Multiobjective Optimization of Airline Crew Roster Recovery Problems Under Disruption Conditions

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***Abstract*—This paper proposes an evolutionary approach for optimizing crew roster recovery (CRR) problems, in which rosters for multiday flight duties are reassigned after disruptions, under a set of constraints involving practical management issues, safety regulations, and preallocated activities. In the proposed approach, CRR problems are first formulated as combinational optimization problems containing multiple objectives and constraints, and a variant of the nondominated sorting genetic algorithm II method is used to explore Pareto solutions. To analyze the effectiveness of the proposed approach, a real-world rostering problem was studied. For the test instance, experimental results showed the advantages of the proposed approach compared with previous work in the literature. By simulating disruption events on the real-world rostering plan, we studied two recovery scenarios containing sufficient and insufficient available crews in the experiments. In particular, a constraint-loosening mechanism that conditionally replaced preallocated tasks with flight duties was proposed in a resource-shortage case to explore the Pareto solutions. The experimental results show that the proposed approach attains a favorable solution quality and can generate multiple recovery plans for decision makers.**

***Index Terms*—Combinational optimization, crew rostering, evolutionary optimization, recovery schedule.**

I. Introduction

AIRLINE crew scheduling usually contains two consequent phases [1]: crew pairing and crew rostering. In crew pairing, flight duties are first divided into pairings [2], after which a rostering operation is designed to arrange all the duty pairings for crews [3]. According to the scheduling coverage, rostering problems are generally classified into three types [4]: 1) shift, or working time of the day, scheduling; 2) days-off, or nonworking days of the week, scheduling; and 3) tour scheduling, which combines the first two types. This paper focuses on tour-type crew rostering, which is required not only for dispatching flight duties and rest time for crews in a multiday period but also for adjusting practical preallocated activities such as flight examinations and meetings for crews. In general, an approach proposed for optimizing tour scheduling problems must handle both shift and day-off requirements in a single flow. Therefore, the challenge of tour scheduling is relatively larger than that of regular scheduling tasks.

In particular, if disruption events, such as mechanical problems and unexpected crew unavailability, occur in the execution phase of rostering, a recovery operation should be initiated to renew the rostering plan [5]. In the literature, two types of approach are proposed for solving recovery problems. One approach is to preinclude possible disturbance tolerances into the planning phase, which is sometimes specified as robustness scheduling. The main consideration for robustness is that disruptions originating from interrupted events are less likely to cause changes in subsequent duties under a robust schedule [6]. Yen and Birge [7] formulated the robust crew scheduling problem for flight delays as a two-stage integer stochastic program, in which the first stage is the crew-scheduling problem and the second stage involves delay penalties. Ehrgott and Ryan [8] also studied robust crew schedules on the basis of a measure for avoiding disruptions. They developed a bicriteria problem to obtain Pareto optimal crew schedules in which the robustness of the roster was measured by the anticipated amount of change in aircraft historical data. Their results showed that at a small cost, robustness can be built into generated rosters. Schaefer *et al.* [9] proposed a stochastic extension to the deterministic crew scheduling problem and developed an objective function by measuring the operational costs with delay penalties for possible disruption. They solved the optimization problem by using the parallel primal–dual simplex algorithm. Clausen *et al.* [10] provides a more complete survey on approaches for crew scheduling and recovery.

The other approach is to recover the schedule directly according to practical situations. Lettovský *et al.* [11] used preprocessing techniques to extract a subset of the schedule, and developed a fast pairing generation method that enumerated feasible continuations of partially flown crew trips. A tree-based framework was used to reassign crews to restore a disrupted crew schedule. In this manner, the original schedule was disturbed as little as possible in determining an optimal recovery schedule. Abdelghany *et al.* [12] proposed a decision support tool for airlines that adopted the hub-spoke network structure. In the tool, the schedule is recovered by means of delaying, swapping, deadheading, and using standby crews.

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However, because of the stepwise flow, it is a sub-optimal solution approach. Guo *et al.* [13] proposed a genetic algorithm to explore the recovery schedule. In the evolutionary process, the disrupted flights are reassigned, and a local search mechanism is used to improve the slow convergence problem. Chen *et al.* [14] studied the fleet factor for the crew recovery problem. If an interfleet model is used, a superior solution can be obtained in comparison to a general approach based on an intra-fleet model. Chang [15] proposed an efficient approach that adopts a duty-based model with a dynamic leg binding mechanism and uses genetic algorithms to obtain the crew recovery schedule. In the model, the rotation generation is eliminated to enable the recovery application to handle flight legs directly. However, these studies have not been verified as suitable for multiday roster recovery with multiple objectives and constraints.

In this paper, a direct recovery approach is studied. We first formulate the crew roster recovery (CRR) problem as a multiobjective combinational optimization problem [16] with NP-hard complexity [17]. That is, as the problem size becomes large, the number of the combinations of crew and duty assignments in the solution space grows exponentially. A global exhaustive search for this type of problems is impossible; therefore, we employed a multiobjective optimization genetic algorithm (MOGA), a variant version [18] of the nondominated sorting genetic algorithm II (NSGA-II), as the global solver. In the NSGA-II variant, a hybrid crowding sort is adopted for the front reservation in order to improve the convergence of the NSGA-II in highly constrained problems.

To verify the effectiveness of the proposed approach, a real-world crew rostering problem was studied to compare the performance with the work of Jeng *et al.* [19]. The results suggest the advantages of the proposed approach. Disruption events were then simulated and a CRR operation was initialized. The studied CRR problem contains a group of pairings to be reassigned to crews during a biweekly period after the disruption. The practical constraints of the CRR problem, such as legal working days and preallocated activities, must also be considered in the recovery process to optimize multiple objectives. Furthermore, for cases where the recovery schedule cannot be obtained because of tight resources after the disruptions, a constraint-loosening mechanism (CLM) is proposed to enable the evolutionary cancellation of flexible nonflight tasks. Through implementation of the CLM method, our proposed approach can recover the rostering schedule from severe disruptions.

II. Problem Definition and Formulation

In airlines, practical rostering operations generally involve arranging lines of work for a biweekly or monthly period. However, the planned schedule may be interrupted because of unexpected disruptions. A common method to solve the interruption is to make a recovery plan. The general goal of roster recovery is to renew the schedule as close as possible to the original one. In other words, the difference between the recovery schedule and the original plan should be minimized to narrow the disruption effect. However, in practice, the difference is multifaceted and cannot be easily measured by a simple cost value but rather by several criteria related to practical resource or management issues.

A. Multiobjective Roster Recovery

In general, even a simple disruption in schedule execution may require a series of changes to complete the execution, for example, additional overloads assigned for some crews, flight tasks exchanged between crews or even the cancellation of some preallocated tasks. Therefore, practical recovery rosters typically focus on the minimization of side effects related to flight duties because these involve not only crews but airline flights and passengers.

In this paper, we study several objectives to measure the difference between the original roster plan and the recovery schedule. The first group of objectives tends to minimize the effects of flight duty changes after recovery, in which the flight duty changes for each crew, the total number of flight duty changes, the largest duty change number for a crew, and the derivation of the changed duties are the main targets. The second group of objectives measures the influence or overhead from a change in flight time, which contains two objectives: 1) the largest changed flight-time for a crew and 2) the derivation of the changed flight time. These objectives cannot be independently solved because of the mutual interactions between objectives. A multiobjective reasoning among them is the typical method to represent the actual tradeoff between objectives [20].

While reasoning the objectives, several constraints exist, mainly related to safety regulations, and cost and management issues in airline rostering practices. This paper focuses on the practices of a short-haul airline in Taiwan. The studied airline has prepared daily pairings according to safety regulations. Therefore, some constraints in a pairing, for example, the daily flight time, the daily flight period, deadhead flights in a duty, turn-around time, and flow connection [21], have met the short-haul airline's requirements. The main focus of the rosters is on the constraints crossing multiday periods including the multiday flight time and consecutive working day constraints.

To optimize the specified objectives under the constraints, we formulated the CRR problem as a constrained combinational optimization problem. Although different airline companies may have different affairs, they can modify or replace the aforementioned constraints and objectives but use the same evolutionary reasoning and execution flow of the proposed approach to solve their CRR problems.

B. Formulation of the Roster Recovery Problem

A multiday rostering schedule is modeled as a duty assignment matrix as follows:

$$R = \begin{bmatrix} r_{1,1} & & \cdots & & r_{1,\beta} \\ & \ddots & & & \\ \vdots & & r_{i,j} & & \vdots \\ & & & \ddots & \\ r_{\alpha,1} & & \cdots & & r_{\alpha,\beta} \end{bmatrix} \tag{1}$$

where α is the number of crews, β is the days in the schedule period, and $r_{i,j}$ is a task assignment denoted as the task assigned for the ith crew on the jth day. Each rostering task is a vector of attribute $\langle s\tilde{p}, \hat{s}, \bar{s}, \hat{t}, \bar{t}, \tilde{t}, \hat{\mu}, \bar{\mu}, \bar{v}\rangle$ where the attribute $\tilde{p}$ is defined as follows:

$$\tilde{p} = \begin{cases} 0, & \text{if a stand by or day-off} \\ -1, & \text{if a preallocated task} \\ \text{positive value}, & \text{if a flight-duty pairing.} \end{cases} \quad (2)$$

If $\tilde{p}$ is a nonpositive value (not a flight-duty pairing), all the other attributes are set to zeros. If $\tilde{p}$ is a flight-duty pairing, the other attributes are defined as follows.

1) $\hat{s}, \bar{s}$: The start and end stations.
2) $\hat{t}, \bar{t}$: The start and end times.
3) $\tilde{t}$: The actual flight time.
4) $\hat{\mu}$: The number of the deadhead linking the home base and start station.
5) $\bar{\mu}$: The number of the deadhead linking the end station and home base.
6) $\bar{v}$: The layover (overnight duty) count of $\tilde{p}$.

On the basis of these definitions, we can formulate the objectives and constraints.

1) Objectives of the Roster Recovery Criteria: Suppose that the original rostering plan is $R = \{r_{i,j} | 1 \leq i \leq \alpha, 1 \leq j \leq \beta\}$ and the recovery schedule is defined as $R' = \{r'_{i,j} | 1 \leq i \leq \alpha 1 \leq j \leq \beta\}$ where $r'_{i,j}$ is the recovery task assignment containing recovery attributes $\langle \tilde{p}', \hat{s}', \bar{s}', \hat{t}', \bar{t}', \tilde{t}', \hat{\mu}', \bar{\mu}', \bar{v}'\rangle$. The objectives of the roster recovery are formulated as follows.

1) The crew change objective evaluates the number of crews whose duties are changed after the recovery operation. The evaluation function is formulated as follows:

$$\theta_1(R, R') = \sum_{i=1}^{\alpha} x_i^1 \quad (3)$$

where if

$$x_i^1 = \begin{cases} 0 & \sum_{j=1}^{\beta} y_{i,j}^1 = 0, \\ 1, & \text{otherwise} \end{cases} \quad y_{i,j}^1 = \begin{cases} 0, & r_{i,j} = r'_{i,j} \\ 1, & \text{otherwise.} \end{cases}$$

2) The duty change objective evaluates the total number of duty tasks assigned for different crews. The evaluation function is formulated as follows:

$$\theta_2(R, R') = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} x_{i,j}^2 \quad (4)$$

where if

$$x_{i,j}^2 = \begin{cases} 0, & r_{i,j} = r'_{i,j} \\ 1, & \text{otherwise.} \end{cases}$$

3) The maximal duty changes for a crew objective evaluates the maximal number of duty changes for a crew. The evaluation function is formulated as follows:

$$\theta_3(R, R') = \max_{i=1}^{\alpha} x_i^3 \quad (5)$$

where if

$$x_i^3 = \sum_{j=1}^{\beta} y_{i,j}^3 \quad y_{i,j}^3 = \begin{cases} 0, & r_{i,j} = r'_{i,j} \\ 1, & \text{otherwise.} \end{cases}$$

4) The largest changed flight time for a crew objective computes the flight time change for each crew, the aim of which is to minimize the maximal change value after disruptions. The evaluation function is formulated as follows:

$$\theta_4(R, R') = \max_{i=1}^{\alpha} x_i^4 \quad (6)$$

where if

$$x_i^4 = \sum_{j=1}^{\beta} \left(\left(\hat{t}'_{i,j} - \bar{t}'_{i,j} \right) - \left(\hat{t}_{i,j} - \bar{t}_{i,j} \right) \right).$$

5) The derivation of the changed duties objective evaluates the derivation value of the changed duties of crews. The evaluation function is formulated as follows:

$$\theta_5(R, R') = \sqrt{\frac{1}{\alpha} \sum_{i=1}^{\alpha} \left(x_i^5 - \mu^5\right)^2} \quad (7)$$

where if

$$x_i^5 = \sum_{j=1}^{\beta} y_{i,j}^5, \quad y_{i,j}^5 = \begin{cases} 0, & r_{i,j} = r'_{i,j} \\ 1, & \text{otherwise} \end{cases}$$

$$\mu^5 = \frac{1}{\alpha} \sum_{i=1}^{\alpha} x_i^5.$$

6) The derivation of the changed flight time objective evaluates the derivation value of the changed flight time of crews. The evaluation function is formulated as follows:

$$\theta_6(R, R') = \sqrt{\frac{1}{\alpha} \sum_{i=1}^{\alpha} \left(x_i^6 - \mu^6\right)^2} \quad (8)$$

where if

$$x_i^6 = \sum_{j=1}^{\beta} \left(\left(\hat{t}'_{i,j} - \bar{t}'_{i,j} \right) - \left(\hat{t}_{i,j} - \bar{t}_{i,j} \right) \right) \quad \mu^6 = \frac{1}{\alpha} \sum_{i=1}^{\alpha} x_i^6.$$

2) Practical Constraints: Because some basic constraints have been met in the pairing operation, the studied roster recovery constraints are formulated as follows.

1) The legal home base assignment constraint avoids the wrong assignment of a pairing to a crew where the departure station of the pairing is different from the home base of the crew. This case is illegal for a short-haul airline. The evaluation function is formulated as follows:

$$\eta_1(R') = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} \tilde{x}_{i,j}^1 \quad (9)$$

where if

$$\tilde{x}_{i,j}^1 = \begin{cases} 1, & \text{if } \hat{s}'_i \notin H \text{ or } \bar{s}'_i \notin H \\ 0, & \text{otherwise} \end{cases}$$

and H denotes the legal home base set. It is noted that because multihome bases are considered, an overnight duty (layover) in this paper case is not the main focus.

2) The multiday flight time constraint constrains the flight time of a crew during the time period of the schedule. The evaluation function is formulated as follows:

$$\eta_2\left(R'\right) = \sum_{i=1}^{\alpha} \tilde{x}_i^2 \tag{10}$$

where if

$$\tilde{x}_i^2 = \begin{cases} 0, & \text{if } \sum_{j=1}^{\beta}\left(\bar{t}_i' - \hat{t}_i'\right) \le T_{\mathrm{MFT}} \\ 1, & \text{otherwise} \end{cases}$$

and T_{MFT} is a customizable constant that denotes the upper bound limit of the flight time in the multiday period.

3) The one day leave in seven consecutive days constraint ensures that the working days meet safety rules. However, it is only a basic constraint during working days; in most situations, the rosters assign more free-days for crews. The evaluation function is formulated as follows:

$$\eta_3\left(R'\right) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta-7} \prod_{k=1}^{j+7} \tilde{x}_{i,k}^3 \tag{11}$$

where if

$$\tilde{x}_{i,k}^3 = \begin{cases} 0, & \text{if } \bar{p}_{k,d}' = 0 \\ 1, & \text{otherwise.} \end{cases}$$

This constraint takes both flight and nonflight duties into consideration. The airline requires that there is at least one day of leave in seven consecutive days.

Equations (9)–(11) formulate the studied constraints into three evaluation functions $\eta_1(R')$, $\eta_2(R')$, and $\eta_3(R')$. For a valid schedule, the constraint values should all be 0 as formulated in the optimization problem.

C. Additional Objectives From the CLM

If the recovery schedule cannot be obtained because of tight resources after the disruption, a possible solution is to adjust some constraints that can be conditionally cancelled. In this paper, we study a CLM to demonstrate this recovery practice. Under this mechanism, the preallocated nonflight activities of crews are first divided into two categories: 1) must-have and 2) nice-to-have. The must-have tasks cannot be changed but nice-to-have tasks can be replaced with flight duties. The categorized decision depends on the practices of individual airlines. This method increases the flexibility and possibility for roster recovery. However, it is still necessary to monitor the usage of task replacements. Therefore, a special objective is designed, and its value is evaluated by the number of the replaced nice-to-have tasks. The evaluation function is formulated as follows:

$$\theta_7\left(R, R'\right) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} x_{i,j}^7 \tag{12}$$

where if

$$x_{i,j}^7 = \begin{cases} 1, & \text{if}(r_{i,j} \text{ is "nice-to-have") and } \left(r_{i,j}' > 0\right) \\ 0, & \text{otherwise.} \end{cases}$$

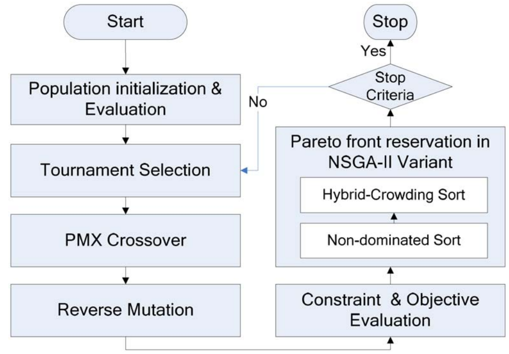

Fig. 1. Variant flow of the NSGA-II method.

D. Multiobjective Optimization Problems

According to the formulations in the previous sections, the optimal CRR problems are defined as follows:

$$\begin{aligned} &\text{Minimize} && \theta_i\left(R, R'\right), 1 \le i \le 6 \\ &\text{Subject to} && \eta_j\left(R'\right) = 0, 1 \le j \le 3. \end{aligned} \tag{13}$$

It is noted that when using the CLM in the solver, the additional objective specified in (12) is included into the optimization problem, and there are a total of seven objectives in the optimal CRR-CLM problem under the insufficient resource condition.

III. Solution by Using Variant of the NSGA-II Method

Evolutionary algorithms (EAs) use a population-based schema to explore the solutions in generations [22]. This feature makes EAs suitable for maintaining a set of nondominated solutions that forms a Pareto front in the population. To ensure the solution quality, various multiobjective objective evolutionary algorithms have developed different front reservation mechanisms [23]–[25]. The well-known NSGA-II [26] first adopts a nondominated sorting in the population to identify the fronts in population individuals, and then performs a crowded distance sort (CDS) on the fronts to obtain an improved and diverse population to join the new generation for evolution. Because of its effectiveness in locating the Pareto front, many researchers have reported the advantages of the NSGA-II method for solving multiobjective optimization problems (MOPs) [27], [28]. However, there is still room for improvement in terms of the convergence performance of the NSGA-II. Therefore, a variant of NSGA-II was proposed in our previous work [18] for a global solver of MOPs. In this paper, we only summarize the kernel flow of the NSGA-II variant (our previous study provides full details for the NSGA-II variant).

The algorithm flow of the variant version is shown in Fig. 1. Like the original NSGA-II, the front reservation mechanism is used in the population replacement phase. However, the variant adopts a different reservation mechanism that uses both the CDS and the genotype distance sort (GDS) to obtain a larger diversity in the population. The pseudosteps of the NSGA-II variant are summarized in Algorithms 1–3.

Algorithm 1 Variant of the NSGA-II Method

Input:
1) A (parent) population P.
2) Generic parameters such as the offspring size, crossover rate and mutation rate.
3) The stop criteria.

Output: The population containing the optimal solutions.

Begin
  Initialize the population.
  Evaluate the application-specific constraint violations and objective values of P.
  Repeat
    Choose the individuals of P into the offspring C by using the tournament selection method.
    Perform crossover and mutation operations on the individuals of C.
    Evaluate the application-specific constraint violations and objectives of C.
    Let Q=P+C, and perform a nondomination sort on Q.
    Call the *hybrid crowding method* on Q to obtain a new parent population and replace P.
  Until (the stop criteria is met).
End.

Algorithm 2 Hybrid Crowding Method

Input:
1) Fronts $f_1, \cdots, f_k$ after the non-domination sort where $f_i.n$ denotes the individual number in front f_i.
2) ρ is the customization ratio constant for bounds, $\rho \in [0.5, 1]$.
3) l is the total individual number to be reserved.

Begin
  Set m to be the parent size.
  For i=1 to k,
    If $f_i.n$ is less than or equal to $\rho \times m$ **Then**
      Reserve all individuals of f_i.
      $m = m - f_i.n$.
    Else
      Execute the CDS on f_i to select$(\rho \times m)/2$.
      Execute the GDS on the unselected individuals of f_i.
      Select and reserve the other $(\rho \times m)/2$.
      $m = m \times (1 - \rho)$.
    End IF
  Next i
  (After the *for-loop*, m is not zero.)
  Select m/2 from the superior unselected individuals.
  Randomly select the other m/2 from the others.
End

In the algorithm, both the CDS and GDS methods are used to decide the reservation of the Pareto fronts. The CDS maintains the diversity of the objective domain and the GDS maintains the diversity in the genotype space. The hybrid crowding method can improve premature convergence under highly constrained conditions.

Algorithm 3 GDS

The pseudosteps of GDS are specified as follows:

Input:
  Population $P=\{P_1, \ldots, P_m\}$with size m for elimination evaluation.

Begin
  Define the genotype distance array: $G=\{G_1, \ldots, G_m\}$.
  For each i, $G_i = 0$.
  For each i,$1 \leq i \leq m$,
    For each j, $1 \leq j \leq m$,
      Compute the Hamming distance, h, of Pi and Pj.
        $G_i = G_i + h$.
    Next j
  Next i
  Sort G in a descent order.
End

A. Encoding and Decoding

Order-based coding was used in the encode schema. We first collected and sorted the crew members who have not been assigned with preallocated tasks in scheduling days. These crews are called "free crews" in this paper. The genes in a chromosome represent the identifiers for the free crews, which are sequentially dispatched to the planned duty pairings in the decode phase. In general, the number of free crews should be larger than or equal to the flight-duty number. Otherwise, the task assignment decoded from the chromosome is infeasible because some flight duties have no crews to execute them.

After the disruption, some resources may be lacking and the CLM is considered in the coding phase to include both the free crews and crews with preallocated nice-to-have tasks in the chromosome.

B. Genetic Operators

A tournament selection [29], [30] was used to cooperate with the constraint-domination rule [26] to select the best-fit individuals for the mating pool. The partially mapped crossover method [31] was used to produce offspring because it is effective for order-based coding as discussed in [32]. A reverse mutation was used for the mutation operator, which reversed the genes between two randomly selected gene positions.

IV. Experimental Results

In general, it is more convincing to compare and analyze the solution capabilities of different methods based on the same problem. Therefore, we first studied a real-world rostering problem in a short-haul airline, which was examined by the previous method of inequality-based multiobjective genetic algorithm (MMGA) work [19] in the literature. We used the NSGA-II variant to explore the Pareto solutions and compared the results. After the study, disruption events originating from unexpected crew leaves were simulated and applied to the real-world rostering schedule. We used this scenario to validate the recovery capability of the proposed approach.

TABLE I
REAL-WORLD BIWEEKLY DUTY PAIRINGS

DAY	DAILY PAIRINGS
#1	M05b, K, M03a, P1, M, D, M07, M01b, M03b, M02a, M02b, M06, M05a, M01a, M04a, P
#2	M06b, M06a, N1, M13b, I, M04a, M03b, M01, M12, M, M07, M05a, M05b, M02, M13a, M03a, H, N, M04b
#3	M04a, P1, I, M01a, M, M03a, M07, D, P, M01b, M03b, M02a, M05a, M02b, M06, M04b, M05b
#4	M01aq, M07, M03aq, M13ap, M02aq, M, M03bp, M05b, I, M05a, D, M01bp, N, P, M02b, M13bp, M04a, M06p
#5	K, M01aq, N, M06p, M03aq, M, I, M05a, M02bp, M07, M02aq, M04bq, M03bp, D, M04a, M05bp, M01bp, P1
#6	M05b, N1, M02aq, M04a, M06p, M01aq, P, M01bp, M03aq, H, M03bp, I, M07, M, M02b, M13ap, M05a
#7	M03a, D, M07, M03b, M05b, M05a, I, K, M02a, M01a, M02b, M, M06, P, P1, M01b, M04a
#8	D, M13a, M07, M03ar, M05bp, M01bp, I, N, M03bq, M02aq, M, M05ap, M04b, P1, M06a, M06b, M04ar, M01aq, M13b, M02bq
#9	M, N1, M04ap, M12, M07, M04b, M13a, I, M03ap, M03bp, M01, M02, M06b, N, H, M05ap, M05bp, M13b, M06a
#10	M04aq, M01bp, M02ap, M06, D, I, P1, M03aq, M, M07, M03bp, M02b, M05ap, M05b, M04bp, M01ap, P
#11	M01aq, M02aq, M07, D, M06p, M, M05a, M03aq, M02b, I, N, M01bp, M03bp, P, M13bp, M05b, M04a, M13ap
#12	M04a, I, M03bp, P1, M02aq, M03aq, M06, M, D, M04br, K, M07, M03bp, M01bp, M02bp, M01aq, N, M05bp, M05a
#13	M02aq, N1, M03aq, I, M06p, M03bp, M04a, M13bp, M01bp, M05b, M, M07, M13ap, M05a, P, M02b, M01aq, H
#14	P1, M01bp, M02aq, M01aq, M03ar, M03bq, N, I, M06b, D, M05bp, M, M07, M06a, M04ar, M04b, M02bq, M05ap, M13b, M13a
#15	M07, D, M01a, M, I, P, M04a, M03a, M01b, M02a, M03b, M06, K, M05a, M02b, M05b, P1

TABLE II
REAL-WORLD FLIGHT DATA IN THE EXAMPLE PAIRINGS

DUTY CODE	DUTY DEPT	Flt.No	803	810	809	816	821	FDP
		Sector	TSA-KHH	KHH-TSA	TSA-KHH	KHH-TSA	TSA-KHH	0935
M01a	TSA	ETD	07:50	09:10	10:40	12:40	15:20	FT
	0705	ETA	08:40	10:00	11:30	13:30	16:10	0410
DUTY CODE	DUTY DEPT	Flt.No	808	807	814	889	890	FDP
		Sector	KHH-TSA	TSA-KHH	KHH-TSA	TSA-KNH	KNH-TSA	0750
M02a	KHH	ETD	08:20	09:45	11:05	12:30	14:00	FT
	0735	ETA	09:10	10:35	11:55	13:25	14:55	0420
DUTY CODE	DUTY DEPT	Flt.No	806	805	812	811		FDP
		Sector	KHH-TSA	TSA-KHH	KHH-TSA	TSA-KHH		0625
M03a	KHH	ETD	07:20	08:50	10:10	11:40		FT
	0635	ETA	08:10	09:40	11:00	12:30		0320

A. Rostering Results Using Different MOGA Methods

The airline in the case study generated a multiday pairing table in the crew pairing operation before the rostering operation. Table I shows the real-world biweekly pairings created by experts, in which there were total 270 pairings and 1048 flights in the problem. Table II lists the activities in the case study. Table III shows the pairing content table in which 51 templates were used in the pairing operation. Each pairing template contained the summary of a duty including the duty code name, the departure airports and times, the flight duty period (FDP) and the flight time. In practice, the rostering operation should consider the preallocated activities of crews. Table IV shows the real-world flights in some pairings for reference. Because the crew number was fixed in the experiments, the crew cost arising from the crew salaries was also fixed, and the focus was mainly on the minimization of differences related to the flight-duty assignments in the recovery schedules.

The previous work [19] studied four objectives to qualify rostering schedules including the day-off (DO), positioning nonduty crews (PNCs), the ratio of the total flight time period to the total flight time (FT/FDP), and flight time equalization (FT-STD). These objectives are summarized as follows.

The DO objective is a maximum-based objective for evaluating the number of free crews and is defined as follows:

$$\phi_1(R) = \sum_{i=1}^{\alpha} \bar{x}_i^1 \tag{14}$$

where

$$\bar{x}_i^1 = \begin{cases} 1, & \sum_{j=1}^{\beta} \bar{y}_{i,j}^1 = 0, \\ 0, & \text{otherwise,} \end{cases} \quad \bar{y}_{i,j}^1 = \begin{cases} 1, & \tilde{p}_{i,j} = 0 \\ 0, & \text{otherwise.} \end{cases}$$

The PNC objective is a minimum-based objective because it requires extra costs. The evaluation function is defined as follows:

$$\phi_2(R) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} \bar{x}_{i,j}^2 \tag{15}$$

where

$$\bar{x}_{i,j}^2 = \begin{cases} 3, & \text{if } \hat{\mu}_{i,j} \neq 0 \text{ and } \bar{\mu}_{i,j} \neq 0 \\ 1, & \text{else if } \hat{\mu}_{i,j} \neq 0 \text{ or } \bar{\mu}_{i,j} \neq 0 \\ 0, & \text{otherwise.} \end{cases}$$

It is noted that for the rostering case with two PNC flights (using PNC flights at both the beginning and end of a duty pairing), the value is set to 3 to include a penalty.

The FT/FDP is a minimum-based objective and is defined as follows:

$$\phi_3(R) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} \tilde{t}_{i,j} \Big/ \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} \left(\bar{t}_{i,j} - \hat{t}_{i,j}\right). \tag{16}$$

The FT-STD objective is also a minimum-based objective and is evaluated through the standard deviation of the flight time assigned to the crews. Its equation is defined as follows:

$$\phi_4(R) = \sqrt{\frac{1}{\alpha} \sum_{i=1}^{\alpha} \left(x_i^4 - \mu^4\right)^2} \tag{17}$$

where $x_i^4 = \sum_{j=1}^{\beta} \tilde{t}_{i,j}$, and $\mu^4 = \frac{1}{\alpha} \sum_{i=1}^{\alpha} x_i^4$.

We use the NSGA-II variant to solve the optimal rostering problem with the same objectives and constraints used in the previous MMGA work. The hardware and software specifications for the development and execution environment were an Intel i5-2.6G CPU with 4 GB memory, a Windows 7 operation system, and a Visual C++ 6.0 compiler. The customized genetic parameters were set as follows: a population size of 100, a crossover rate of 0.9, and a mutation rate of 0.01. The maximal generation count was set as 20 000.

The result is shown in Table V. Because the admission bound limits [33] used in the MMGA, only a single solution was obtained. The NSGA-II variant can obtain the Pareto front, which contains a set of solutions. Furthermore, compared to the MMGA solution, each solution in this paper had the same value in objective ϕ_1 but smaller values in objectives

TABLE III
PAIRING CONTENT

DUTY CODE	DUTY DEPT		FDP	FT
D	KHH	850	1220	940
K	TSA	800	1220	740
M	KHH	530	940	450
M01a	TSA	705	935	410
M01b	TSA	1605	545	230
M02a	TSA	735	750	420
M02b	TSA	1455	810	320
M03a	KHH	635	625	320
M03b	KHH	1225	525	240
M04a	TSA	750	805	320
M05a	TSA	615	650	340
M05b	TSA	1520	640	310
M06	TSA	835	945	500
M07	KHH	1450	920	320
P	TPE	745	1000	720
P1	TPE	840	1200	920
H	TPE	825	1200	900
I	KHH	550	810	530
M01	KHH	1015	1100	510
M02	TSA	1145	935	510
M03ap	KHH	635	950	510
M03bp	KHH	1545	655	320
M04ap	TSA	735	715	330
M04b	TSA	1435	725	320
M05ap	TSA	615	940	520
M05bp	TSA	1520	745	310
M06a	TSA	835	605	310
M06b	TSA	1400	710	330
M12	KHH	1445	705	320
M13a	TSA	635	605	320
M13b	TSA	1535	605	320
N	TPE	720	1030	720
N1	KHH	850	900	620
M01ap	TSA	705	825	410
M01bp	KHH	1445	705	320
M02ap	TSA	620	905	510
M03aq	KHH	635	950	510
M04aq	KHH	605	535	230
M04bp	TSA	1055	755	330
M01aq	TSA	705	655	320
M02aq	KHH	735	755	320
M06p	TSA	835	1015	450
M13ap	TSA	1005	815	340
M13bp	TSA	1335	635	320
M02bp	TSA	1145	1015	510
M04bq	TSA	1400	420	150
M02bq	TSA	1145	935	510
M03ar	KHH	635	1115	510
M03bq	KHH	1225	1015	510
M04ar	TSA	750	700	330
M04br	TSA	1435	415	140

**Remark*: each pair has five attributes including duty code, departure airport, departure time, flight duty period (FDP) and flight time(FT).

TABLE IV
PREALLOCATED ACTIVITIES IN THE STUDIED REAL-WORLD ROSTERING PROBLEM

Crews	Scheduling days in the roster plan															Crews	Scheduling days in the roster plan														
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15
C1					MTG		MTG						GSI			C17	SBB	X/A	X/A					X/A							
C2	SCK	SCK	SCK			O/W	MTG			O/W						C18	R/T	R/T	R/T												X/A
C3		X/A	MTG	MTG	M/C		MTG						SCK	SCK	R/T	C19	X/A	X/A					SBB		X/A						
C4		A/L			MTG											C20															
C5										OTI		SIP	SIP	SIP	SIP	C21												X/A			
C6														SCK	SCK	C22													R/T	R/T	R/T
C7			X/A	X/A			MTG	A/L	A/L			R/T	R/T	R/T	R/T	C23						SBB		SBB							X/A
C8	X/A	X/A							SB							C24						M/C									
C9	R/T	R/T	R/T				D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O	C25				SB						SB					
C10																C26			SB		MTG										SBB
C11	A/L	A/L														C27					SBB										
C12								A/L	A/L	A/L						C28		SB													
C13													GS			C29	X/A												SB		
C14											SBA					C30													GS		
C15	X/A												GS	SB		C31	R/T		A/L	A/L	A/L	A/L	A/L	O/W	O/W		O/W	MTG			
C16		X/A				SBB					X/A																				

***Remark**: SCK: training; MTG: meeting; R/T: recurrent-training; SBB: standby; X/A: pre-planned rest day: A/L: pre-planned annual leave: X/L: pre-planned personal leave; D/O: pre-planned day-off; GS: grounded training.

ϕ_2 to ϕ_4. In other words, concerning the problem under study, all the solutions of this paper dominated the MMGA solution, and the comparison result is convincing because of the clear domination relation.

B. Recovery Schedules

Following the rostering problem, we studied the case of disruptions occurring to the real-world rostering plan shown in Table VI. We directly studied larger disruptions where some crews were absent during all the scheduling days. Two different cases were used to validate the evolutionary recovery solutions.

1) Recovery Result Without the CLM: The first scenario was a resource-tight situation in which crew #1 was set to be unavailable during the time period. The roster recovery took objectives θ_1 to θ_6 and constraints η_1 to η_3 into consideration. The genetic parameters were the same as those used in the rostering problem.

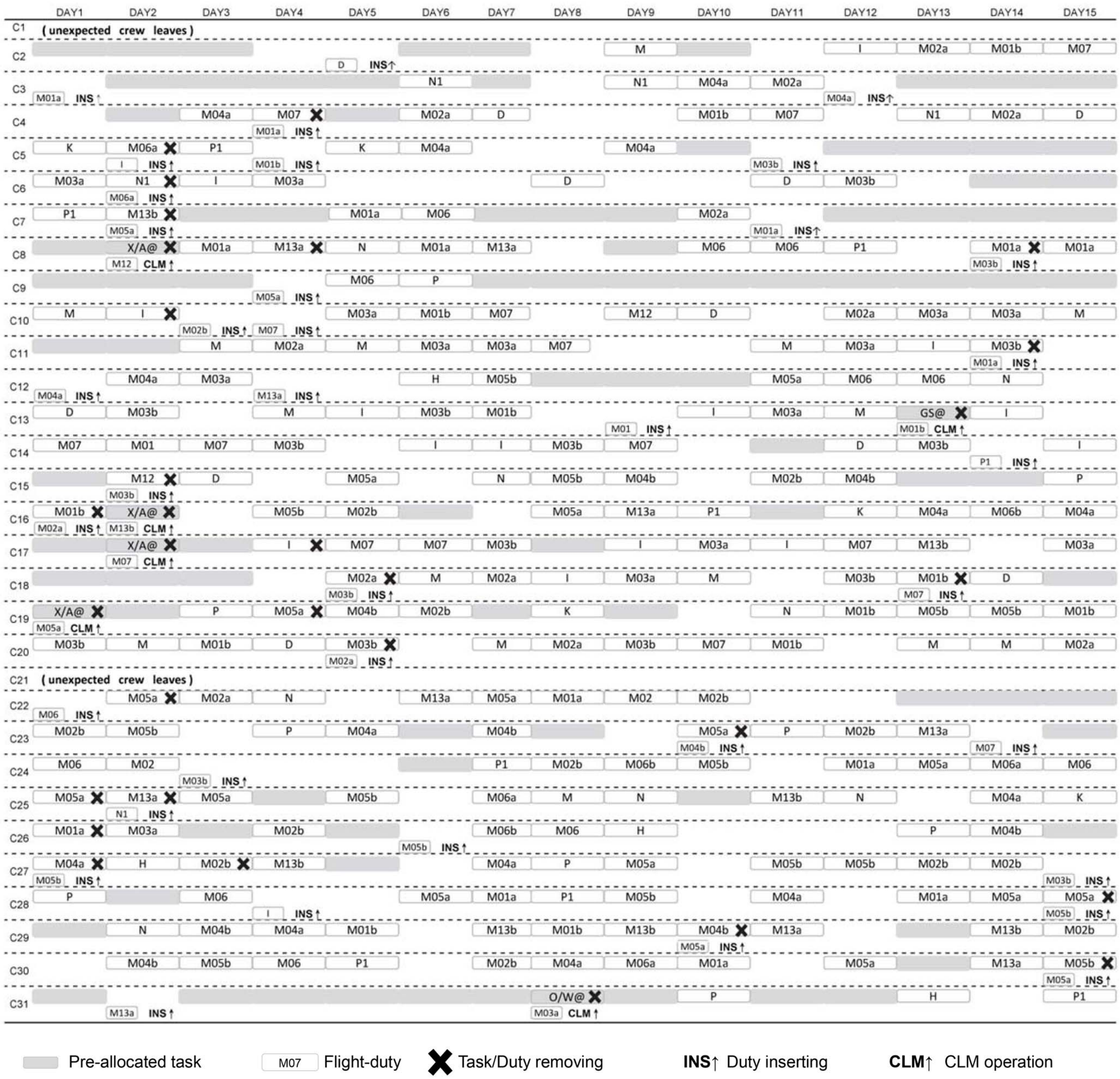

Fig. 2. Content of CRR-CLM solution #12 which changes the original plan with a series of removing, inserting, and CLM operations.

TABLE V
COMPARATIVE RESULTS FOR THE ROSTERING SCHEDULING CASE

Objectives		ϕ_1	ϕ_2	ϕ_3	ϕ_4
MMGA (Jeng et al., [19])		130	41	2.83	0.409
This work	#1	130	34	1.56	0.19
	#2	130	33	1.56	0.23
	#3	130	32	1.56	0.24
	#4	130	31	1.56	0.25
	#5	130	30	1.56	0.28

The results after execution are shown in Table VII. A total of 19 solutions were explored in the Pareto front. In the solutions, the duties released from crew #1 had to be dispatched to other crews. If these crews already had flight duties, these duties had to be dispatched again. The repetition condition resulted in a larger number of duty-pairing reassignments. For example, solution #1 reassigned 16 duty pairings, and solution #19 reassigned 54 duty pairings. However, although solution #19 had a larger duty-pairing change number, it was a fairer plan than solution #1 because of a superior equalization in the duty reassignment. It is a typical trade-off between solutions, and these recovery schedules can be used for final decision making.

2) Recovery Result With the CLM: The other scenario was a resource-shortage situation in which another crew, crew #21, also had to take a long leave in the scheduling period. A possible solution is to recruit or temporarily transfer new crews to take over the released duties. However, if practical management rules cannot add new crews on time, a direct recovery is necessary to obtain a workable schedule.

TABLE VI
SUMMARY OF THE REAL-WORLD ROSTERING PLAN MADE BY EXPERTS

Crews	Scheduling days in the roster plan														
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15
C1	M05b	M06b		M01a	MTG	M05b	MTG	M03a			M01a	M04a	GSI	P1	
C2	SCK	SCK	SCK			O/W	MTG		M	O/W		I	M02a	M01b	M07
C3		X/A	MTG	MTG	M/C	N1	MTG		N1	M04a	M02a		SCK	SCK	R/T
C4		A/L	M04a	M07	MTG	M02a	D			M01b	M07		N1	M02a	D
C5	K	M06a	P1		K	M04a			M04a	OTI		SIP	SIP	SIP	SIP
C6	M03a	N1	I	M03a				D			D	M03b		SCK	SCK
C7	P1	M13b	X/A	X/A	M01a	M06	MTG	A/L	A/L	M02a		R/T	R/T	R/T	R/T
C8	X/A	X/A@	M01a	M13a	N	M01a	M13a		SB	M06	M06	P1		M01a	M01a
C9	R/T	R/T	R/T		M06	P	D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O
C10	M	I			M03a	M01b	M07		M12	D		M02a	M03a	M03a	M
C11	A/L	A/L	M	M02a	M	M03a	M03a	M07			M	M03a	I	M03b	
C12		M04a	M03a			H	M05b	A/L	A/L	A/L	M05a	M06	M06	N	
C13	D	M03b		M	I	M03b	M01b			I	M03a	M	GS@	I	
C14	M07	M01	M07	M03b		I	I	M03b	M07		SBA	D	M03b		I
C15	X/A	M12	D		M05a		N	M05b	M04b		M02b	M04b	GS	SB	P
C16	M01b	X/A@		M05b	M02b	SBB		M05a	M13a	P1	X/A	K	M04a	M06b	M04a
C17	SBB	X/A@	X/A	I	M07	M07	M03b	X/A	I	M03a	I	M07	M13b		M03a
C18	R/T	R/T	R/T		M02a	M	M02a	I	M03a	M		M03b	M01b	D	X/A
C19	X/A@	X/A	P	M05a	M04b	M02b	SBB	K	X/A		N	M01b	M05b	M05b	M01b
C20	M03b	M	M01b	D	M03b		M	M02a	M03b	M07	M01b		M	M	M02a
C21	M02a	M07	M03b	M01b	D				M01	M03b	M03b	X/A	M07	M07	M03b
C22		M05a	M02a	N		M13a	M05a	M01a	M02	M02b			R/T	R/T	R/T
C23	M02b	M05b		P	M04a	SBB	M04b	SBB		M05a	P	M02b	M13a		X/A
C24	M06	M02				M/C	P1	M02b	M06b	M05b		M01a	M05a	M06a	M06
C25	M05a	M13a	M05a	SB	M05b		M06a	M	N	SB	M13b	N		M04a	K
C26	M01a	M03a	SB	M02b	MTG		M06b	M06	H				P	M04b	SBB
C27	M04a	H	M02b	M13b	SBB		M04a	P	M05a		M05b	M05b	M02b	M02b	
C28	P	SB@	M06			M05a	M01a	P1	M05b		M04a		M01a	M05a	M05a
C29	X/A	N	M04b	M04a	M01b		M13b	M01b	M13b	M04b	M13a		SB	M13b	M02b
C30		M04b	M05b	M06	P1		M02b	M04a	M06a	M01a		M05a	GS	M13a	M05b
C31	R/T		A/L	A/L	A/L	A/L	A/L	O/W@	O/W@	P	O/W@	MTG	H		P1

***Remark**:The task marked with @ is "*nice-have*".

TABLE VII
RECOVERY SCHEDULES FOR THE CRR PROBLEM
WITH SUFFICIENT FREE CREWS

CRR Solutions	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6
#1	6	16	3	590	0.27	66.18
#2	7	16	2	560	0.26	64.94
#3	8	16	2	560	0.26	64.3
#4	9	16	1	560	0.25	63.71
#5	11	18	1	560	0.25	63.5
#6	13	20	1	560	0.25	63.24
#7	15	22	1	560	0.25	62.8
#8	17	24	1	560	0.25	62.39
#9	20	28	2	560	0.25	61.64
#10	21	28	1	560	0.24	61.15
#11	22	30	2	580	0.24	60.92
#12	23	30	1	560	0.24	60.38
#13	24	32	2	560	0.24	60.09
#14	25	32	1	560	0.23	59.73
#15	26	34	2	560	0.23	59.12
#16	27	36	2	560	0.23	58.68
#17	28	36	2	560	0.23	58.31
#18	30	52	3	760	0.23	58.22
#19	31	54	2	730	0.22	57.53

In particular, because the number of free crews on day #2 was less than the number of flight-duty pairings, feasible recovery schedules could not be obtained according to the setting in Section IV-B1. Therefore, the CLM was used to solve the resource-shortage condition. That is, nice-to-have tasks could be replaced by flight-duty pairings, but the additional objective θ_7 was included in the CRR-CLM problem to monitor the usage of the constraint-loosening number.

TABLE VIII
RECOVERY SCHEDULES FOR THE CRR-CLM PROBLEMS
IN THE RESOURCE-SHORTAGE CASE

CRR-CLM Solutions	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7
#1	15	38	4	770	0.42	102.11	5
#2	17	48	3	780	0.40	102.42	4
#3	19	48	4	780	0.44	106.42	2
#4	21	52	3	910	0.41	100.51	1
#5	22	46	2	890	0.40	98.77	2
#6	23	58	4	800	0.41	98.03	1
#7	26	74	5	1120	0.4	95.84	3
#8	27	80	5	960	0.4	94.53	6
#9	28	76	4	880	0.39	92.94	7
#10	29	80	4	920	0.37	89.13	4
#11	30	88	4	820	0.36	85.06	5
#12	31	92	4	830	0.35	81.82	6

The execution result is shown in Table VIII. Again, the NSGA-II variant could explore multiple solutions. In this case, there were 12 solutions explored in the Pareto front. Because the crew resource was lacking, each solution contained a value of objective θ_7 that represented the number

TABLE IX
ROSTER RECOVERY PLAN FOR CRR-CLM SOLUTION #12

Crews	Scheduling days in the roster recovery plan														
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15
C1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C2	SCK	SCK	SCK		D	O/W	MTG		M	O/W		I	M02a	M01b	M07
C3	M01a	X/A	MTG	MTG	M/C	N1	MTG		N1	M04a	M02a	M04a	SCK	SCK	R/T
C4		A/L	M04a	M07 M01a	MTG	M02a	D			M01b	M07		N1	M02a	D
C5	K	M06a I	P1	M01b	K	M04a			M04a	OTI	M03b	SIP	SIP	SIP	SIP
C6	M03a	N1 M06a	I	M03a				D			D	M03b		SCK	SCK
C7	P1	M13b M05a	X/A	X/A	M01a	M06	MTG	A/L	A/L	M02a	M01a	R/T	R/T	R/T	R/T
C8	X/A	**X/A@** M12	M01a	M13a	N	M01a	M13a		SB	M06	M06	P1		M01a M03b	M01a
C9	R/T	R/T	R/T	M05a	M06	P	D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O
C10	M	I	M02b	M07	M03a	M01b	M07		M12	D		M02a	M03a	M03a	M
C11	A/L	A/L	M	M02a	M	M03a	M03a	M07			M	M03a	I	M03b M01a	
C12	M04a	M04a	M03a	M13a		H	M05b	A/L	A/L	A/L	M05a	M06	M06	N	
C13	D	M03b		M	I	M03b	M01b		M01	I	M03a	M	**GS@** M01b	I	
C14	M07	M01	M07	M03b		I	I	M03b	M07		SBA	D	M03b	P1	I
C15	X/A	M12 M03b	D		M05a		N	M05b	M04b		M02b	M04b	GS	SB	P
C16	M01b M02a	**X/A@** M13b		M05b	M02b	SBB		M05a	M13a	P1	X/A	K	M04a	M06b	M04a
C17	SBB	**X/A@** M07	X/A	I	M07	M07	M03b	X/A	I	M03a	I	M07	M13b		M03a
C18	R/T	R/T	R/T		M02a M03b	M	M02a	I	M03a	M		M03b	M01b M07	D	X/A
C19	**X/A@** M05a	X/A	P	M05a	M04b	M02b	SBB	K	X/A		N	M01b	M05b	M05b	M01b
C20	M03b	M	M01b	D	M03b M02a		M	M02a	M03b	M07	M01b		M	M	M02a
C21	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C22	M06	M05a	M02a	N		M13a	M05a	M01a	M02	M02b			R/T	R/T	R/T
C23	M02b	M05b		P	M04a	SBB	M04b	SBB		M05a M04b	P	M02b	M13a	M07	X/A
C24	M06	M02	M03b			M/C	P1	M02b	M06b	M05b		M01a	M05a	M06a	M06
C25	M05a	M13a N1	M05a	SB	M05b		M06a	M	N	SB	M13b	N		M04a	K
C26	M01a	M03a	SB	M02b	MTG	M05b	M06b	M06	H				P	M04b	SBB
C27	M04a M05b	H	M02b	M13b	SBB		M04a	P	M05a		M05b	M05b	M02b	M02b	M03b
C28	P	SB@	M06	I		M05a	M01a	P1	M05b		M04a		M01a	M05a	M05a M05b
C29	X/A	N	M04b	M04a	M01b		M13b	M01b	M13b	M04b M05a	M13a		SB	M13b	M02b
C30		M04b	M05b	M06	P1		M02b	M04a	M06a	M01a		M05a	GS	M13a	M05b M05a
C31	R/T	M13a	A/L	A/L	A/L	A/L	A/L	**O/W@** M03a	O/W@	P	O/W@	MTG	H		P1

***Remark**: The symbols in the table are the same with those in the previous table. The cells filled with gray are the new assignments in the recovery schedule.

of the nice-to-have tasks replaced by fly-duty pairings. For example, there were six "nice-to-have" tasks replaced by fly duties in solution #12 as shown in Table IX. This table displays the usage of the CLM to allow the decision maker to select a suitable recovery plan. Fig. 2 displays the recovery content of solution #12 to show the duty and task changes in more detail.

In summary, the experiments showed that the proposed evolutionary approach had a favorable solution quality and could successfully obtain recovery solutions after disruptions.

Because the execution time of our recovery algorithm is approximately 18 min in a notebook computer with an Intel i5-2.6G CPU, the proposed approach can achieve even shorter response times, for example, an hourly response. This can help airlines in efficiently reviewing new schedules after disruptions. Furthermore, because the disruptions discussed in this paper are general in airlines, our approach can be used to solve the similarly recovery problems of the other airlines through a proper modification.

V. Conclusion

The goal of CRR is to reschedule rostering plans interrupted by disruptions to ensure all fly duties have crews to complete them. In the recovery scheduling, directly assigning free crews to take over the duties of disrupted crews would result in other management issues such as a heavy workload, insufficient rest, or even violating safety regressions. Therefore, rescheduling crew resources by swapping their flight duties or even cancelling nonflight activities is necessary to optimize the recovery objectives.

Because the CRR problem involves large combinations of crew and duty assignments in a multiday period under several practical constraints and objectives, it is extremely challenging and complex. This paper thus uses a variant of NSGA-II in cooperation with a CLM to explore recovery solutions under severe disruptions. From this perspective, our approach differs considerably from typical approaches that process only a single objective by arranging undisrupted crews to take over the flight duties of disrupted crews.

To verify the effectiveness of the approach, a real-world rostering plan was first studied to conduct a comparison with previous MMGA work in the literature. In the experiment, the proposed approach obtained superior solutions to those of the MMGA work. By simulating disruption events on the rostering plan, two recovery scenarios containing sufficient and insufficient available crews were then studied. The proposed approach successfully explored Pareto solutions for both recovery scenarios. The positive results suggest the advantage of the proposed approach for CRR problems.

In future research, an extended CLM can be studied to include additional loosened constraints in the CRR problems with the aid of airline experts (e.g., the predefined pairings can be adjusted if allowed). This can assist airlines in recovering schedules from severe disruptions.

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