BP-750 and BN-750 in the tight trip travelling scenario with the TSH.

With all these findings, the company could more suitably choose the meal break type according to sample sizes, scenarios and heuristics. For example, no meal break allocation would be highly recommended in the four-hour working shift due to the possibility of a required increase in manpower. Furthermore, the four-hour working shift is short and mostly applies to casual workers.

Table 7.9: Computational results of meal-break duration sensitivity

	100 aircraft	250 aircraft	500 aircraft	750 aircraft
Average interval of differences	[-0.5, 2.63]	[-2.78, 4.75]	[0.18, 8.08]	[-0.33, 21.03]
Min. gap	0	0	0.3	0.3
Max. gap	4	10.1	18.6	39.1
Smallest difference settings	Loose trip travelling, TSH, four-hour shift: 0 - 1 unit meal break, [-0.2, 0.8]	Loose trip travelling, TSH, four-hour shift: 0 - 1 unit meal break, [0.1, 0.6]	Loose trip travelling, TSH, four-hour shift: 0 - 1 unit meal break, [-0.6, 1.1]	Loose trip travelling, TSH, eight-hour shift: 1 - 2 units meal break, [3.2, 4.5]
Biggest difference settings	Loose trip travelling, IA, four-hour shift: 0 - 1 unit meal break, [3.1, 4]	Tight trip travelling, TSH, eight-hour shift: 0 - 1 unit meal break, [7.9, 10.1]	Tight trip travelling, TSH, eight-hour shift: 0 - 1 unit meal break, [16.7, 18.6]	Tight trip travelling, TSH, four-hour shift: 0 - 1 unit meal break, [10.9, 39.1]
Smallest difference duration types	Eight-hour shift: 1 - 2 units meal break, [-0.1, 0.8]	Eight-hour shift: 1 - 2 units meal break, [1.55, 1.78]	Eight-hour shift: 1 - 2 units meal break, [2.8, 3.25]	Eight-hour shift: 1 - 2 units meal break, [3.65, 5.3]
Biggest difference duration types	Four-hour shift: 0 - 1 unit meal break, [0.83, 2.63]	Four-hour shift: 0 - 1 unit meal break, [1.98, 4.75]	Four-hour shift: 0 - 1 unit meal break, [3.38, 8.08]	Four-hour shift: 0 - 1 unit meal break, [3.95, 21.03]
Negative differences	BN & BP, IA, Six- & eight-hour shifts: 0 - 1unit meal break	BN & BP, IA, Four-, six- & eight-hour shifts: 0 - 1 unit meal break	BN & BP, IA, Four-, six- & eight-hour shifts: 0 - 1 unit meal break	BN & BP, IA, Four-, six- & eight-hour shifts: 0 - 1 unit meal break

7.4.8. Discussion of Case Study and Experiment Test

By comparing the computational results obtained from the case study analysis (section 2) and experimental tests (section 4.1-4.7), we found that the results contradict each other. In section 2, the TSH dominates the IA in all five-day test problems, even when synchronisation of the loading teams is applied. However, the IA outperforms the TSH in most of the experimental tests in section 4, regardless of the demand pattern and the problem size.

The main factor that affects the IA's performance, as illustrated in section 4.3, is the wide time windows, especially when a meal break is not considered. The number of teams required in a scenario without meal-break allocation is greater than in those scenarios with meal-break allocation. This is due to one of the evaluation components of the IA that emphasizes choosing wide time windows, and causes the aggregation tasks with tight time windows to be restricted later.

Similar performance conditions for the IA are found in real data, even when a meal break is considered. There is a mixture of wide and tight time windows in real data as defined in the B type data. However, the wide time window ratio in the real data is far greater than the maximum ratio of 10 in the simulated B type data. For example, Day 2 has a largest ratio value of 65, for an outbound flight that requires fifteen minutes of loading in the late evening. The frequency of wide time windows in Day 2 is shown in Table 7.10. This explains the better performance of the TSH in real data compared to the IA.

Table 7.10. Frequency of time window ratio (Day 2)

Time window ratio	Frequency (%)
1	35.76
1-2	27.15
2-3	19.21
3-5	4.64
5-10	3.31
10-20	6.62
>20	3.31

7.5. Managerial analysis

In section 4, the computational results demonstrate the strengths and weaknesses of both the IA and the TSH under different scenarios. Due to their fast computing time, we highly suggest computing using both heuristics simultaneously and then choosing the better solution. Using this approach, the quality of the solution can be greatly improved; for instance, when not restricted by the tightness of time windows, one might use the IA.

In this section, an analysis is conducted in order to draw some managerial insight into scheduling manpower in in-flight catering application. Since we are not comparing the performance of the two heuristics, but comparing the number of loading teams needed in different managerial setting, we take the best solution provided by the two heuristics.

The best solution among the two heuristics is reported in Table 7.11. The table shows less manpower is needed in all loose trip travelling settings (in grey rows). This makes sense since "looser" trip restrictions achieve greater savings in travelling time back and forth depots. Thus, it is more efficient and requires less loading teams to serve the aircrafts. The company can increase the capacity of the loading truck in order to loosen trip restriction but international food exposure standard should not be compromised.

Table 7.11. Hybrid solution

Working Shift	**4 hours**		**6 hours**			**8 hours**			
Meal break duration	**0**	**1**	**0**	**1**	**2**	**0**	**1**	**2**	**4**
AP_100_tight	33	37	25	26	27	21	22	22	24
AP_100_loose	31	32	23	23	24	20	20	20	21
AN_100_tight	34	38	24	25	27	19	21	21	23
AN_100_loose	32	32	23	23	23	18	19	20	21
BP_100_tight	32	34	24	23	24	18	18	17	19
BP_100_loose	28	29	21	19	20	17	16	16	17
BN_100_tight	34	34	23	22	23	17	17	17	19
BN_100_loose	28	28	21	19	20	15	15	16	17
AP_250_tight	75	82	56	58	61	47	49	50	53
AP_250_loose	72	73	53	51	52	44	45	46	48
AN_250_tight	77	84	54	56	59	43	45	46	50
AN_250_loose	73	73	52	50	51	39	41	42	45
BP_250_tight	82	82	54	53	56	42	41	42	45
BP_250_loose	68	70	50	45	47	39	36	37	40

BN_250_tight	82	80	50	50	53	38	38	40	43
BN_250_loose	67	68	50	43	45	35	34	35	38
AP_500_tight	147	160	105	110	114	88	92	94	98
AP_500_loose	141	141	98	94	98	82	82	86	91
AN_500_tight	149	163	103	107	111	81	87	90	96
AN_500_loose	143	144	96	93	98	78	79	82	87
BP_500_tight	174	171	113	110	115	86	83	85	93
BP_500_loose	145	148	103	93	98	78	74	77	82
BN_500_tight	162	155	99	100	101	72	76	79	84
BN_500_loose	131	135	98	85	89	69	67	70	74
AP_750_tight	220	240	156	162	170	132	137	141	149
AP_750_loose	213	226	144	143	148	124	125	130	138
AN_750_tight	219	241	150	157	164	115	123	128	136
AN_750_loose	212	228	139	135	141	110	111	117	125
BP_750_tight	254	244	160	157	162	117	119	122	133
BP_750_loose	204	209	151	132	137	109	105	110	117
BN_750_tight	246	228	144	145	149	103	110	116	124
BN_750_loose	190	201	143	124	129	101	97	100	108

7.5.1. Working shift sensitivity study

Here, working shift sensitivity is conducted based on demand sizes. As presented in Figure 7.9, the number of loading teams needed to serve all the tasks decreases in a similar pattern when the shift length increases, for all demand sizes. When a meal break is allocated during the working shift, all test problems require more loading teams. Furthermore, the number of loading teams keeps increasing by the increment of the meal break duration. This is reasonable as the working hours have been deduced by break time allocation.

In addition, we conducted the working shift sensitivity study on the best solution in a manner similar to that we conducted the study in section 4.6. A four-hour working shift with a fifteen-minute meal break remains the ratio base that will be used to compare to other working shift patterns with varied meal-break durations. The working-shift pattern that required the least amount of manpower for each data type and scenario is presented in Table 7.12.

In Table 7.12, the six-hour working shift with a fifteen-minute meal break dominates the other shift patterns in the test problems with a mixture of tight and wide time windows. Meanwhile, the four-hour working shift with a fifteen-minute meal break requires less manpower in most of the test problems.

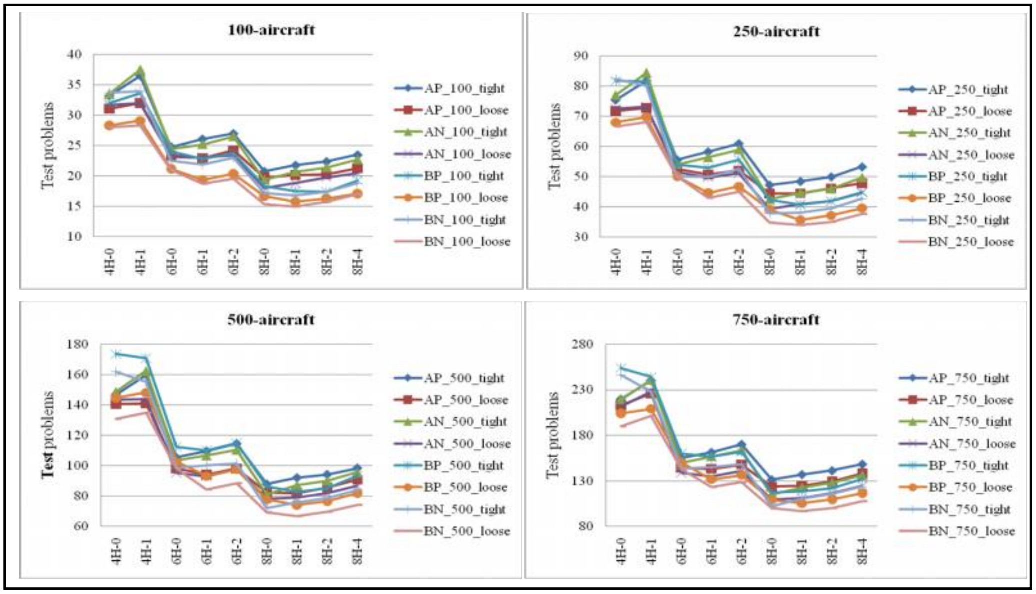

Figure 7.9: Working shift sensitivity study based on demand sizes

Table 7.12. Working-shift sensitivity study (with meal-break allocation)

	Tight trip travelling	**Loose trip travelling**
AP_100	4H	4H
AP_250	4H	4H
AP_500	4H	4H
AP_750	4H	6H (15-min meal break)
AN_100	4H	4H
AN_250	4H	4H
AN_500	6H (15-min meal break)	6H (15-min meal break)
AN_750	6H (15-min meal break)	6H (15-min meal break)
BP_100	4H	4H
BP_250	6H (15-min meal break)	6H (15-min meal break)
BP_500	6H (15-min meal break)	6H (15-min meal break)
BP_750	6H (15-min meal break)	6H (15-min meal break)
BN_100	6H (15-min meal break)	6H (15-min meal break)
BN_250	6H (15-min meal break)	6H (15-min meal break)
BN_500	6H (15-min meal break)	6H (15-min meal break)
BN_750	6H (15-min meal break)	6H (15-min meal break)

We continued to conduct the sensitivity analysis with no meal-break consideration. In this study, the four-hour working shift outperforms other working shift patterns in most of the test problem sets, as illustrated in Table 7.12. On the other hand, the six-hour and eight-hour working shifts perform better in larger sample sizes of test problems with a mixture of tight and wide time windows.

Table 7.12. Working-shift sensitivity study (without meal-break allocation)

	Tight trip travelling	**Loose trip travelling**
AP_100	4H	4H
AP_250	4H	4H
AP_500	4H	4H
AP_750	4H	4H
AN_100	4H	4H
AN_250	4H	4H
AN_500	4H	4H
AN_750	4H	6H’
BP_100	4H	4H
BP_250	6H’	4H
BP_500	6H’	4H
BP_750	8H’	6H’
BN_100	4H	4H
BN_250	6H’	4H
BN_500	8H’	4H
BN_750	8H’	4H

The findings from Tables 7.11 and 7.12 suggest which working-shift pattern is suitable for each scenario in order to keep manpower at a minimum. In addition, it suggests other potential solutions, such as developing an eight-hour shift by grouping every two four-hour shift solutions when a meal break exists. When a meal break is not considered, the use of a four-hour working shift as the shortest shift length is highly recommended. It is also justified when the company considers part timer for a four-hour shift.

7.5.2. Total labour hours sensitivity study

In this section, shift working hours are multiplied by the number of teams needed to generate the total labour hours, to serve all the servicing tasks. These total labour hours can be used to compare the use of labour under different settings, including labour cost.

The sensitivity result is reported in Figure 7.10 based as a function of demand sizes. In general, the total labour hours increase as the working shift length is longer, regardless of the demand sizes. This can be explained by the additional flexibility and efficiency of shorter working shifts in workload assignment. In addition, the inclusion of a longer meal break in six- and eight-hour working shifts that increases the total working hours directly.

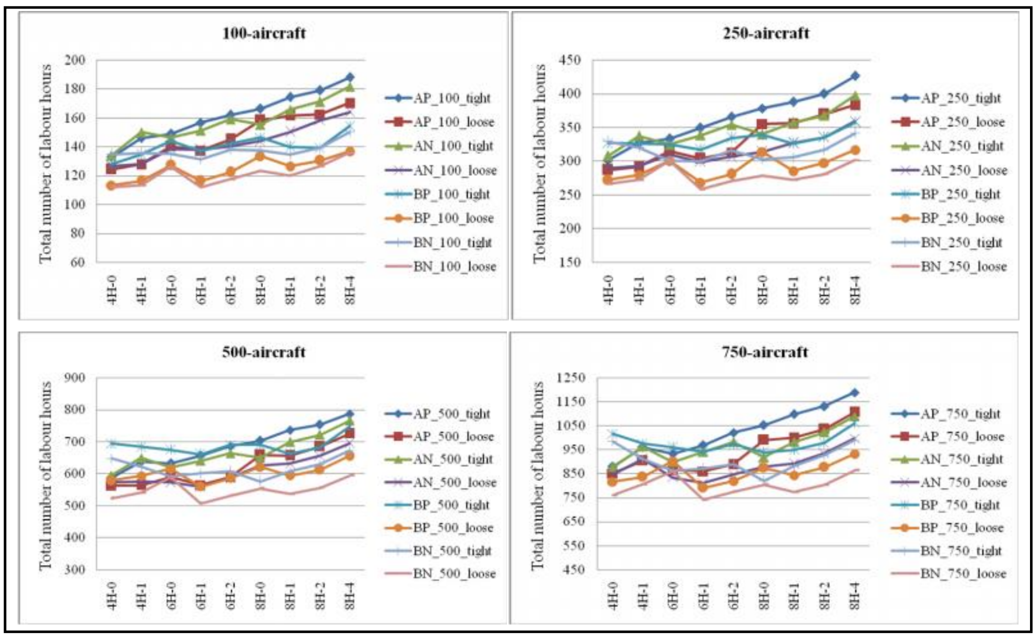

Figure 7.10: Total working hours sensitivity study based on demand sizes

7.5.3. Demand Distributions Sensitivity Study

In this section, the demand distributions (peak and without peak) sensitivity analysis is studied as a function of demand sizes. Figure 7.11 reports the total number of labour hours required on both peak (on the left side) and without peak (on the right side) distributions, as a function of demand sizes. It is apparent that it is beneficial to use the Time Window Reduction (TWR) as pre-processing algorithm to smoothen the peak demand, in order to enhance the effectiveness of heuristic.

In comparison, the total number of labour hours required on demand distribution without peak (on the left side) is significantly smaller than the distribution with peak (on the right side), regardless of the sample sizes. This is because the manpower required will be greatly increased due to the existence of peak demand. Besides, Figure 7.12 shows the impact of the length of working shift in the demand pattern. The differences in total working hours between demand with and without peak are gradually increased from four-hour working shifts to eight-hour working shifts. This is reasonable as smaller shift length provides more flexibility to cope with the peak.

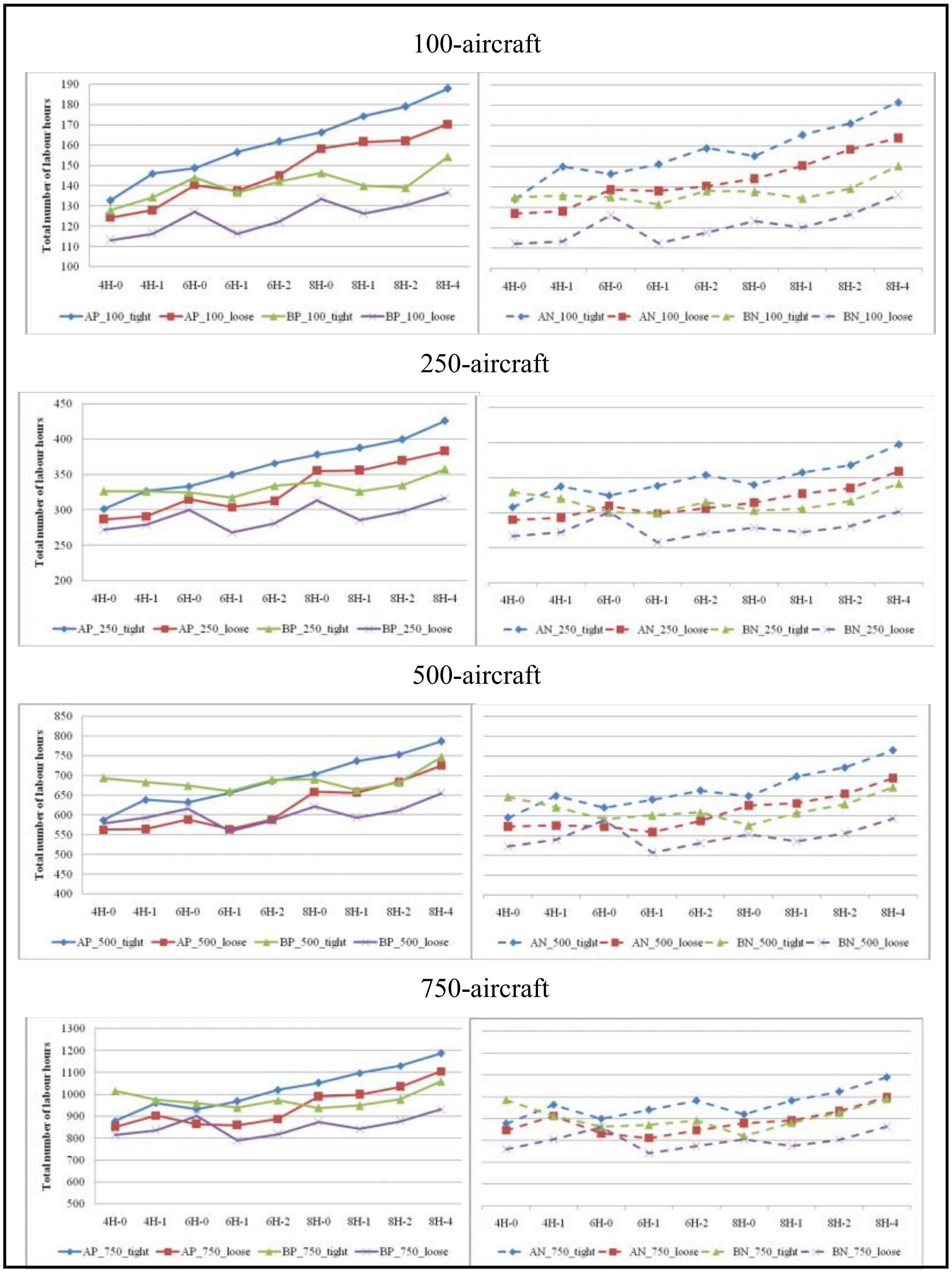

Figure 7.11: Demand distribution analysis based on demand sizes

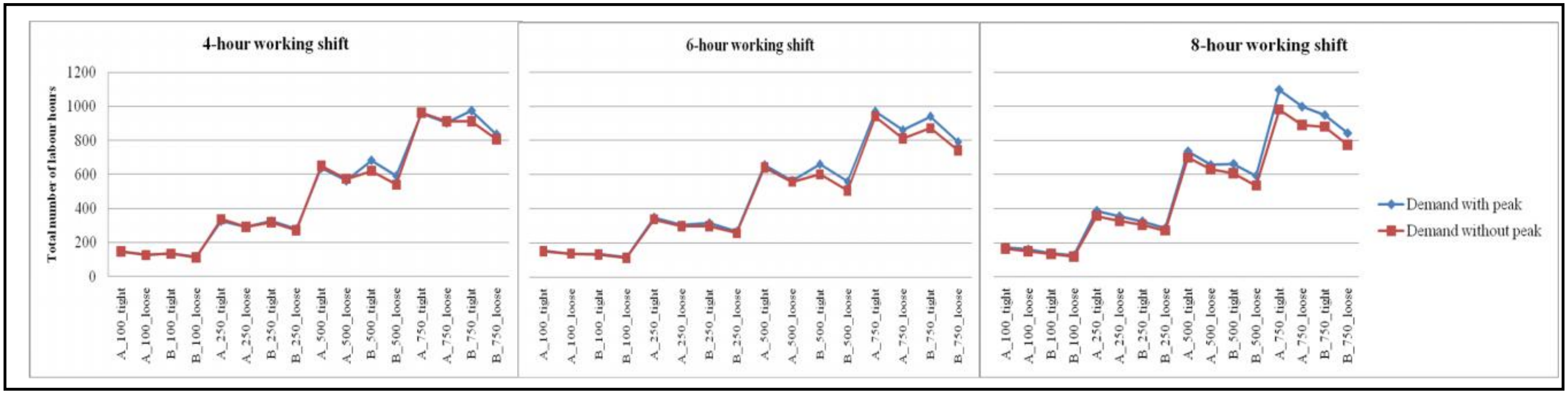

Figure 7.12: The impact of the working shift's length

7.6. Conclusion

In this chapter, both heuristic solutions, the IA and the TSH, were analysed using different demand sizes, distributions and time windows to evaluate their performance.

Both heuristics showed effectiveness and efficiency in solving the scheduling problem, regardless of sample size. Furthermore, they were quick in generating solutions that fulfilled the need for a swift response by the industry.

Compared to each another, both heuristics demonstrated their strengths and weakness in particular scenarios or data types. Since IA provided better solutions in 2319 out of 2880 settings while TSH was dominant in only 717 cases, we conclude that IA performs better than TSH on the manpower scheduling problem when synchronisation of loading teams is not considered. When there is a peak in demand distribution and time window is tight, IA outperforms TSH. However, TSH outperforms IA in most of the settings where meal break allocation is not applied or when there is a mixture of tight and wide time windows.

In terms of managerial settings, a series of sensitivity studies were conducted to analyse the impact of different assumptions on the number of teams required. In the study, the four-hour working shift is highly recommended in the workload assignment when meal break allocation can be excluded, while six-hour working shifts appear to be best for the setting with meal break consideration.

Due to the fast computing time of the heuristics, the hybrid solution is also suggested to generate the best solution from both IA and TSH. The hybrid solution provides a superior solution in all test problems for looser trip travelling settings than tight one.

Chapter 8: Discussion & Conclusion

8.1. Conclusion

In this thesis, we successfully solved a manpower scheduling problem with time windows and multiple trips. This research was conducted based on a case study, mainly focused on an in-flight food loading operation at the biggest international airport in Malaysia.

Three weeks of fieldwork were conducted during the study in order to understand and observe the loading operations holistically. Real data for aircraft movement and the actual roster were also collected to analyse potential solutions. In order to cope with peak and off-peak aircraft movement, an original data pre-processing algorithm, called the Time Window Reduction (TWR) heuristic, was designed to spread the servicing demand of the aircraft as evenly as possible throughout the planning horizon.

In the study, we firstly modelled the problem mathematically as a Multiple Trips Vehicle Routing and Scheduling Problem with time windows and meal break consideration (MTVRSPTW-MB). Even though the problem's complexity is yet to be proven in the literature, previous studies show that the problem is difficult to solve efficiently when the problem size is large. Then, we presented a model of a relaxed version of the MTVRSPTW-MB and solved it optimally by the CPLEX solution. Unfortunately, the computational time of CPLEX is sensitive to the sample size and the tightness of time windows. Therefore, the experiment tests were limited to 30 customers (or aircraft based on the case study).

Due to the difficulty of solving the problem optimally in large problem instances, and also industry's need to obtain a fast generating solution, an original Two-stage Scheduling Heuristic (TSH) was proposed. A simple aircraft's laxity sorting rule and vehicle priorities were used in assigning and scheduling the teams in two stages.

In order to evaluate the effectiveness of the TSH to solve the case study, we tested the proposed solution with aircraft movement data from industry. The computational results show that the TSH is able to solve the problem in seconds.

Additionally, the TSH outperforms the actual roster by the company's expert planner by 20% in manpower reductions or 77 teams over a 5-day period.

Then, an Insertion algorithm (IA) was developed to solve the same case study simulation. An IA was chosen because of its simplicity and flexibility in accommodating varied complicated vehicle routing constraints. Even though it is popular among heuristics, the IA has not been applied in the MTVRSPTW-MB to our knowledge. Like the TSH, we implemented the IA in stages due to the problematic nature of multiple trips travelling. We tested the IA on the same real data and compared it. The numerical results show that the IA is capable of solving the scheduling problem efficiently, and reduced the manpower by 10.39% compared to the real roster. However, it performs worse than the TSH (19.59% reduction compared to the real roster), when synchronisation of loading teams is not applied.

Finally, we further evaluated the IA and TSH with simulation data with different sample sizes, distribution types and different tightness of time windows. All the test problems were tested under a series of sensitivity studies, such as meal break and working shift sensitivity.

The computational results demonstrate that both heuristics are able to solve the problem efficiently and effectively regardless of the sample sizes. Moreover, they are robust and computationally bounded. The results also show the pros and cons of each heuristic solution in detail. For example, the IA outperforms the TSH in most of the experimental tests, but performs unreasonably in certain scenarios, such as when a meal break is not applied, and so more manpower is required in that case. Furthermore, IA is unable to handle the constraint on synchronisation of loading teams as TSH.

8.2. Our contribution

Aside from solving the specific manpower scheduling problem faced everyday by in-flight catering companies, the model can be adapted to other aspects of airline operations and to other industries as well. For example, aircraft maintenance, operations at seaports, train stations etc. This thesis also contains theoretical and computational heuristics values of more general interest. We classify our contribution to the following categories:

- *Introduction of a new mathematical model in the MTVRSPTW-MB*

Most of the MTVRSTW cases (without meal break consideration) have been solved by applying heuristic solutions from past studies. In recent years, a basic model of the MTVRSPTW has been presented and solved optimally, but limited to small instances However, we need to consider more complicated constraints, which have not been studied to the best of our knowledge. The constraints are meal break allocation and synchronisation of teams. Furthermore, there is more than one constraint affecting the multiple travelling needs, which makes the modelling even more complicated.

- *Heuristic solutions*
  - Pre-processing algorithm

    A fast and effective heuristic, call TWR has been developed to spread the service demand more evenly throughout the planning period. This can not only reduce congested demand but can also help in providing better solutions regardless of the heuristic or mathematical optimal solution.
  - Heuristic solution: IA

    The IA was firstly applied to solving the MTVRSTW-MB by relaxing a team's synchronisation constraint, as in the case study. It is both fast and capable of solving the scheduling problem.
  - Heuristic solution: TSH

    An original two-stage heuristic has been developed to solve the manpower planning problem. Its simplicity and flexibility are able to accommodate all complicated constraints, as illustrated in the case study, including the synchronisation of loading teams. It is also rapid (in seconds) in generating high quality solutions even for large problem instances.
- *Excellent initial solutions*
  - Both proposed heuristics, the IA and the TSH, can rapidly generate high quality solutions, as demonstrated in the numerical results. This makes them perfect as initial solutions for meta-heuristics, such as Tabu Search, Genetic Algorithm and so on, in solving the MTVRSTW-MB.
- *Time and cost saving for the company*

- Applying the proposed heuristics allows the company to employ the minimum manpower to cope with all the aircraft loading demand. Thus, the solutions would provide wide economic effects of having fewer teams, such as less pension and healthcare costs for workers, fewer vehicles – less insurance, maintenance, and petrol costs and so on. In addition, the company would able to take further actions in improving contingency plans. Even though contingency procedures or re-optimisation are not included in this study, the proposed heuristics could be very helpful in handling both conditions, simply because they are so fast.
- Undeniably, the proposed heuristic solutions could speed up the manpower planning process from days to a few seconds with a minimal number of planners. Indirectly, the manpower from the planner department could also be greatly reduced.

8.3. Future perspectives

Future work on heuristic solutions for MTVRSPTW-MB and the models presented in this thesis is likely to be shaped by the needs of in-flight caterers and other companies. There are a number of ways to proceed from this point, and to improve the models and methods further, focussing more specifically on one area would be required.

The MTVRSPTW-MB model has proven hard to solve optimally, and another approach to this issue may be more successful. Instead of using Branch and Bound in CPLEX directly, it might be useful to integrate more heuristic components into the algorithm to generate more feasible solutions.

In terms of the IA, it would be worth investing more time and effort to applying more complicated constraints. For example, Parallel Insertion is one way of trying to accommodate the constraint of teams' synchronisation. More numerical experiments would be needed to tune the suitable parameters' value for different objective functions. On the other hand, more evaluation components could be added to the TSH in order to strengthen the robustness of the algorithm, especially in the packaging objective in the second stage. In future, it would also be interesting to look into more challenging scheduling tasks, such as skill set requirements, something very common in industry.

This thesis only deals with daily, operational planning. In all the presented problem instances, the teams had workloads of only 50% on average, and hence considerable savings could be expected from optimizing the long-term, tactical planning process, including the number of teams and working hours. A contingency plan to cope with emergency circumstances should be considered in future, a requirement in high demand, for example one that minimises the chances of an initial plan coping with emergency scenarios, such as flight delays or aircraft swapping. With a few changes, the proposed solutions could be used to indicate how the working hours and number of teams could be advantageously redistributed for specific daily planning problems.

Finally, more research in developing meta-heuristics could be carried out efficiently as our algorithms could provide initial solutions for manpower scheduling. At the same time, our heuristics need a post-processing algorithm. More effort is needed to investigate and facilitate the optimality with respect to the number of teams required, and simultaneously adjust the solution to be more applicable in a real-world schedule. If the decision is made to include an optimal solver within software, a post-processing algorithm would have to be developed.

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