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Multiobjective Evolutionary Scheduling and Rescheduling of Integrated Aircraft Routing and Crew Pairing Problems

CHIU-HUNG CHEN¹, FU-I CHOU², AND JYH-HORNG CHOU^{3,4,5}, (Fellow, IEEE)

¹Department of Mechanical and Computer-Aided Engineering, Feng Chia University, Taichung 407, Taiwan

²Department of Automation Engineering, National Formosa University, Yunlin 632, Taiwan

³Department of Electrical Engineering, National Kaohsiung University of Science and Technology, Kaohsiung 807, Taiwan

⁴Department of Mechanical Engineering, National Chung Hsing University, Taichung 402, Taiwan

⁵Department of Healthcare Administration and Medical Informatics, Kaohsiung Medical University, Kaohsiung 807, Taiwan

Corresponding authors: Fu-I Chou (alvis.cfi@gmail.com) and Jyh-Horng Chou (choujh@nkust.edu.tw)

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ABSTRACT This paper presents a multiobjective evolutionary approach that can solve integrated airline scheduling and rescheduling problems under conditions of disruption. The integrated problem simultaneously considers both aircraft routing and crew pairing to meet several objectives under real-world constraints and disturbance events. Because of their high complexity, we formulated integrated problems as combinational optimization problems and used the NSGA-II variant method combined with a repair strategy as the solver. To verify and validate the proposed approach, real-world flight data were used to build study cases. In the experiment, we first studied the convergence of the algorithm by using the repair method. We then reviewed real-world plans and evaluated the improvement obtained using the proposed integrated approach. Finally, a disruption was simulated to study rescheduling capability. Experimental results showed that the proposed approach yields better schedules than real-world expert-made plans and that Pareto solutions after the disruption can, under safety and legal constraints, be successfully explored in rescheduling problems.

INDEX TERMS Airline rescheduling, aircraft routing, crew pairing, integrated airline scheduling, multiobjective optimization.

I. INTRODUCTION

The aircraft and crew are two essential factors to consider in the operating costs of the aviation industry. Arranging these two resources during the process of planning to reduce such costs or achieve more effective management has considerable economic benefits for airlines. In a typical airline planning operation, the arrangement of aircraft and crew is assigned in sequential steps [1]. Numerous studies have explored the use of sequential planning [2], [3], as shown in Figure 1. Generally, fully integrating these sub-problems into a single operation to find a more economical plan remains an intractable issue. Therefore, improving cost-effectiveness by integrating some of the stages into a single schedule has been the goal of several scholars in recent years [4]–[6]. This paper

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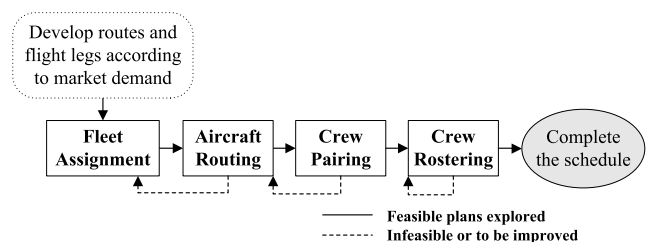


FIGURE 1. Typical phase-by-phase scheduling in airlines.

thus proposes an integrated scheduling approach to unify two important stages: aircraft routing and crew pairing.

Previous studies have explored the sequential planning of independent aircraft routing problems [7], [8] as well as independent crew pairing problems [9]–[11]. Although the stage-by-stage approach can reduce the complexity of the

solution, the result of the previous step limits the flexibility of the subsequent stage. As a result, only a limited amount of information is communicated between stages. Therefore, only local or even infeasible solutions can be obtained [12]. For example, if the aircraft routing decision is made first, the connection time between two consecutive flight legs assigned to the same crew is advised to be lengthened because the different aircrafts are used on both legs. The disadvantage of staged scheduling can therefore be improved by integrated scheduling, and the overall result is a significant reduction in the total cost of routing and pairing optimization [12], [13].

However, routing and pairing problems are NP-hard complexity [7]. In an integration scheme, as the number of parameters increases, the combination of solutions grows by the number of powers. Consequently, the complexity of the integration problem increases and becomes more difficult, which presents a substantial challenge.

The high complexity and difficulty of integrated scheduling mean that only a few research studies have been conducted on this topic. For instance, Cordeau *et al.* [14] studied the effects of short-connect selection on the final pairing and integrated Bender decomposition as a solution when integrating routing and pairing. Mercier *et al.* [15] gave a penalty value for the delay case based on the short-connect issue and then improved this by reversing the decomposition method. Papadakos [4] used a simplified pairing rule combined with the shortest path algorithm in the Bender decomposition to improve the efficiency of the solution. Specifically, the short-connect means that the crew's minimum landing time between flight legs will be greater than the aircraft's turn-around time if different aircrafts are used in a crew pair; however, if two duty flights are quickly connected to the same aircraft, this reduces the crew landing time. This mainly applies to the study of short-connect as a basis for solving the integrated problems. In practice, there is still considerable room for improvement as the real world involves multiple constraints and conflicting goals apart from short-connect. In this paper, the integrated routing and pairing (IRP) problem involves optimizing an overall evaluation function. This is composed of various conflicting objectives and constraints originating from limitations imposed by safety regulations, union contract agreements, complex working rules and management policies. Previous research [3], [12] has proposed approaches by using an objective function formulation constructed by a weighted sum or a master-slave reasoning for aircraft routes and crew pairings. However, a single-objective conversion cannot reflect real-world requirements. Therefore, a set of nondominated solutions, known as the Pareto set, should be explored to represent trade-offs between objectives for decision makers [5].

Furthermore, when unexpected real-world events occur that prevent the airline from completing its mission, such as bad weather and mechanical failures that interferes with the flight schedule, the demand for disruption management becomes relatively critical, and providing flexible recovery solutions will avoid high operating costs due to

disturbances [16]. Therefore, this paper also discusses the minimization of interference in recovery IRP (RIRP) problems. This requires the inclusion of additional recovery objectives in the solution model. A reasoning process to proceed and optimize multiple objectives is essential in the solution methods of both IRP and RIRP problems. Previous studies on robust scheduling have addressed integrated recovery problems [12], [17]. However, these have mainly focused on pre-analyzing historical data to propose a robust integrated schedule; they have not been used to directly handle disruption events. Maher [18] proposed a linear programming (LP) model approach for the integrated airline recovery problem, which is solved by implementing column-and-row generation. Cacchiani and Salazar-González [19] also proposed a mixed integer linear programming model but instead used heuristic algorithms to obtain solutions. With integrating more than one stage, these integrated approaches have proven to be higher quality solutions to airline recovery scheduling problems. However, these solutions are still limited by a single-objective architecture that cannot meet multiple non-linear or compromise goals and provide multiple candidate recovery solutions to assist in subsequent decisions.

In the literature, some methods have been proposed to solve multiobjective problems and successfully explored the exact Pareto front (for example, see [20]). However, for larger-size NP-hard problems, such as the TSP problem [21] and the studied integrated scheduling problem, in theory, no algorithm can guarantee availability of the exact best solution in a limited (polynomial) time [22] even in a single objective case. Therefore, more studies are focused on how to effectively explore high-quality Pareto solutions even if the obtained front is only approximate or suboptimal [23]. In previous research, multiobjective evolutionary algorithms (MOEAs) have emerged as extremely promising tools for exploring multiple nondominated solutions. By adopting different strategies to maintain diverse solutions in the population, various MOEAs have been developed to explore high-quality Pareto solutions; for example, MOGA [24], NSGA [25], SPEA [26], and SPEA-II [27]. In particular, NSGA-II [28] is one of the most widely used algorithms in the multiobjective optimization field [29]; it uses nondominated sorting and the crowded distance sort as the basis of ranking, and an evenly distributed Pareto front was obtained to provide promising quality solutions for evolutionary applications. Later research then improved solution convergence; for example, MOEA/D [30], NSGA-III [31], and MOEA/D-M2M [32]. These algorithms employed either objective decomposition methods or reference points in the hyper plane of objectives to guide the solver and obtain a more efficient convergence. However, no robust results have been reported that the new NSGA-III has fully maintained an evenly distributed Pareto front while solving multiobjective combinatorial optimization problems with a local search [33]. In our previous work, the NSGA-II variant [5] was found to be useful in solving such problems; thus, this study uses the NSGA-II variant in conjunction with

a repair strategy and customized genetic operators to optimize both IRP and RIRP problems.

In this paper, the proposed evolutionary approach first requires the development of an integrated model that defines two matrix structures to formulate aircraft routing and crew pairing, followed by shared flight data to construct the correlation between the two matrices. This framework can be used to formulate the objectives and constraints of the IRP and RIRP problems into multiobjective optimization problems. Finally, routing and pairing problems are encoded into two different chromosome segments, which have different customized genetic operators, and the NSGA-II variant is used as the solver. To verify the availability and effectiveness of the proposed scheme, we compared the convergence of algorithms to solve IRP in a real-world flight table and evaluated the improvement of the integrated solution against the manmade staged plan. Additionally, a practical disturbance problem due to bad weather was used as an experimental case to explore the quality of the solution for recovery scheduling.

The contribution of this paper includes three aspects: 1) by embedding a repair strategy in the NSGA-II variant, we propose an effective solver for IRP and RIRP problems, which obviously improves the plans made by experts in a stage-by-stage manner; 2) instead of using a completely different solution architecture, we develop a multiobjective reasoning mechanism with a unified representation and framework to solve both IRP and RIRP problems in the real world; in general, a unified approach helps decision makers to handle the two different tasks more consistently; 3) in the literature, to the best of the authors' knowledge, no research has been fully conducted a multiobjective recovery solution to integrated airline scheduling problems, and this paper is the first result that determines the benefits of solving and applying the multiobjective RIRP solutions.

II. PROBLEM DEFINITION AND FORMULATION

This paper primarily focuses on the real-world daily scheduling of short-haul airlines. We explored IRP and RIRP problems that involve the allocation of flight legs to two different execution units, aircraft and crew, and considered the rationality and effectiveness of the task in achieving the daily flight schedule to meet market demands. By convention, in aircraft routing, the draft flight needs to be adjusted repeatedly for aircrafts until all restrictions are met and all targets are achieved [34]. By contrast, crew pairing [35] is primarily assigned to a group of crew members in combination with several shifts of the flights [36]. When considering the pairing formation process, relevant safety and cost issues must be addressed.

These two sub-problems involve an optimization problem in that the solution must find a set of flight sub-sets that can be assigned to the execution unit so that all flights are covered exactly once and the overall cost is as low as possible. Manual scheduling is relatively time consuming and cannot be easily adapted to meet dynamic environments, such as immediate rescheduling in response to sudden disturbances.

TABLE 1. Summary of notation.

F	the flight leg table where each flight leg in F contains a couple of attributes: d: the flight number. \hat{a} : the departure airport. \bar{a} : the arrival airport. \hat{t} : the departure time. \bar{t} : the arrival time.
$f(x)$	the auxiliary function that gives the flight leg with input of flight number x .
$g(x)$	the auxiliary function that gives the used aircraft with input of flight number x .
m	the number of aircraft available in one day.
n	the maximum number of flight legs per aircraft per day.
s	the maximum number of pairs available in one day.
t	the maximum number of duty flights that can be executed per pair per day.
$r_{i,j}$	the j -th flight number assigned to the i -th aircraft (or 0 if not assigned).
$p_{i,j}$	the j -th flight number assigned to the i -th crew pair (or 0 if not assigned).
$p_{i,1}$	the first non-zero flight number in the i -th crew pair.
$p_{i,last}$	the last non-zero flight number in the i -th crew pair.
$\tilde{r}_{i,j}$	the j -th flight number assigned to the i -th aircraft (or 0 if not assigned) in the recovery schedule.
$\tilde{p}_{i,j}$	the j -th flight number assigned to the i -th crew pair (or 0 if not assigned) in the recovery schedule.
T_{fc}	the required flight-connection time between two aircraft flight legs.
T_{st}	the required sit time between two flight duties in a crew pair.
T_{ft}	the legal flying time.
T_{fp}	the legal flying period time.

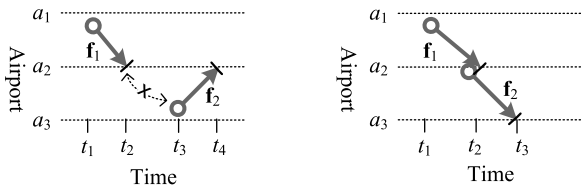
*Remark: Pattern $f(x).y$ is used to represent the attribute value y of the flight leg with flight number x ; for example, $f(816).\bar{t}$ represents the arrival time of Flight 816; and time values are in minutes.

In the literature, this is often classified as a set covering problem [37] with only one weight-sum-based optimization objective. However, in practice, the setting of this cost model is difficult because it typically involves multiple demands and is nonlinear. Moreover, a cost value that is not applicable will cause deviations in the solution and lead to confusion under the influence of multiple targets. Therefore, when faced with multiple targets that need to be considered simultaneously, the typical single objective solution is not sufficiently robust.

In this paper, we derive the IRP and RIRP problems into discrete combinatorial problems [38], and generalize them into multiple constraint and objective evaluation equations. The overview of the notation used in the equations is shown in Table 1.

For a given flight table **F** and its auxiliary functions $f(\cdot)$ and $g(\cdot)$, we define aircraft routing table **R** to be a $m \times n$ matrix:

$$\mathbf{R} = \begin{bmatrix} r_{1,1} & \cdots & r_{1,n} \\ \vdots & \ddots & \vdots \\ r_{m,1} & \cdots & r_{m,n} \end{bmatrix}, \quad (1)$$



(a) Failed to connect flight legs. (b) No enough time to link flight legs.

FIGURE 2. Flight connection constraints in a short-haul airline.

and crew pairing table \mathbf{P} is defined as a $s \times t$ matrix:

$$\mathbf{P} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,t} \\ \vdots & p_{i,j} & \vdots \\ p_{s,1} & \cdots & p_{s,t} \end{bmatrix}. \quad (2)$$

The recovery routing and pairing matrixes of the new schedule are \mathbf{R} and $\hat{\mathbf{P}}$ separately. Based on the data structures above, we formulate the optimization problems as follows:

A. INTEGRATED ROUTING AND PAIRING MODEL

Different requirements and limitations are considered when assigning flight legs for the two sub-problems. Based on the aforementioned definition, relevant restrictions and objectives are defined.

1) CONSTRAINTS

In aircraft routing, there are two main constraints to consider in scheduling, as shown in Fig. 2: *flow connection* and *ground turn-around time*.

Constraint *flow connection* (FC) requires two consecutive flight legs with the same departure airport and destination airport; its equation is defined as follows:

$$\eta_1(\mathbf{R}) = \sum_{i=1}^m \sum_{j=1}^{n-1} x_{i,j}^{(1)}, \quad (3)$$

where $x_{i,j}^{(1)} = \begin{cases} 1, & \text{if } f(r_{i,j}) \cdot \bar{a} \neq f(r_{i,j+1}) \cdot \hat{a}. \\ 0, & \text{otherwise.} \end{cases}$

Constraint *turn-around-time* (TA) requires two consecutive flight legs with enough ground-stay time T_{fc} ; its equation is defined as follows:

$$\eta_2(\mathbf{R}) = \sum_{i=1}^m \sum_{j=1}^{n-1} x_{i,j}^{(2)}, \quad (4)$$

where $x_{i,j}^{(2)} = \begin{cases} 0, & \text{if } f(r_{i,j+1}) \cdot \hat{t} - f(r_{i,j}) \cdot \bar{t} \geq T_{fc}. \\ 1, & \text{otherwise.} \end{cases}$

In crew pairing, several legal and safety constraints are required to make a feasible plan. Constraint *duty connection* (DC) ensures that in a duty pair, two consecutive duty flights must be located in the same airport. This is similar to the *flow connection* requirement in routing operations, and its equation is defined as follows:

$$\eta_3(\mathbf{P}) = \sum_{i=1}^s \sum_{j=1}^{t-1} x_{i,j}^{(3)}, \quad (5)$$

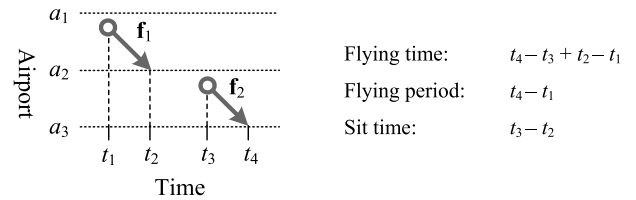


FIGURE 3. Timing relations in the pairing operation.

where $x_{i,j}^{(3)} = \begin{cases} 1, & \text{if } f(p_{i,j}) \cdot \bar{a} \neq f(p_{i,j+1}) \cdot \hat{a} \\ 0, & \text{otherwise} \end{cases}$

The *sit time* (ST) constraint ensures a suitable time period T_{tt} between two adjacent duty flights in a crew pair; unlike the *legal turn-around time* considered in aircraft routing, *sit time* also consider the crew switch time if two different aircrafts are used in a pair. Its equation is defined as follows:

$$\eta_4(\mathbf{P}) = \sum_{i=1}^s \sum_{j=1}^{t-1} x_{i,j}^{(4)}, \quad (6)$$

where $x_{i,j}^{(4)} = \begin{cases} 0, & \text{if } f(p_{i,j+1}) \cdot \hat{t} - f(p_{i,j}) \cdot \bar{t} \geq T_{st}. \\ 1, & \text{otherwise.} \end{cases}$

The *legal flying time* and *legal flying period* constraints separately ensure that the flying time and flying period cannot exceed the regality limits T_{ft} and T_{fp} . The timing relations among these definitions are shown in Fig. 3.

Flying time is the total number of minutes of actual flight time, whereas flying period refers to total working minutes, including sit time and flight time. The *flying-time* (FT) constraint is defined as follows:

$$\eta_5(\mathbf{P}) = \sum_{i=1}^s x_i^{(5)}, \quad (7)$$

where $x_i^{(5)} = \begin{cases} 0, & \text{if } \sum_{j=1}^t (f(p_{i,j}) \cdot \bar{t} - f(p_{i,j}), \hat{t}) \leq T_{ft}. \\ 1, & \text{otherwise.} \end{cases}$

The *flying-period* (FP) constraint is defined as follows:

$$\eta_6(\mathbf{P}) = \sum_{i=1}^s x_i^{(6)}, \quad (8)$$

where $x_i^{(6)} = \begin{cases} 0, & \text{if } (f(p_{i,last}) \cdot \bar{t} - f(p_{i,1}), \hat{t}) \leq T_{fp}. \\ 1, & \text{otherwise.} \end{cases}$

2) OBJECTIVES

Objectives are drawn for several issues relating to cost or management practice. The *pair-number* (PN) objective, which measures the required crew source, is directly related to the cost. Its equation is defined as follows:

$$\phi_1(\mathbf{P}, \mathbf{R}) = \sum_{i=1}^s x_i^{(7)}, \quad (9)$$

where $x_i^{(7)} = \begin{cases} 0, & \text{if } \sum_{j=1}^t p_{i,j} = 0 \\ 1, & \text{otherwise} \end{cases}$

The *non-home-base* (NHB) objective counts pairs whose start airport and end airport are different. A non-home base pair requires an additional cost to link crews to the home base (the original airport) either by deadhead or layover. Deadhead denotes an additional cost to move the pilot from the current position to that where the next mission begins. Layover denotes the crew cost for the entire night because team

members cannot return to the base after completing the task. Its equation is defined as follows:

$$\phi_2(\mathbf{P}, \mathbf{R}) = \sum_{i=1}^s x_i^{(8)}, \quad (10)$$

where $x_{i,j}^{(8)} = \begin{cases} 0, & \text{if } f(p_{i,1}), \hat{a} = f(p_{i,last}) \cdot \bar{a}. \\ 1, & \text{otherwise.} \end{cases}$

The *non-short-connect* (NSC) objective counts how often the used aircraft is changed in a pair. Since legal connection times have been ensured through constraint equations, this objective is only used to measure the number of different aircraft used between consecutive flight legs. Its equation is defined as follows:

$$\phi_3(\mathbf{P}, \mathbf{R}) = \sum_{i=1}^s \sum_{j=1}^{t-1} x_{i,j}^{(9)}, \quad (11)$$

where $x_{i,j}^{(9)} = \begin{cases} 0, & \text{if } g(p_{i,j+1}) = g(p_{i,j}). \\ 1, & \text{otherwise.} \end{cases}$

3) IRP PROBLEM

Based on the aforementioned definition, the optimization equation for the integrated scheduling problem can be defined as follows:

$$\begin{aligned} & \text{minimize } \phi_i, \quad 1 \leq i \leq 3 \\ & \text{subject to } \eta_j = 0, \quad 1 \leq j \leq 6 \end{aligned} \quad (12)$$

In this definition, a *non-short-connect* is adopted as one of the objectives rather than an absolute single goal. This allows the final scheduling result to take other equally important goals into account. Furthermore, these objectives cannot be met at the same time because they mutually conflict. For example, two small-size pairs can be merged to form a new larger pair. This reduces the number of *pair-numbers* used but increases the number of *non-short-connects* if the aircraft is changed in the new pair. Thus, these objectives can be reached only through a trade-off, and the scheduling result does not contain a unique solution. In most cases, it contains multiple solutions and is called the Pareto set.

B. RESCHEDULING UNDER DISRUPTION

The need for a disturbance response usually occurs after a disturbance event, and new planning is required within a limited time. Unlike normal scheduling, the recovery schedule considers how to complete the original mission with limited resources. When necessary, certain normal restrictions will be relaxed depending on the disturbance situation to achieve additional goals. At the same time, because the original plan already exists, the small difference between the new plan and the original plan is usually an important demand for the rescheduling process. In this paper, the following restrictions and objectives are discussed.

1) RECOVERY CONSTRAINTS AND OBJECTIVES

Rearrangement schedules must usually be close to the original plan, reducing the scope of the change. However, in practice, it is not easy to use a single equation to give values measuring the degree of change, usually multiple faces

are involved. This paper focuses on the more direct target of the passenger under disturbance. The recovery objectives are defined as follows:

The *total-delay-flights* (TDF) objective monitors the number of delay flights, as any flight delay has a substantial impact on passenger travel.

$$\theta_1(\tilde{\mathbf{P}}, \tilde{\mathbf{R}}, \mathbf{P}, \mathbf{R}) = \sum_{i=1}^s x_i^{(10)} \quad (13)$$

where $x_i^{(10)} = \sum_{j=1}^t y_j^{(10)}$ and $y_j^{(10)} = \begin{cases} 1, & \text{if } f(\tilde{p}_{i,j}) \cdot \hat{t} \geq f(p_{i,j}) \cdot \hat{t}. \\ 0, & \text{otherwise.} \end{cases}$

The *maximum-delay-time* (MDT) objective monitors the degree of delay, as a longer delay has a larger impact on passenger travel.

$$\theta_2(\tilde{\mathbf{P}}, \tilde{\mathbf{R}}, \mathbf{P}, \mathbf{R}) = \max_{i=1}^s x_i^{(11)}, \quad (14)$$

where $x_i^{(11)} = \max_{j=1}^t y_j^{(11)}$ and $y_j^{(11)} = \begin{cases} 0, & \text{if } f(\tilde{p}_{i,j}) \cdot \hat{t} = f(p_{i,j}) \cdot \hat{t}. \\ f(\tilde{p}_{i,j}) \cdot \hat{t} - f(p_{i,j}) \cdot \hat{t}, & \text{otherwise.} \end{cases}$

The original *non-home-base* and *non-short-connect* objectives are also used. However, for a more complete view of manpower usage, the *pair-count* objective is modified to an *extra-pair-count* (EPC) constraint, which avoids any extra manpower to be included. Its equation is defined as follows:

$$\begin{aligned} & \varphi_1(\tilde{\mathbf{P}}, \tilde{\mathbf{R}}, \mathbf{P}, \mathbf{R}) \\ & = \begin{cases} 0, & \phi_1(\tilde{\mathbf{P}}, \tilde{\mathbf{R}}) \leq \phi_1(\mathbf{P}, \mathbf{R}). \\ \phi_1(\tilde{\mathbf{P}}, \tilde{\mathbf{R}}) - \phi_1(\mathbf{P}, \mathbf{R}), & \text{otherwise.} \end{cases} \end{aligned} \quad (15)$$

2) RIRP PROBLEM

Based on the aforementioned definitions, a rescheduling problem must monitor the disturbance to minimize the impact of the original schedule. To ensure a good schedule, several objectives in recovery scheduling rules are also considered.

$$\begin{aligned} & \text{minimize } \theta_1, \theta_2, \phi_2, \phi_3 \\ & \text{subject to } \varphi_1 = 0 \\ & \text{and } \eta_i = 0, 1 \leq i \leq 6. \end{aligned} \quad (16)$$

III. SOLUTION BY USING NSGA-II VARIANT

In the proposed genetic flow of the NSGA-II variant, the evolutionary population should, like any typical genetic algorithm (GA) [39], be operated by iterations through initialization, fitness computation, selection, crossover, and mutation to generate offspring [40]. As stated in our previous work [5], the hybrid crowding sort algorithm can obtain an improved and diverse front by using both the crowded distance sort (CDS) and the genotype distance sort (GDS). Therefore, nondomination sorting is then cooperated with the hybrid crowding sort to reserve the Pareto solutions and determine the survival population.

For IRP and RIRP problems, multiple objectives and constraints need to be considered simultaneously in one chromosome. To solve the aforementioned integration problem, this

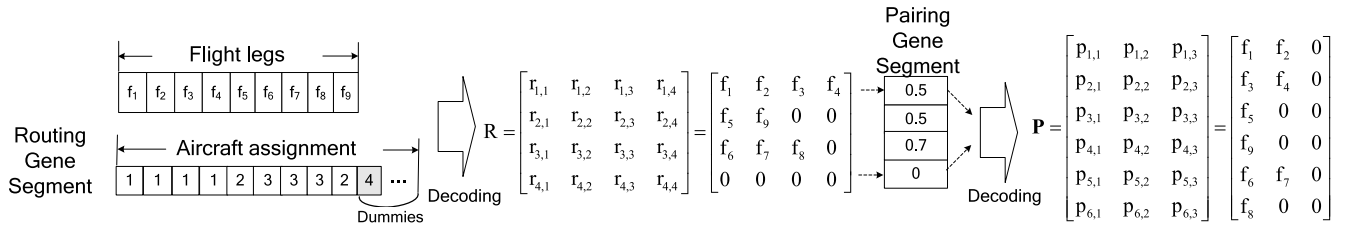


FIGURE 4. An example chromosome and its coding schema.

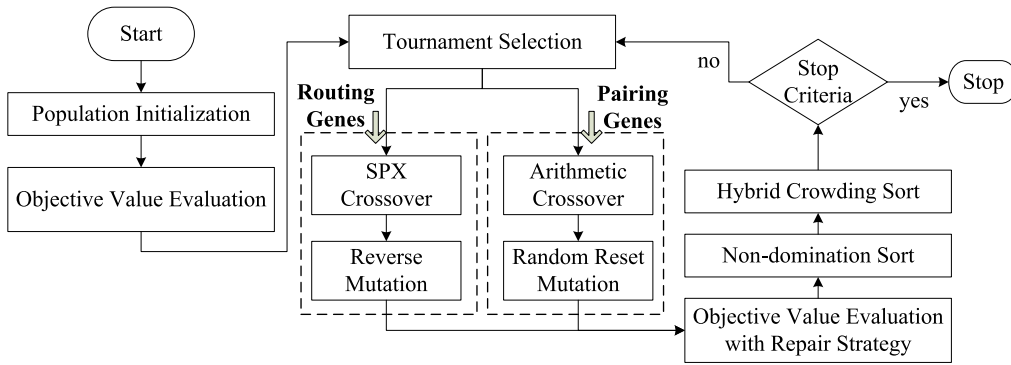


FIGURE 5. Flow chart of the proposed algorithm.

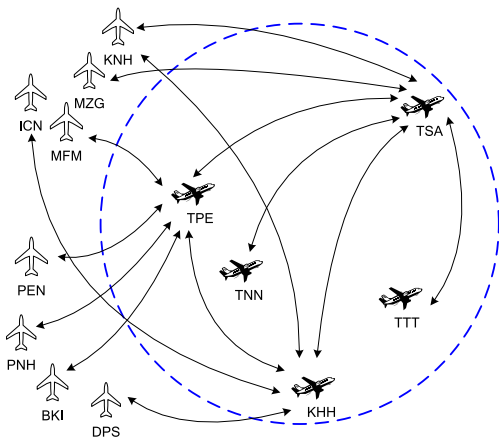


FIGURE 6. Simulated scenarios in which airports in the blue circle are temporarily closed because of bad weather.

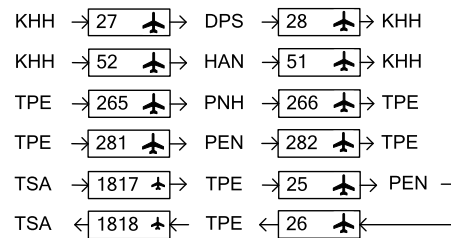


FIGURE 7. Preprocessed routing and pairing plans.

paper proposes a two-segmented chromosome structure in the evolutionary algorithm, where each sub-problem is independently encoded as an independent segment. This method allows different coding methods to directly reflect the characteristics of individual problems; for example, discrete coding and real number can be mixed in a chromosome. An example chromosome is shown in Fig. 4 to demonstrate the proposed coding schema where in the routing segment, chromosome genes represent the aircrafts, and in the pairing segment, chromosome genes represent the splitting positions of aircraft flight legs to form different pairs. In each generation, a selection method is used to select the best-fitting parent

for mating pool, and each segment has standalone genetic operators. Thus, each segment has different crossover and mutation operators. Only at the end of each generation are the constraints in the two-segment chromosome considered and calculated along with the objective values based on shared flight data. The related flow chart is shown in Fig. 5.

For practical applications, how to provide an effective method to meet the demand is usually one of the focuses of research. Since the effectiveness of the NSGA-II variant has been discussed and verified in our previous work [5], in this paper, we mainly propose to combine the repair strategy in the algorithm to solve the highly complex IRP and RIRP problems in the real world and compare the results with practical expert-made schemes to verify the effectiveness of the proposed approach.

A. CODING AND DECODING

In the routing segment, we adopt an indirect order-based coding schema. Each gene in a chromosome represents assignment of a duty or dummy flight to a route. When decoding,

TABLE 2. Real-world flight legs to be scheduled.

(a) The flight legs in the first study case.

Flight Number	Dept. Port	Ariv. Port	Dept. Time	Ariv. Time	Flight Number	Dept. Port	Ariv. Port	Dept. Time	Ariv. Time	Flight Number	Dept. Port	Ariv. Port	Dept. Time	Ariv. Time
902	KHH	TPE	6:40	7:30	604	MZG	TSA	10:35	11:20	282	PEN	TPE	15:30	20:10
883	TSA	KNH	7:00	7:55	25	TPE	BKI	10:40	14:00	859	TSA	TTT	15:40	16:30
806	KHH	TSA	7:20	8:10	809	TSA	KHH	10:40	11:30	28	DPS	KHH	15:50	20:40
803	TSA	KHH	7:50	8:40	814	KHH	TSA	11:05	11:55	908	KHH	TPE	16:00	16:50
808	KHH	TSA	8:20	9:10	886	KNH	TSA	11:40	12:35	613	TSA	MZG	16:05	16:50
882	KNH	TSA	8:30	9:25	811	TSA	KHH	11:40	12:30	826	KHH	TSA	16:30	17:20
901	TPE	KHH	8:30	9:20	855	TSA	TTT	11:50	12:40	823	TSA	KHH	16:50	17:40
853	TSA	TTT	8:35	9:25	889	TSA	KNH	12:30	13:25	892	KNH	TSA	16:55	17:50
805	TSA	KHH	8:50	9:40	266	PNH	TPE	12:35	17:15	860	TTT	TSA	17:00	17:50
265	TPE	PNH	8:55	11:35	816	KHH	TSA	12:40	13:30	612	MZG	TSA	17:25	18:10
810	KHH	TSA	9:10	10:00	8222	MFM	KHH	13:05	14:40	830	KHH	TSA	18:30	19:20
1817	TSA	TPE	9:10	9:40	815	TSA	KHH	13:05	13:55	907	TPE	KHH	18:40	19:30
603	TSA	MZG	9:20	10:05	877	KHH	KNH	13:10	14:05	829	TSA	KHH	18:40	19:30
807	TSA	KHH	9:45	10:35	856	TTT	TSA	13:20	14:10	1818	TPE	TSA	19:20	19:50
281	TPE	PEN	9:50	14:30	890	KNH	TSA	14:00	14:55	831	TSA	KHH	19:30	20:20
27	KHH	DPS	10:00	14:50	820	KHH	TSA	14:35	15:25	910	KHH	TPE	20:25	21:15
885	TSA	KNH	10:00	10:55	891	TSA	KNH	14:45	15:40	835	TSA	KHH	20:30	21:20
812	KHH	TSA	10:10	11:00	26	BKI	TPE	15:00	18:20	836	KHH	TSA	20:40	21:30
8221	KHH	MFM	10:20	11:55	876	KNH	KHH	15:00	15:55	840	KHH	TSA	21:45	22:35
854	TTT	TSA	10:20	11:10	821	TSA	KHH	15:20	16:10	909	TPE	KHH	22:50	23:40

(b) The flight legs in the second study case.

Flight Number	Dept. Port	Ariv. Port	Dept. Time	Ariv. Time	Flight Number	Dept. Port	Ariv. Port	Dept. Time	Ariv. Time	Flight Number	Dept. Port	Ariv. Port	Dept. Time	Ariv. Time
902	KHH	TPE	6:40	7:30	809	TSA	KHH	10:40	11:30	859	TSA	TTT	15:40	16:30
802	KHH	TSA	6:50	7:40	814	KHH	TSA	11:05	11:55	28	DPS	KHH	15:50	20:40
52	KHH	ICN	7:00	10:45	886	KNH	TSA	11:40	12:35	908	KHH	TPE	16:00	16:50
883	TSA	KNH	7:00	7:55	811	TSA	KHH	11:40	12:30	613	TSA	MZG	16:05	16:50
801	TSA	KHH	7:05	7:55	887	TSA	KNH	11:40	12:35	826	KHH	TSA	16:30	17:20
806	KHH	TSA	7:20	8:10	51	ICN	KHH	11:45	13:30	823	TSA	KHH	16:50	17:40
803	TSA	KHH	7:50	8:40	855	TSA	TTT	11:50	12:40	892	KNH	TSA	16:55	17:50
808	KHH	TSA	8:20	9:10	889	TSA	KNH	12:30	13:25	860	TTT	TSA	17:00	17:50
882	KNH	TSA	8:30	9:25	266	PNH	TPE	12:35	17:15	612	MZG	TSA	17:25	18:10
901	TPE	KHH	8:30	9:20	816	KHH	TSA	12:40	13:30	828	KHH	TSA	17:30	18:20
853	TSA	TTT	8:35	9:25	8222	MFM	KHH	13:05	14:40	825	TSA	KHH	17:50	18:40
805	TSA	KHH	8:50	9:40	815	TSA	KHH	13:05	13:55	830	KHH	TSA	18:30	19:20
265	TPE	PNH	8:55	11:35	877	KHH	KNH	13:10	14:05	907	TPE	KHH	18:40	19:30
810	KHH	TSA	9:10	10:00	856	TTT	TSA	13:20	14:10	829	TSA	KHH	18:40	19:30
603	TSA	MZG	9:20	10:05	888	KNH	TSA	13:25	14:20	832	KHH	TSA	19:30	20:20
807	TSA	KHH	9:45	10:35	890	KNH	TSA	14:00	14:55	831	TSA	KHH	19:30	20:20
281	TPE	PEN	9:50	14:30	817	TSA	KHH	14:10	15:00	910	KHH	TPE	20:25	21:15
27	KHH	DPS	10:00	14:50	820	KHH	TSA	14:35	15:25	835	TSA	KHH	20:30	21:20
885	TSA	KNH	10:00	10:55	891	TSA	KNH	14:45	15:40	836	KHH	TSA	20:40	21:30
812	KHH	TSA	10:10	11:00	876	KNH	KHH	15:00	15:55	837	TSA	KHH	21:20	22:10
8221	KHH	MFM	10:20	11:55	821	TSA	KHH	15:20	16:10	840	KHH	TSA	21:45	22:35
854	TTT	TSA	10:20	11:10	822	KHH	TSA	15:30	16:20	909	TPE	KHH	22:50	23:40
604	MZG	TSA	10:35	11:20	282	PEN	TPE	15:30	20:10					

we search for actual flight legs according to gene values and record them into the routing plan. In the pairing element, we adopt a real-coded schema that encodes the position splitting of each route into pairs as genes. When decoding, we look for routing information according to the routing matrix decoded from the routing segment. We then record the related flight legs and the splitting ratio into the pairing matrix.

B. CUSTOMIZED GENETIC OPERATORS

In genetic operators, a tournament selection method is used in conjunction with a constraint domination relation to

determine the pros and cons of two chromosomes [28]. Thus, chromosome A is better than chromosome B only if the following conditions are met: a) A is feasible but B is not; b) A and B are infeasible, and A has a smaller constraint; and c) A and B are feasible, and A's objectives dominate B's.

The other cooperated genetic operators are specified as follows:

1) CROSSOVER AND MUTATION OPERATOR

Because coding schemas in the two segments are not the same, different types of crossover and mutation operations are used separately for each segment.

TABLE 3. The real-world schedule developed by experts.

(a) The man-made schedule in the first study case.

Aircraft Routing (Aircraft Flight legs)	
Route NO	Flight Legs
#1	803.810.809.816.823.830.835
#2	808.807.814.889.890.859.860.831.840
#3	806.805.812.811.877.876.826
#4	853.854.821
#5	883.882.885.886.815.820.613.612.829.836
#6	603.604.855.856.891.892
#7	902.901.8221.8222.908.907.910.909

Crew Pairing (Crew Duty Pair)	
Pair NO	Flight Legs
#1	803.810.809.816.821
#2	823.830.835
#3	808.807.814.889.890
#4	859.860.831.840
#5	806.805.812.811
#6	877.876.826
#7	853.854.815.820
#8	883.882.885.886
#9	613.612.829.836
#10	603.604.855.856.891.892
#11	902.901.8221.8222
#12	908.907.910.909

(b) The man-made schedule in the second study case.

Aircraft Routing (Aircraft Flight legs)	
Route NO	Flight Legs
#1	803.810.809.816.817.822.823.830.835
#2	801.808.807.814.889.890.859.860.831.840
#3	806.805.812.811.877.876.826.825.832.837
#4	802.853.854.887.888.821.828
#5	883.882.885.886.815.820.613.612.829.836
#6	603.604.855.856.891.892
#7	902.901.8221.8222.908.907.910.909

Crew Pairing (Crew Duty Pair)	
Pair NO	Flight Legs
#1	902.901.8221.8222
#2	859.860.831.840
#3	613.612.829.836
#4	603.604.855.856.891.892
#5	908.907.910.909
#6	826.825.832.837
#7	883.882.885.886.815.820
#8	803.810.809.816.817
#9	822.823.830.835
#10	801.808.807.814.889.890
#11	806.805.812.811.877.876
#12	802.853.854
#13	887.888.821.828

TABLE 4. The experimental results for the study cases.

(a) The Pareto solutions in the first study case.

Pareto Solutions	Pair number (PN)	Non home base (NHB)	Non short connect (NSC)
This Work	#1-#47	10	2
	#48-#71	11	0
Expert-made Plan	12	4	2

(b) The Pareto solutions in the second study case.

Pareto Solutions	Pair number (PN)	Non home base (NHB)	Non short connect (NSC)
This Work	#1-#4	11	2
	#5-#40	12	2
Expert-made Plan	13	2	0

In the routing segment, we use the SPX method [41] as the crossover and the reverse method as the mutation.

Supposing that two parents are *chromosome1* and *chromosome2*, their offspring are *new_chromosome1* and *new_chromosome2*, and the number of genes is *len*, the pseudo codes used in the SPX are as follows:

TABLE 5. Detailed content of the IRP example solutions.

(a) The first solution in the first study case.

Aircraft Routing Information	
Chromosome Genes	5,5,0,5,3,0,0,5,5,4,4,4,6,1,1,1,1,2,3,3,3,2,2,2,0,4,4,6,3,1,6,4,0,2,2,3,5,0,1,4,1,2,6,6,4,5,2,6,3,2,0,3,5,0,6,4,6,1,1,3,5,4,6,6,1,0,0,3,5
NO	Decoded Content (Aircraft Flight legs)
#1	808,807,814,889,890,823,830,835
#2	902,901,812,811,877,876,826
#3	853,854,815,820,613,612,829,840
#4	883,882,885,886,891,892
#5	603,604,855,856,821
#6	803,810,809,816,859,860,831,836
#7	806,805,8221,8222,908,907,910,909

Crew Pairing Information	
Chromosome Genes	0,8,1,0,0,5,1,0,1,0,0,5,0,5
NO	Decoded Content (Crew Duty Pair)
#1	808,807,814,889,890,823
#2	902,901,812,811,877,876,826
#3	853,854,815,820
#4	613,612,829,840
#5	883,882,885,886,891,892
#6	603,604,855,856,821,830,835
#7	803,810,809,816
#8	859,860,831,836
#9	806,805,8221,8222
#10	908,907,910,909

(b) The first solution in the second study case.

Aircraft Routing Information	
Chromosome Genes	0,2,2,2,2,2,3,3,3,3,3,0,0,5,4,5,5,5,5,5,2,5,0,0,3,1,1,1,1,1,1,3,3,0,4,6,6,4,6,4,4,4,3,6,4,2,1,2,3,5,5,0,4,6,6,2,0,0,6,6,1,1,1,4,6
NO	Decoded Content (Aircraft Flight legs)
#1	803,810,809,816,817,908,907,910,909
#2	801,808,885,886,815,820,613,612,829,836
#3	902,901,812,811,877,876,826,825,832,837
#4	806,805,8221,8222,822,823,830,835
#5	883,882,807,814,889,890,821,828
#6	802,853,854,855,856,891,892
#7	603,604,887,888,859,860,831,840

Crew Pairing Information	
Chromosome Genes	0,7,0,6,0,6,1,0,0,5,1,0,0,5
NO	Decoded Content (Crew Duty Pair)
#1	803,810,809,816,817
#2	908,907,910,909
#3	801,808,885,886,815,820
#4	613,612,829,836
#5	902,901,812,811,877,876
#6	826,825,832,837
#7	806,805,8221,8222
#8	822,823,830,835
#9	883,882,807,814,889,890,821,828
#10	802,853,854,855,856,891,892
#11	603,604,887,888
#12	859,860,831,840

```

j = 1
for i = 1 to len
    if chromosome1_genes[i] ∈ S1 then
        new_chromosome1_genes[j] = chromosome1_genes[i]
        j = j + 1
    end if
    if chromosome2_genes[i] ∈ S2 then
        new_chromosome2_genes[j] = chromosome2_genes[i]
        j = j + 1
    end if
next i
    
```


TABLE 6. Rescheduling results after the disruption.

(a) The Pareto solutions in the first rescheduling study case.

Pareto Solutions		Total delay flights (TDF)	Maximum delay time (MDT)	Non home base (NHB)	Non short connect (NSC)
This Work	#1	10	140	2	0
	#2-#3	12	120	0	0
Direct delay on the original plan		14	120	1	0

(b) The Pareto solutions in the second rescheduling study case.

Pareto Solutions		Total delay flights (TDF)	Maximum delay time (MDT)	Non home base (NHB)	Non short connect (NSC)
This Work	#1	19	130	1	1
	#2	20	130	1	0
	#3	21	120	1	0
Direct delay on the original plan		21	120	1	0

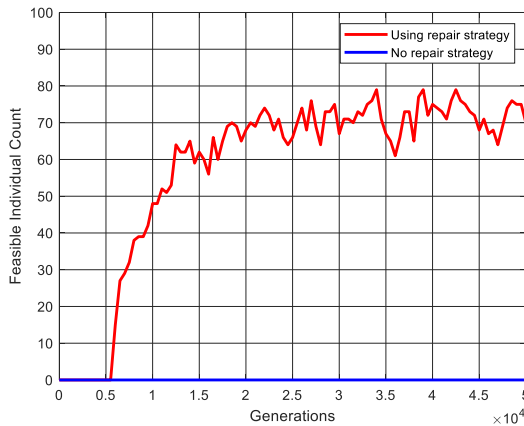


FIGURE 8. Convergence of methods with or without repair operations.

S_1 and S_2 are two exclusive and non-empty subsets, and $S_1 \cup S_2$ is just equal to the aircraft set; for example, a legal assignment is $S_1 = \{1, 3, 6\}$ and $S_2 = \{2, 4, 5, 7\}$ if there are 7 aircrafts in total; and in the reverse mutation, if the two selected positions for reversing are i and j separately, and the source chromosome is $\{g_1, \dots, g_i \dots g_j \dots g_{len}\}$, the mutated chromosome after the operation is $\{g_1, \dots, g_j \dots g_i \dots g_{len}\}$.

On the other hand, in the pairing segment, we use an arithmetic crossover [42] and a random reset mutation. The specific operations are as follows: supposing that the selected position for cutting is i and two parents are $\{g_1^1 \dots g_i^1 \dots g_{len}^1\}$ and $\{g_1^2 \dots g_i^2 \dots g_{len}^2\}$; the offspring after the crossover are as follows:

$$\left\{ g_1^2 \dots g_{i-1}^2 g_i^1 g_{i+1}^1 \dots g_{len}^1 \right\}$$

and

$$\left\{ g_1^1 \dots g_{i-1}^1 g_i^2 g_{i+1}^2 \dots g_{len}^2 \right\}, \quad (17)$$

where $g_i^1 = g_i^1 + \beta(g_i^2 - g_i^1)$, $g_i^2 = g_i^2 \pm \beta(g_i^2 - g_i^1)$, and $\beta \in [0, 1]$; and in the mutation, if the selected position for resetting is i , and the source chromosome is $\{g_1, \dots, g_i \dots g_{len}\}$, the mutated chromosome is $\{g_1, \dots, g'_i \dots g_{len}\}$ where g'_i is set by a random value.

2) REPAIR STRATEGY

Because the new chromosomes are generated in the evolutionary process, the values of genes are usually determined by probability. Therefore, the flight assignments corresponding with the gene values often violate the restriction [22]. Nevertheless, the continuous evolution of generations provides an opportunity to ultimately obtain a good solution. However, the overall convergence speed will become slow and it is not easy to obtain a good solution in a limited time.

A repair strategy is therefore used in the objective evaluation to improve infeasible solutions. This technique is similar to some previous methods of solving optimization problems [43], [44]. We first reorder the flight time so that flights appear in departure time order. In doing so, the number of chromosomes that violate the restriction formula can be reduced. Furthermore, in each flight pair, if too many departure stations differ from the home base stations, the solution will clearly be poorer. Swapping the poorer flight legs means the pair will have a stronger opportunity of being returned to the departure station. The two local-search mechanisms are used in the repair method.

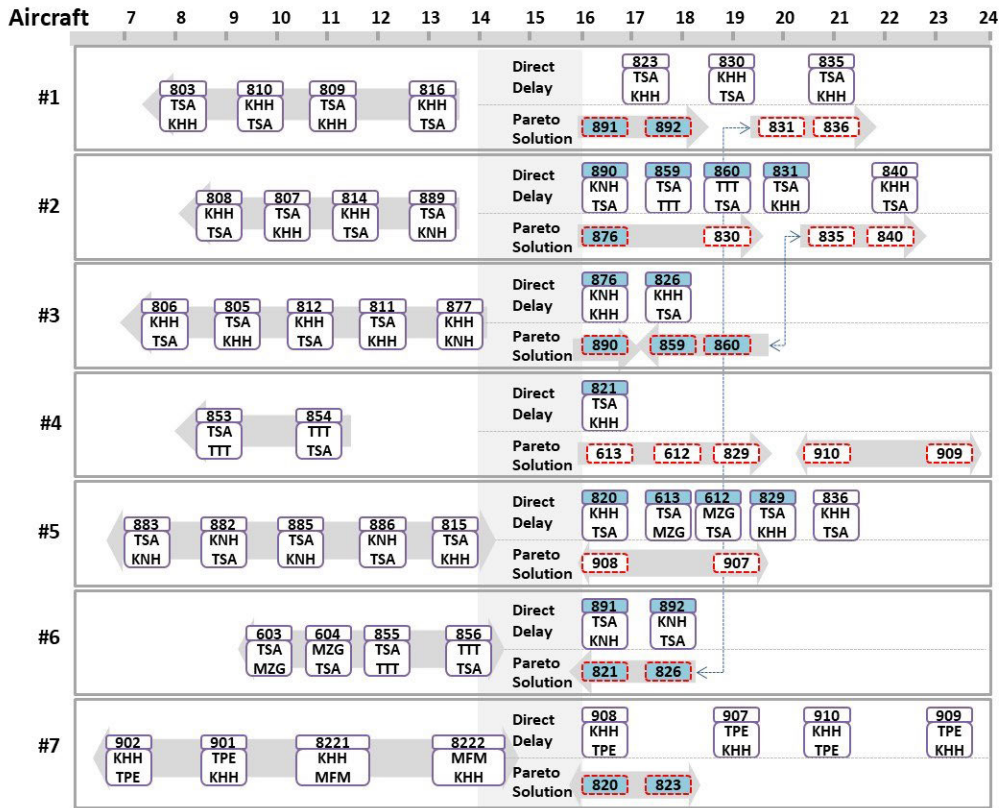
IV. EXPERIMENTAL RESULTS

This paper uses real-world flight data on short-haul airlines to build study cases. Table 2 shows the two sets of flight legs. The flight data are the product of the airline’s comprehensive market demand and the rights sought in relation to the route. In these studies, all constraints and objectives are solved using information on the specified flight legs to obtain an integrated schedule. Furthermore, to study the rescheduling of flight duties due to an unexpected disturbance, we used a simulated scenario in the experiment, as shown in Fig. 6, to verify the rescheduling capability in cases where some airports have been temporarily closed due to extreme rain [45].

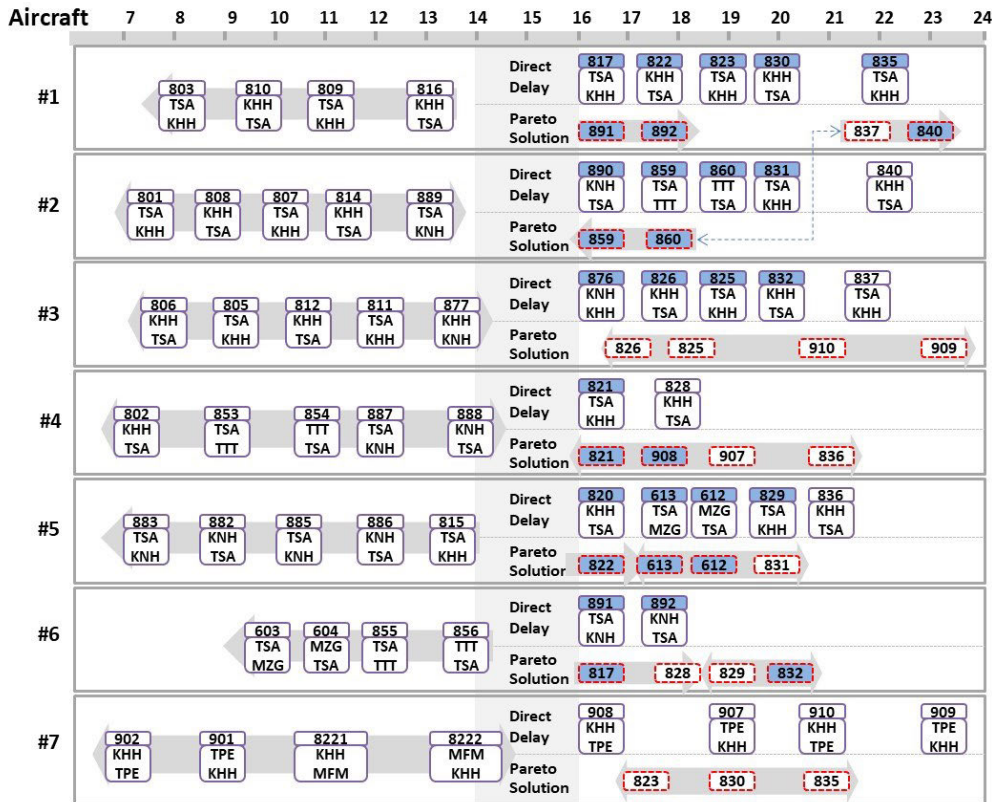
The development and execution environment contains the following hardware and software specifications: Intel i7 3.2 GHz PC with 8 GB memory, Windows 10 OS, and Visual C++ compiler. The additional experimental parameters are as follows: the population size is 100, the offspring size is 80, the crossover and mutation rates are 0.9 and 0.3, respectively. In each study case, execution will stop after a preset number of generations, and these parameters are selected through repeated experiments. In the execution, the customized parameters in the equations are set as (in minutes): $T_{tt} = 20$, $T_{ft} = 480$, and $T_{fp} = 720$; there are eleven aircraft to be routed, and each route contains a maximum of ten flight legs for an aircraft and a maximum of eight flight legs for a crew.

A. PREPROCESSING OPERATIONS

For certain special routes, airlines can use dedicated or charter flights; for example, KHH-DPS, KHH-HAN, TPE-PNH, TPE-PEN, and TPE-BKI in the cases studied. These are short-haul international routes. In practice, the routing and pairing plans are usually fixed for special routes, although



(a) The example schedules recovered in the first study case.



(b) The example schedules recovered in the second study case.

FIGURE 9. Graphical representation of the rescheduling result.

preset pairs still have to join the others to determine final crew assignment in the rostering phase. These are also shown in the daily flight table.

Preprocessing, which directly picks out international routes containing airports DPS, HAN, PNH, PEN and BKI, can be used to separate related flights to bypass the following optimal flow. The preprocessed routes (each route is directly covered by a pair) for the study cases are listed in Fig. 7.

B. SOLVING IRP PROBLEMS

After preprocessing, IRP problems contain 7 aircrafts. For comparison, real-world expert-made plans are listed in Table 3. In the experiments, the NSGA-II variant executed 50000 generations to explore solutions, the results of which are listed in Table 4. As shown, the Pareto solutions show the compromise between objectives. These all satisfy related constraints and requirements specified in the airline operation specification. For example, in Table 4(a), the first solution uses less pairs (PN) than the second solution; however, it contains a greater number of pairs not returning to the home base (NHB) and a non-short-connect (NSC) pair. As such, the proposed multiobjective approach reflects practical trade-offs in real life cases and provides diverse solutions. The example schedules decoded from the Pareto solutions are shown in Table 5.

To assess the solution quality of the proposed approach, the following aspects are discussed:

1) CONVERGENCE OF ALGORITHMS

Figure 8 shows the convergence trends when using or not using the repair strategy, and the difference between the two is large. With the repair strategy, approximately 5000 generations are required to obtain feasible solutions, whereas without a repair strategy, a feasible solution is not available in all generations. Thus, for the IRP problem, a large number of combinations in the solution space mean that if the proposed solution cannot effectively guide the search direction, it will slow the convergence and may even fall into a poor local solution only. Furthermore, as shown in Figure 8, even in final generations, the NSGA-II variant retains both feasible and infeasible solutions in the population, which ensures greater diversity.

2) IRP SCHEDULING AND EXPERT-MADE PLAN

As shown in Table 4(a), the first Pareto solution explored by the proposed IRP solver has better values in all objectives than the expert-made plan (listed in the third item). Their detailed schedules can refer to Table 5(a) and Table 3(a) respectively. Similarly, the second solution in Table 4(a) also yields better objectives than the expert-made plan; that is, both the two Pareto solutions dominate that made by experts.

In Table 4(b), the second Pareto solution explored in the proposed method is still better than the expert-made plan (also listed in the third item) according to the objective values. Although the first solution of Table 4(b) with a NSC pair cannot dominate the expert-made plan, the two schedules are

TABLE 7. Example solutions in the rescheduling study.

(a) The first recovery solution in the first study case.

Aircraft Routing Information	
Chromosome Genes	6,1,1,2,2,2,0,1,1,5,5,6,3,3,3,0,0,0,4,4,3,3,4,1,5,0,6,6,5,4,3,6,4,1,6,0,3,5,2,2,5,3
NO	Decoded Content (Aircraft Flight legs)
#1	803,810,809,816,891,892,831,836
#2	808,807,814,889,876,830,835,840
#3	806,805,812,811,877,890,859,860
#4	853,854,613,612,829,910,909
#5	883,882,885,886,815,908,907
#6	603,604,855,856,821,826
#7	902,901,8221,8222,820,823
Crew Pairing Information	
Chromosome Genes	0,8,0,8,0,8,0,7,0,7,0,7,0,7
NO	Decoded Content (Crew Duty Pair)
#1	803,810,809,816,891,892
#2	808,807,814,889,876,830
#3	806,805,812,811,877,890
#4	859,860,835,840
#5	853,854,613,612,829
#6	910,909
#7	883,882,885,886,815
#8	908,907
#9	603,604,855,856
#10	821,826,831,836
#11	902,901,8221,8222
#12	820,823

(b) The first recovery solution in the second study case.

Aircraft Routing Information	
Chromosome Genes	5,4,6,6,6,1,1,1,4,0,2,2,2,5,0,3,5,6,4,4,5,3,0,0,3,3,2,2,3,0,5,6,6,5,0,1,1,4
NO	Decoded Content (Aircraft Flight legs)
#1	803,810,809,816,891,892,837,840
#2	801,808,807,814,889,890,859,860
#3	806,805,812,811,877,876,826,825,910,909
#4	802,853,854,887,888,821,908,907,836
#5	883,882,885,886,815,822,613,612,831
#6	603,604,855,856,817,828,829,832
#7	902,901,8221,8222,820,823,830,835
Crew Pairing Information	
Chromosome Genes	0,8,0,8,0,6,0,6,0,7,0,8,0,5
NO	Decoded Content (Crew Duty Pair)
#1	803,810,809,816,891,892
#2	801,808,807,814,889,890
#3	859,860,837,840
#4	806,805,812,811,877,876
#5	826,825,910,909
#6	802,853,854,887,888
#7	821,908,907,836
#8	883,882,885,886,815,822
#9	613,612,831
#10	603,604,855,856,817,828
#11	829,832
#12	902,901,8221,8222
#13	820,823,830,835

equivalent because the expert-made plan also cannot dominate the first solution.

In summary, the proposed approach obtains at least one better solution in each execution instance, and all other solutions explored are at least equivalent compared to plans made by experts.

C. SOLVING RIRP PROBLEMS

We used the practical (originally made by experts) schedule in Table 3 to study the RIRP problem, where the disturbance period is set to 14:00-16:00. In this case, airports TSA, TPE, TNN, TTT and KHH are temporarily closed throughout the period. This type of situation usually occurs in the summer afternoon.

Table 6 shows the Pareto solutions after the rescheduling algorithm executes for 15000 generations. Table 7 shows the content of the example solutions. Figure 9 provides a graphical representation of the rescheduling result to provide a clearer view. In the diagram, the delayed flights are marked by light blue. As shown in Table 6(a), in the first study case, the first solution has a total of 10 delayed flights due to rain and is less than the second solution and the direct delay case of the original plan (listed in the third item); however, the first solution also has a maximum delay time of up to 140 minutes for some flight legs. This is longer than others. It is therefore another compromise condition. In addition, it is worth noting that the second solution dominates the direct delay case of the original plan and provides a better choice. Again, all other solutions obtained in the execution instances are at least equivalent to schedules that directly delay the original plan. On the other hand, as shown in Table 6(b), in this test case, no solution can dominate other solutions so all solutions are just equivalent.

Based on the experiments conducted, the proposed approach can effectively solve the scheduling of practical IRP and RIRP problems. At the same time, it can provide multiple solutions that enable decision makers to choose a preferred schedule after considering additional factors. For example, if the actual need is to prioritize objectives requiring fewer delayed flights, the first solution in Table 6(a) is preferred for the recovery schedule.

V. CONCLUSION

It is important to study and develop new methods to improve the quality and capability of airline scheduling for two significant reasons: first, cost savings are immense, even if only a small improvement is achieved in the airline industry; second, the stage-by-stage scheduling method only provides incomplete solution coverage and usually a local solution is obtained. It is therefore quite valuable if a global solution can be obtained through an integrated approach. Moreover, single-objective conversions commonly used in the sequential planning cannot reflect the multiobjective needs of practical environments.

This paper therefore studied improvements achieved by integrating both aircraft routing and crew pairing into a unified scheduling step to explore global solutions. By formulating integrated problems as combinatorial optimization problems, a multiobjective evolutionary approach based on the NSGA-II variant was proposed and a two-segmented chromosome structure was created that cooperated with customized genetic operators and a repair strategy. To verify the

proposed approach, real-world flight data were used to conduct several experiments containing IRP and RIRP problems.

The experimental results show that by scheduling routing and pairing at the same time, in each case study, our IRP approach can obtain at least one better solution than a plan made by experts, and similarly, our RIRP approach also obtains better or at least equal solutions compared to those directly delaying the flight schedules in sequence. From the results, our proposed method can really solve IRP and RIRP problems and provide multiple better candidate plans for decision makers.

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CHIU-HUNG CHEN received the B.S. degree in computer engineering from National Chiao Tung University, Taiwan, in 1990, the M.S. degree in computer science and information engineering from National Taiwan University, Taiwan, in 1992, and the Ph.D. degree in engineering science and technology from the National Kaohsiung University of Science and Technology, Taiwan, in 2009. He is currently an Associate Professor with Feng Chia University, Taichung, Taiwan. His research interests include evolutionary computation, multiobjective optimization, industrial robot applications, smart manufacturing, and multimedia systems.



FU-I CHOU received the B.S. degree from the National University of Kaohsiung, Taiwan, in 2010, the M.S. degree from National Dong Hwa University, Taiwan, in 2012, and the Ph.D. degree from National Cheng Kung University, Taiwan, in 2019, all in electrical engineering. He was the Deputy Engineer of the Metal Industries Research and Development Centre, Taiwan, from September 2012 to August 2019. From August 2019 to January 2020, he was an Assistant Professor with the National Chin-Yi University of Technology, Taiwan. He is currently an Assistant Professor with the Department of Automation Engineering, National Formosa University, Taiwan. His research interests include state observer design, automation and control, industrial robotics, artificial intelligence applications, machine learning, quality engineering, evolutionary optimization, and machine vision. He received the 2019 Doctoral Dissertation Award from the Chinese Automatic Control Society, Taiwan. He and his colleagues proposed the research and development achievement entitled Intelligent 3D Visual Automation for Shoes Roughing and Cementing Equipment, which received the 2019 American Edison Bronze Award in the robot field as well as the 6th National Industry Innovation Award from the Taiwan Ministry of Economics.



JYH-HORNG CHOU (Fellow, IEEE) received the B.S. and M.S. degrees in engineering science from National Cheng Kung University, Tainan, Taiwan, in 1981 and 1983, respectively, and the Ph.D. degree in mechatronic engineering from National Sun Yat-sen University, Kaohsiung, Taiwan, in 1988. He is currently the Vice President and the Chair Professor of the Mechanical Engineering Department, National Chung Hsing University, and the Chair Professor of the Electrical Engineering Department, National Kaohsiung University of Science and Technology, Taiwan. His research and teaching interests include intelligent systems and control, computational intelligence and methods, automation technology, robust control, and robust optimization. He is also a Fellow of the Institution of Engineering and Technology (IET), the Chinese Automatic Control Society (CACS), the Chinese Institute of Automation Engineer (CIAE), and the Chinese Society of Mechanical Engineers (CSME). He was a recipient of the 2011 Distinguished Research Award from the National Science Council of Taiwan, the 2012 IEEE Outstanding Technical Achievement Award from the IEEE Tainan Section, the 2014 Distinguished Research Award from the Ministry of Science and Technology of Taiwan, and numerous academic awards/honors from various Societies. Based on the IEEE Computational Intelligence Society (IEEE CIS) evaluation, his Industrial Application Success Story has got the 2014 winner of highest rank, thus being selected to become the first internationally industrial success story being reported on the IEEE CIS website.

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