

## INNOVATIVE FRAMEWORK FOR SKILL SPECIFIC WORKLOAD VARIANCE REDUCTION FOR SRI LANKAN AIRLINES TECHNICAL WORKFORCE CAPACITY PLANNING

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### Abstract

Employee workload variance is a significant issue in skill specific airline ground operations. This study presents a dual objective capacity assignment model with interdependent objectives of operational cost minimization and workload variance minimization. An innovative metaheuristic Tabu Search algorithm is used for solution where equilibrium of the objectives are derived from a feasibility frontier. A numerical experiment is conducted with real time data of Sri Lankan airlines technical workforce segment and the results indicates a significant 70.13% variance minimization compared to manual assignment with a simultaneous cost saving of 2.58% at a substantially lesser planning time. An inverse relationship is observed between job distribution and the workload variance which explains the inefficiencies in manual capacity assignment. The proposed framework enhances the operational planning flexibility as well in terms of interconnected adjustment feasibility of workload variance and workforce cost.

**Keywords:** Airline ground operations, workforce variance, cost minimization, planning flexibility, heuristics

### Introduction

Airline ground operations (AGO) are one of the most essential tasks in the aviation industry. A major portion of these operations is dominated by technical activities and other ground support

activities like baggage handling, ground marshalling, security and boarding related activities. Ground operations contribute significantly to the overall costs where maintenance alone amounts to 10% of the operating cost. AGO tasks are highly human-centered which requires specialized skills. As per the 2017

annual report of International Air Transport Association (IATA), workforce costs are substantially higher than materials and as a percentage, it is only second to the fuel costs. It is also a known fact that overall profits are highly marginal in the airline industry unlike other major industries due to the substantial operational costs and intensive competition (Sasaki, Nishi, & Inuiguchi, 2015). In year 2018 the net profit margin of the entire airline industry is only 4.1% with a significant reduction compared to the previous year's 5% margin. Being a budget airline Sri Lankan airlines is also heavily burdened with these issues and is compelled to focus more on operational cost savings to survive in the global competition. In simpler terms, this situation demands an optimal workforce assignment plan to detail employees for diverse tasks requiring different skills over a variable planning horizon to cater fluctuating workloads at a minimal cost.

A majority of the AGO tasks are skill specific and in technical fields such as maintenance expertise, experience and skills are endorsed through a maintenance certificate. Therefore an optimum task assignment is crucial as these employees with different skill levels are paid differently and planner should optimally match skills with diversified workloads (Defraeye & Van Nieuwenhuyse, 2016). On the other hand, the workload assigned to all employees should be equivalent where no employee should be overloaded with work while ensuring minimum idle time as well. This is determined by the amount of variance in workload distribution which

affects both cost optimization and employee satisfaction enhancement. Due to the intricate nature, workforce capacity assignment is manually done in most AGO environments with experience and gut feeling of operations managers which inevitably result in significant imbalances of workload distribution and added operational costs in terms of capacity idling where this process is further complicated by diversified shift schedules with fluctuating operations workload (Van Den Bergh, Beliën, De Bruecker, Demeulemeester, & De Boeck, 2013). To address the above, an innovative dual objective model is proposed to assign employees for AGOs with minimal cost and variance.

#### Literature Review

Airline workforce planning is analyzed through various tributaries of research during the recent past where cost minimization has been the primary objective with diverse human factor related objectives of fairness, boredom, fatigue and productivity have been analyzed frequently in cohesion as the secondary objectives (Van den Bergh, De Bruecker, Beliën, & Peeters, 2013). However, workload variation analyses are hardly available especially with a dual objective interdependent feasibility frontier with cost minimization. This paper focuses on airline ground operations where there are several works of literature discussing different aspects of the manpower scheduling problem. Marintseva, Yun, & Kachur, (2015) highlights in their discussion on airline resource allocation that fierce industry competition man-

dates continues perusal of operational efficiency improvement and cost minimization as the predominant requisites for sustainability. The prominence of ground operations in terms of overall operational costs is highlighted in Gomez & Scholz, (2009) as they systematically evaluates the relationship between ground operations and direct operations costs(DOC). The fluctuating time based workloads and different task assignment in airline ground operations is analyzed through a hierarchical planning model in Stolletz, (2010). Different workforce size variations (i.e. team compositions) are evaluated by a linear program with flexible work contracts and highlights the relationship between workforce assignment flexibility and economies of scale through a real world tour scheduling problem.

Different methods are used for airline workforce planning where heuristics and enumerative programming are the most prominent. De Bruecker, Van den Bergh, Belien, & Demeulemeester, (2014) presents a heuristic capacity optimization of aircraft maintenance workforce planning where a dual tabu search is used for cost minimization and fairness enhancement. The complex calculation of the optimal equilibrium between skill specific workload and capacity assignment is discussed in Cuevas et al., (2016). A mixed integer program is used to assign multiskilled employees for shortterm demand fulfilment with a modified version of the general tour scheduling problem. This enables operational managers to assign simultaneous shifts

and days-off for heterogeneous workforce to cater their firms work load demand. However the algorithm is based on many assumptions which dilutes the solution efficiency and workload variations are not considered.

Even though workload variation is rarely analysed in aviation literature, several other fields like nurse scheduling and call center capacity assignment discuss fairness in correlation with variable work load distributions. Swiger, Vance, & Patrician, (2016) indicates that comprehensive workload measurement is crucial for optimal staffing in their study on nurse scheduling. They further highlights task diversity and short term workload fluctuations are to be prominent elements which complicates the staffing decision constrained by competency, contractual agreements and fairness in workload distribution. Lim, Mobasher, & J. Côté, (2012) in their multi-objective nursing capacity assignment model consider cost optimization, patient satisfaction, idle minimization and fairness enhancement as the parallel objectives. The multi-objective optimization is based on variable workload fulfilment where the results highlight fairness, optimal assignment and customer satisfaction are negatively affected by the workload variations(Jorne, Philippe, & Liesje, 2012). Despite the above, there is a big scarcity of literature which discusses the equilibrium off cost and workload variations optimization as a majority discuss either staffing, rostering or restrictive combinations of the two decision problems.

### Problem Setting

The time period dependent diversified jobs are grouped according to operational similarities and are again reassigned to teams of employees. A team comprises of employees who possess similar skills and therefore individual job assignment is done within teams. In majority of the AGO environments, this capacity assignment is done on experience and intuition of Sri Lankan airline operations planners which leads to imbalance workload distributions for employees within and in between teams in terms of capacity and skill compatibility. In order to address this problem, a dual objective optimization model is formulated as below. This is differentiated by the existing practice as it assign workloads to individual employees instead of the intermediate job assignment to teams. A job duration consist of one or more eight hours shifts where the object is to assign employees into those shifts to fulfill the workload while minimizing operational costs and workload variation. This decision is constrained by several factors like job vs skill compatibility, job duration, multiple shift transition vs shift duration alignment, assignment capacity and aircraft parking gate capacity. The data sets, indices and decision variables relevant to the model are defined as below.

#### *Sets variables*

$e \in E$  Set of employees  
 $g \in G$  Set of aircraft parking gates  
 $j \in J$  Set of jobs  
 $s \in S$  Set of skills

$P \in P$  Set of Shifts  
 $d \in P$  Days in planning horizon  
 $G_j$  ( $j^{\text{th}}$ ) Job performed at ( $g^{\text{th}}$ ) gate  
 $T_{e|g}$  Time required for ( $e^{\text{th}}$ ) employee to finish ( $j^{\text{th}}$ ) job in ( $g^{\text{th}}$ ) gate  
 $C_{e|g}$  Hourly cost for ( $e^{\text{th}}$ ) employee to finish ( $j^{\text{th}}$ ) job in ( $g^{\text{th}}$ ) gate  
 $P_d$  Shift duration in hours  
 $I_e$  ( $e^{\text{th}}$ ) employee's workload during job schedule  
 $\bar{I}$  Average work load of all employees  
 $I_u$  Upper bound for number of jobs executed during a shift in a gate  
 $P_u$  Upper bound for number of shifts allowed for employees within the job schedule  
 $F$  Job pairs where ( $j$ ) job is preceded by ( $j'$ )  
 $C_F$  Linear compatibility factor  
 $W_V$  Workload variance  
 $C_c$  Cumulative cost  
 $V_{cc}$  Coverage constraints violation  
 $\delta$  Feasibility coefficient  
 $M_1, M_2, M_3$  Large positive values  
 $E_{es}$  Possession of ( $s^{\text{th}}$ ) skill by ( $e^{\text{th}}$ ) employee  
 $C_{qj}$  Compatibility of ( $q^{\text{th}}$ ) skill ( $j^{\text{th}}$ )  
 $A_{e|g|p}$  Assigning ( $e^{\text{th}}$ ) employee for ( $j^{\text{th}}$ ) job in ( $g^{\text{th}}$ ) gate during ( $p^{\text{th}}$ ) shift  
 $F_{ep}$  Feasible shifts ( $e^{\text{th}}$ ) employee working in ( $p^{\text{th}}$ ) shift

The problem is formulated as a dual objective mixed integer program. The first objective ( $Z_1$ ) is to minimize workforce cost and the parallel objective ( $Z_2$ ) is to minimize workload variance.

$$\text{Minimize } Z_1 = \sum_{p \in P} \sum_{e \in E} \sum_{g \in G} \sum_{j \in G_1} C_{ejg} T_{ejg} A_{ejgp} \quad (1)$$

$$\text{Minimize } Z_2 = \left\{ \frac{\sum_{e \in E} (I_e - 1)^2}{E} \right\} \quad (2)$$

$$\text{s.t. } \sum_{p \in P} \sum_{g \in G} \sum_{j \in G_1} T_{ejg} A_{ejgp} = I_e \quad \forall i \in I \quad (3)$$

$$\bar{I} = \left\{ \frac{\sum_{e=1}^E I_e}{E} \right\} \quad (4)$$

$$\sum_{p \in P} \sum_{e \in E} A_{ejgp} = 1 \quad \forall g \in G, \forall j \in G_1 \quad (5)$$

$$\sum_{e \in E} E_{es} C_{qij} \geq A_{ejgp} \quad \forall g \in G, \forall j \in G_1, \forall p \in P, \forall e \in E \quad (6)$$

$$\sum_{g \in G} \sum_{j \in G_1} T_{ejg} A_{ejgp} \leq P_d \quad \forall p \in P, \forall e \in E \quad (7)$$

$$F_{e(2d)} + F_{e(2d-1)} \leq 1 \quad (d = 1, 2, \dots, \frac{P}{2}), \quad \forall e \in E \quad (8)$$

$$F_{ep} \geq A_{ejgp} \quad \forall g \in G, \forall j \in G_1, \forall p \in P, \forall e \in E \quad (9)$$

$$\sum_{p \in P} F_{ep} \leq P_u \quad \forall e \in E \quad (10)$$

$$\sum_{p \in P} \sum_{j \in G_1} A_{ejgp} \leq j_u \quad \forall g \in G, \forall p \in P \quad (11)$$

$$\sum_{p \in P} \sum_{e \in E} P A_{eg(j)p} \leq \sum_{p \in P} \sum_{e \in E} P A_{eg(j')p} \quad \forall (j, j') \in f \quad (12)$$

The equations (3) and (4) define substitutional values of ( $Z_2$ ) in terms of

squared deviations average value of ( $I_e$ ) and ( $\bar{I}$ ) mean (i.e. to calculate workload distribution variance). Equation no (5) defines the relationship between jobs duration, shift assignment and individuality. In other words, one job is to be carried out by a single employee within a single shift. Constraint (6) define the relationship between job performance and skill requirement where an employee is permitted to carry out a job only if he is skilled to do so. Constraint set (7) limits the working hours of an employee to a maximum of single shift duration. In other words, no employee is permitted to work on two consecutive shifts. Constraint sets (8) & (9) ensure that there is no possibility for continuous shift transition and each employee get to rest in between two shifts. The maximum number of shifts on which an employee works during the planning horizon is restricted by constraint set (10) through an imposed upper limit. This is mainly to ensure that shift assignment is in accordance with the industry related labor regulations. Aircraft parking gate capacity is constrained by several factors such as space, terminal location, distance to runway, and etc. Hence, constraint set (11) define the relationship between job execution and gate capacity during a shift duration. As mentioned earlier, job precedence sequence is important as large scale jobs are decomposed into sub jobs to fit within a shift schedule. However, the correct precedence cannot be overlooked as the primary task should always be followed by the secondary task. Constraint set (12) ensure this precedence sequence in terms of the associated jobs. As most of the workforce

assignment problems, the above problem is also NP-hard making it computationally intricate. It can be easily proven by using a special case of this problem to be equivalent to the known NP-hard knapsack problem. Nonlinearity combined with the NP-hardness makes this problem computational intricate demanding an innovative solution algorithm. Therefore an innovative solution algorithm is desired for feasible solutions where a novel metaheuristic approach is used. A tabular representation of the heuristic solution algorithms is given in Table 1.

Tabu search, one of the proven methods of metaheuristics for these types of operations researches is used for an iterative search sequence of finding feasible solutions in the neighborhood. This solution algorithm is distinguished from the rest by two reasons. First, a novel compatibility criterion is defined to direct the search towards a feasible frontier. Then, the algorithm is customized with an initial solution where aviation two specially designed moves are utilized in the neighborhood search.

Table 1. Heuristic solution algorithm

Step	Process
One →	Initialization
Two →	Initial feasible solution generation and parameter definition for compatibility criterion.
Three →	Feasibility assessment and customized move definition.
Four →	Compatibility assessment relative to customized moves
Five →	Feasible solutions filtration through compatibility score assessment
Six →	Tabu updating (i.e. the list) and Solution assessment (i.e. interms of Feasibility)
Seven →	Compatibility criterion met? Yes → move to next step No → move to step three
Eight →	Stopping criterion met? Yes → END No → move to step two

Fulfilment of the constrained job assignment, skill compatibility and constrained numbered shift transition for the initial solution (i.e. constraint sets 5, 6, 8, 9, 10) are ensured through a two-step

enumeration. Initially, the shift availability is divided in to two domains, in terms of feasible and infeasible shifts. A feasible shift is defined as a ( $p^{th}$ ) shift during which ( $e^{th}$ )employee is detailed work where ( $F_{ep} = 1$ ) and an infeasible

shift is the vice versa of the above where  $(F_{ep'} = 0)$  maximum number of feasible shifts assigned per day are equivalent to one and further  $(F_{ep})$  is constrained by  $(p_u)$  which denotes the upper bound for number of shifts allowed for employees within the job schedule. Subsequently, job vs skill compatibility is ensured by assigning  $(e^{th})$  employee for  $(j^{th})$  job during  $(p^{th})$  feasible shift. However the derived solution's compatibility needs to be evaluated in terms of objective function fulfilment (i.e. in terms of minimal cost and workload variance) and coverage constraint violation  $(V_{cc})$ . Therefore a linear compatibility factor  $(C_F)$  is defined in equation (13) as below which is calculated with workload variance  $(W_v)$ , cumulative cost  $(C_c)$  and coverage constraints violation  $(V_{cc})$  with a variable feasibility coefficient  $(\delta)$ . This allows the feasibility variation in terms of the dual objective functions. For instance if  $(\delta = 0)$  the objective is solely cost minimization and if  $(\delta = 1)$  workload variance minimization is the sole objective.

$$\delta W_v + (1 - \delta) C_c + V_{cc} = C_F$$

$$\forall g \in G, \forall p \in P$$

(13)

Equation (14) defines the coverage constraint violation  $(V_{cc})$  function in terms of parking gate capacity as defined in constraint set (11), shift precedence as in constraint set (12) and shift duration as in constraint set (7) is defined as below where  $(M_1, M_2, M_3)$  are positive big numbers.

$$M_1 \left\{ \sum_{p \in P} \sum_{e \in E} \sum_{g \in G} \sum_{j \in G_j} T_{ejg} A_{ejgp} - \sum_{p \in P} \sum_{e \in E} P_d \right\} +$$

$$M_2 \left\{ \sum_{p \in P} \sum_{e \in E} \sum_{g \in G} \sum_{j \in G_j} A_{ejgp} - \sum_{p \in P} \sum_{g \in G} I_u \right\} +$$

$$M_3 \sum_{(j,j') \in f} \left\{ \sum_{p \in P} \sum_{e \in E} P A_{eg(j)p} - \sum_{p \in P} \sum_{e \in E} P A_{eg(j')p} \right\} = V_{cc}$$

(14)

Solution feasibility is determined by the percentile fulfillment of cost and variance minimization with adherence to coverage constraints. The feasible ones out of all solutions, are compartmentalized separately. During each iteration, the solutions are compared with the available feasible solutions and is added to the selected lot only if it supersedes previously available solution in term of workload variance  $(W_v)$ , cumulative cost  $(C_c)$  and percentile coverage constraints violation  $(V_{cc})$ . In addition, two types of customized moves are used in terms of job transition and shift merging. In job transition moves, a single job is transferred to another employee with the same skill category who is working in different available shift (i.e.  $(e)$  employee's  $(j^{th})$  job during  $(p)$  feasible shift is transferred to  $(e')$  employees in  $(p')$  shift). This enables the exploration of the solution neighbourhood apart from the current solutions in terms of individual tasks and to derive more feasible solutions. In contrast the shift merging move enable complete assignment of a shift to another available shift (i.e.  $(e)$  employee's set of jobs during

( $p$ ) feasible shift is transferred entirely to ( $p'$ ) shift). This type of moves are essential in cases where shift capacity in terms of employees exceeds the parking gate capacity. The neighbor search is carried out accordingly and during each iteration the feasibility frontier and end criterion are checked. When the parking gate capacity and shift precedence constraints are not fulfilled, all possible job transition and shift merging moves are examined where their compatibility is examined as per equation number (14) and the solution with highest compatibility score is selected as the feasible solution. In order to cut down unwanted computational time, the jobs assignment which is once evaluated through job transition move are not examined again as long as it remains in the Tabu list. As indicated in Table.1 once the max number of iterations are reached by the neighborhood search or no further improvements, the iteration returns back to initial with a new start. Then the feasibility coefficient ( $\delta$ ) is increased to ( $\delta + \Delta(\delta)$ ) till ( $\delta \geq 1$ ) which defines the algorithm's end criterion.

#### *Numerical experiment*

In order to derive more insights in to the efficiency and the effectiveness of the proposed model a numerical experiment is conducted based on real-life data of Sri Lankan airlines with regard to assigning technical employees (i.e. maintenance technicians) for ground operations within a duration of four shifts. A set of 210 ground operational jobs are to be conducted at two parking gates on four airliners. A team of 15 employees

with three different skill levels are allocated for these jobs with skills ( $s_1, s_2, s_3$ ) where  $s_1$  is the preliminary level and  $s_3$  being the highest skill level with different unit costs allocated for different skill levels. The equilibrium of workload variance and cumulative cost is derived from the feasibility frontier shown in Figure 1, where individual objective optimization forms the boundaries. Pertaining to this specific experiment the cost minimization objective forms the left most boundary of the feasibility frontier with the gradients of (104.84, 2.38) and the variance minimization objective corresponds to the right most boundary with (110.37, 0.32). Once these attributes are compared with the manual schedule a feasible margin is identified as the gradient (109.23, 0.43) which corresponds to an average 1:50 proportion gradient in terms of variance vs total cost declared by the management. But it is to be noted that this feasibility frontier could easily be varied according to the operational requirements through the above model.

Table 3 depicts the manually prepared detailed capacity assignment plan by operations managers and is compared with Table 4 which indicates the optimal assignment plan derived through the dual objective solution algorithm. This comparison leads to several interesting findings in terms workload variance, cumulative cost and job distribution variance. For this specific problem, the manual assignment (as indicated in Table 3) results in a 22.67% variance (i.e. 1.44hrs from the average employee workload of 6.35hrs) with a standard



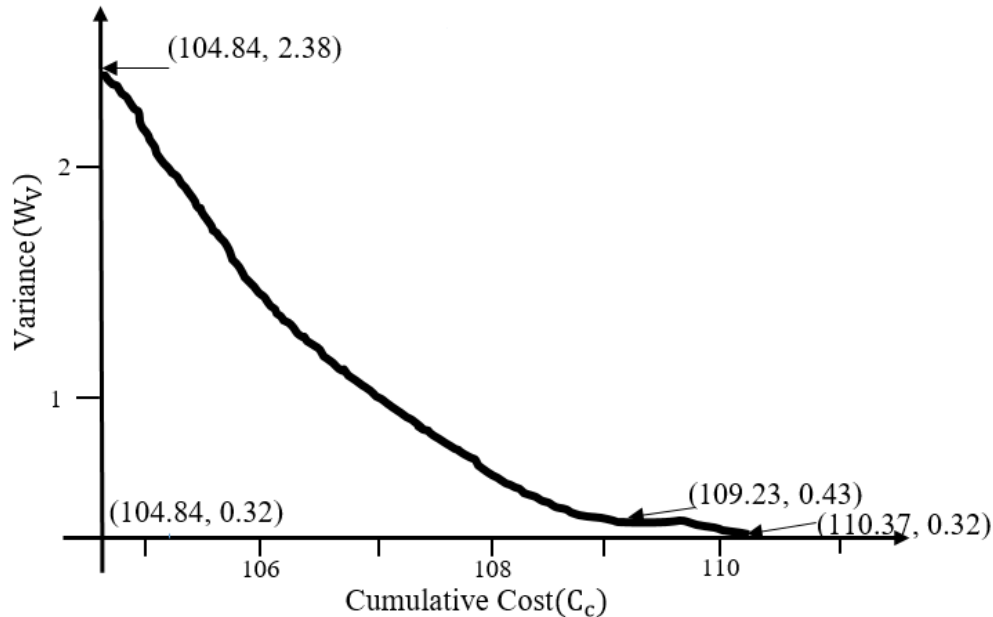


Figure 1. Dual objective feasibility frontier

deviation of 1.12. In comparison, optimal assignment derived through the dual objective solution algorithm (as indicated in Table 4) results in with only 6.77% work load variance (i.e. 0.43hrs from the average employee workload of 6.35hrs) with a standard deviation of only 0.65. In other words, for this specific experiment there is 70.13% improvement in terms of workload variance minimization which is a significant contribution to this area of research. In addition, this improvement is achieved without compensating the cost efficiency as there is a 2.58% cumulative cost reduction in the optimized assignment compared to the manual assignment. In addition, the operational flexibility of the above model is highlighted by the fact that this margin of cost efficiency can

also be easily varied through the feasible solution frontier with relatively higher variance as desired by the operational managers.

The above optimal assignment plan took less than 60 minutes all-inclusive for computation and feasibility frontier analysis compared to the manual plan which on average takes more than half a day for a single planner to finalize. Generally a large number of these types of custom plans are worked every day by a set of experienced planners and our framework will save significant time in this respect as well. In addition, a significant inverse relationship is observed between job distribution variance (i.e. number of jobs assigned for an employee

Table 2. Manual Job assignment by operations mangers

Employee	Skill	Shift	No of Jobs	Workload (hrs)	Unit Cost
e <sub>1</sub>	s <sub>1</sub>	q <sub>1</sub>	5	5.12	5.12
		q <sub>4</sub>	8		
e <sub>2</sub>	s <sub>2</sub>	q <sub>2</sub>	6	7.22	8.66
		q <sub>3</sub>	6		
e <sub>3</sub>	s <sub>1</sub>	q <sub>2</sub>	6	6.31	6.31
		q <sub>4</sub>	8		
e <sub>4</sub>	s <sub>2</sub>	q <sub>1</sub>	8	8.26	10.32
		q <sub>2</sub>	7		
e <sub>5</sub>	s <sub>3</sub>	q <sub>2</sub>	8	4.87	7.79
		q <sub>4</sub>	9		
e <sub>6</sub>	s <sub>1</sub>	q <sub>2</sub>	5	6.02	6.02
		q <sub>4</sub>	8		
e <sub>7</sub>	s <sub>2</sub>	q <sub>2</sub>	6	7.22	9.02
		q <sub>1</sub>	6		
e <sub>8</sub>	s <sub>1</sub>	q <sub>2</sub>	6	6.31	6.31
		q <sub>4</sub>	8		
e <sub>9</sub>	s <sub>2</sub>	q <sub>1</sub>	8	7.36	7.36
		q <sub>4</sub>	7		
e <sub>10</sub>	s <sub>3</sub>	q <sub>2</sub>	8	4.65	5.81
		q <sub>4</sub>	9		
e <sub>11</sub>	s <sub>1</sub>	q <sub>1</sub>	5	5.34	5.34
		q <sub>4</sub>	8		
e <sub>12</sub>	s <sub>2</sub>	q <sub>2</sub>	6	7.31	9.13
		q <sub>3</sub>	6		
e <sub>13</sub>	s <sub>1</sub>	q <sub>2</sub>	6	5.22	5.22
		q <sub>4</sub>	5		
e <sub>14</sub>	s <sub>2</sub>	q <sub>1</sub>	8	8.56	10.7
		q <sub>2</sub>	7		
e <sub>15</sub>	s <sub>3</sub>	q <sub>2</sub>	8	5.57	8.912
		q <sub>4</sub>	9		
Total			210	95.34	112.05
Work load Average		6.35			
Work load Variance		1.44			
Work load Std. Dev		1.12			
Job distribution Average		7			
Job distribution Variance		1.6			
Job distribution Std. Dev.		1.26			

Table 3. Optimal job assignment

Employee	Skill	Shift	No of Jobs	Workload (hrs)	Unit Cost
$e_1$	$s_1$	$q_1$	7	6.61	6.61
		$q_2$	5		
$e_2$	$s_2$	$q_2$	8	5.92	7.10
		$q_3$	10		
$e_3$	$s_1$	$q_2$	9	7.26	7.26
		$q_4$	4		
$e_4$	$s_2$	$q_2$	1	6.13	7.66
		$q_4$	4		
$e_5$	$s_3$	$q_1$	14	5.86	9.37
		$q_2$	9		
$e_6$	$s_1$	$q_4$	7	6.81	6.81
		$q_3$	5		
$e_7$	$s_2$	$q_2$	11	5.67	7.08
		$q_4$	14		
$e_8$	$s_1$	$q_1$	9	7.31	7.31
		$q_4$	4		
$e_9$	$s_2$	$q_2$	1	6.13	7.66
		$q_4$	4		
$e_{10}$	$s_3$	$q_2$	10	5.23	6.53
		$q_3$	5		
$e_{11}$	$s_1$	$q_1$	7	6.91	6.91
		$q_3$	5		
$e_{12}$	$s_2$	$q_2$	11	5.92	7.40
		$q_3$	8		
$e_{13}$	$s_1$	$q_2$	9	7.56	7.56
		$q_4$	4		
$e_{14}$	$s_2$	$q_2$	1	6.13	7.66
		$q_4$	4		
$e_{15}$	$s_3$	$q_1$	9	5.89	6.47
		$q_3$	11		
Total			210	95.34	109.23
Work load Average		6.35			
Work load Variance		0.43			
Work Std. Dev		0.65			
Job distribution Average		7			
Job distribution Variance		12.13			
Job distribution Std. Dev.		3.48			

within a shift) and the workload variance. The job distribution variance of the manual assignment is 1.6 compared to the significantly high variance of 12.13 of the optimized assignment. The anomalies in manual assignment are mainly due to this as managers tend to balance a relative average balance on job assignment (i.e. number of jobs assigned to an employee during a shift) to ensure workload distribution fairness among employees. However in reality, the duration of the jobs vary with the skills associated and type of airliners involved and the skill specific heterogeneous workload distribution demands a highly scattered job assignment plan to achieve optimal results which sometime may not be fully favourable from the employees' perspective.

#### Discussion

This paper presents optimization based dual objective workforce capacity assignment model which assign employees for airline ground operations at minimal cost with least workload variance constrained by skill diversity, parking gate capacity and shift transition constraints. A nonlinear integer program is solved through a metaheuristic Tabu Search algorithm with a novel compatibility function and two types of innovative neighborhood search moves in terms of job transition and shift merging. Solution feasibility is determined by the percentile fulfillment of cost and variance minimization with adherence to coverage constraints. The equilibrium of workload variance and cumulative cost is derived from a feasibility frontier

where individual objective optimization forms the extreme feasible solutions. The solution framework address the interdependent problems of cost and variance which enables airline operation managers to comprehensively evaluate the workforce assignment in terms of variance and cumulative cost.

The heuristics solutions are compared with a manual assignment schedule which highlights several interesting findings. The manual assignment results in a 22.67% variance with a standard deviation of 1.12 where dual objective optimal assignment results with only 6.77% variance which is a 70.13% improvement in terms of workload variance minimization. This is the main mode of novelty in terms of literature which is a significant contribution to this area of research. In addition, this improvement is achieved with a cohesive cost efficiency of 2.58% cumulative cost reduction compared to the existing framework. Our framework is highly efficient in terms of time saving aspect as it took less than 60 minutes compared to the manual plan which on average takes more than half a day where a large number such assignment plans are needed on daily basis. In addition, the proposed model enhances the operational planning flexibility of workforce capacity assignment as the margin of cost efficiency can varied through the feasible solution frontier proportionate to workload variance and vice versa through the proposed model as desired by the operations planners. Moreover, a significant inverse relationship is observed between job distribution variance

and the workload variance where manual assignment incorporates a 1.6 unit job variance compared to significantly high 12.13 unit job variance of the optimized assignment. This clearly justify the anomalies in manual assignment as it is mainly due to the fact planners always try to balance the number of jobs assigned to an employee during a shift to ensure workload distribution fairness. In contrast it is seen that individual job durations vary in a large spectrum with the

skills associated and type of airliners involved. The skill specific heterogeneous workload distribution demands a highly scattered job assignment plan to achieve optimal results which sometime may not be highly favourable from the employees' perspective. So a managerial intervention is highly desirable to maintain the equilibrium of coat and workload variance in order to attain optimal results.

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