Cascading Delay Risk of Airline Workforce Deployments with Crew-Pairing and Schedule Optimization

Abstract

This paper concerns the assignment of buffer time between two connected flights and the number of reserve crews in crew pairing to mitigate flight disruption due to flight arrival delay. Insufficient crew members for a flight will lead to flight disruptions such as delays or cancellations. In reality, most of these disruption cases are due to arrival delays of the previous flights. To tackle this problem, many research studies have examined the assignment method based on the historical flight arrival delay data of the concerned flights. However, flight arrival delays can be triggered by numerous factors. Accordingly, this paper proposes a new forecasting approach using a Cascade Neural Network, which considers a massive amount of historical flight arrival and departure data. The approach also incorporates learning ability so that unknown relationships behind the data can be revealed. Based on the expected flight arrival delay, the buffer time can be determined and a new dynamic reserve crew strategy can then be used to determine the required number of reserve crews. Numerical experiments are carried out based on one year of flight data obtained from 112 airports around the world. The results demonstrate that by predicting the flight departure delay as the input for the prediction of the flight arrival delay, the prediction accuracy can be increased. Moreover, by using the new dynamic reserve crew strategy, the total crew cost can be reduced. This significantly benefits to airlines in flight schedule stability and cost saving in the current big data era.

Keywords:
Robust Crew Pairing, Big Data, Flight Reliability

1. Introduction

Aviation is one of the most significant worldwide industries.[1] As stated in an article by IATA titled “Air Passenger Market Analysis” in 2015, there was a strong growth of 7.1% in global air travel in August 2015 compared to 2014.[2] IATA has forecasted that the rising trend in air travel will remain strong in the future in terms of revenue passenger kilometers. Accordingly, in recent years, many research studies have been undertaken in aviation. Research work related to passengers is particularly attractive, such as airport security,[3] aviation security,[4,5] airline operations,[6] flight reliability,[7] runway,[8,9] customer knowledge,[10] customer satisfaction,[1] etc. Among these, managing airline crew costs is one of the most popular and crucial topics because it yields enormous economic benefits for airlines and ranks the second highest expenditure after fuel cost. More importantly, a poor crew schedule may result in unreliable flight schedules, significantly jeopardizing airline operations and profitability.

A systematic approach for risk analysis is crucial [11,12] for the construction of strategic planning in order to maintain stability.[13] This is especially important in transportation networks.[14] Ball et al.[15] have carried out a very comprehensive analysis on the economic aspects of the impact of flight delays in the United States. The report stated that the total cost of all US air transportation delays in 2007 was $32.9 billion, of which, $8.3 billion was incurred by the passenger component, followed by a $16.7 billion from the airline component, and a $3.9 billion from demand loss. It also brought an indirect effect to the U.S. economy by a reduction of $4 billion in GDP. In the literature, many studies in flight schedule stability focused on capturing the uncertainties arising from flight delays or flight cancellations. For example, Inniss and Ball[16] analyzed incoming arrival flight data to predict available airport capacity. In the study, weather was the main factor considered. Tu et al.[17] applied a statistical approach to estimate the flight departure delay distribution with long-term and short-term patterns. In addition, many papers collected historical data on concerned flights and then applied different statistical analysis approach to identify any potential patterns and to fit the delay patterns into some distribution functions, such as normal distribution, exponential distribution, etc.[7,18] Some studies even categorized the data into different timescales, such as hourly, weekly or monthly, to analyze if there were any seasonal patterns, repeatable patterns, etc. Regression based approaches, such as Linear Regression, ARIMA, etc. are commonly used for prediction as indicated in the literature.[19,20] However, in reality, only studying the historical flight delay data of the concerned flight may not be sufficient as many factors relating to each flight have not been considered, such as the number of aircraft landing in the arrival airport, number of aircraft departing in the departure airport, weather conditions, etc. More importantly, those factors are changing from one flight to another on different occasions, even for the same flight running every day. Accordingly, in order to consider this massive amount of data, a new forecasting approach is proposed, and the traditional approaches are then used for benchmarking in this paper.

A flight schedule is said to be more robust if a flight delay is less likely to happen under disruptions. In general, two measurements are used: schedule stability and schedule flexibility. Schedule stability concerns the ability of a schedule to remain valid under a certain degree of disruption.[21] Schedule flexibility concerns the ability to modify a schedule when disruption occurs.[22,23] To capture uncertainties and make the flight schedule more robust, buffer time is a very useful tool for absorbing flight delays. In the literature, it is usually assigned according to the expected flight delays, which can be estimated by various forecasting methods, such as Regression based approaches.[24-26] Other than buffering time, some authors proposed reserve crews, called standby crews in reality. In common airline practice, crews are called reserve crews when they are on standby duty and they receive a small allowance on top of the salary. However, if they are called back for flight duty, extra payment is then given.[27-28] Lastly, some studies proposed crew swapping, also called duty swapping. The idea is to swap the duties between two crews to cover one with another.[22-23] In our paper, buffer time is determined by a Cascade Neural Network (CNN), while the reserve crew is determined based on a dynamic reserve crew strategy.

Because of the complexity of the problem, the airline crew scheduling problem is usually decomposed into the crew pairing problem (CPP), and the crew assignment problem (CAP).[29] Our paper focuses on CPP, which assigns a crew to each scheduled flight in order to minimize the total crew costs, meanwhile satisfying all the rules and regulations governed by unions, airlines, and aviation authorities. A crew itinerary is called pairing, which is constructed by a set of duties, consisting of a number of flights, with sit-time and rest period in between as needed, according to the regulations.[30] CAP is to find a monthly schedule that covers all the pairing found in CPP,[31] which is usually formulated as a set partitioning problems and solved by using the Column Generation approach.[32] The difficulty of using column generation is the handling of a huge number of column and constraint matrices in the master problem when the problem scale grows larger.[33] For the generation of the new pairings, the sub-problem is usually modeled as a shortest path problem and is solved by using various kinds of methods, such as the Labelling algorithm. For network modeling of the shortest path problems, some studies model the arc as flights, [34,35] and others model as duties.[30,36]

An early work using the Column Generation approach can be found in Lavoie et al. [37]. Later on, Anbil et al.[29] proposed a SPIRINT approach to generate columns for large scale CPPs to increase the optimization efficiency. Barnhart et al.[38] studied the problem complexity of CPP for long haul flights and short haul flights networks. They stated that since the long haul network has fewer connectable flight legs and duty periods, the network size is relatively smaller. Until now, Column Generation is still the main approach in solving CPP. Saddoune et al.[31] applied the column generation approach with the dynamic constraint aggregation technique to solve integrated crew pairing and crew assignment problems. Zhu and Wilhelm[34] proposed a three stage solution approach and a resource-constrained approach to solve the shortest path problem. Saddoune et al.[35] applied Column Generation to CPP with repetitions of the same flight number. Cacchiani and Salazar-González[39] used Column Generation to solve for integrated fleet assignment, aircraft routing, and CPP. The proposed methodology mainly consists of two parts, as outlined as in Fig. 1. First of all, historical flight data is analyzed by using CNN to predict the expected flight arrival delay. Then in the second part, the flights required to determine the crew pairing are input with the expected flight arrival to determine an optimal crew pairing and a corresponding reserve crew assignment plan.

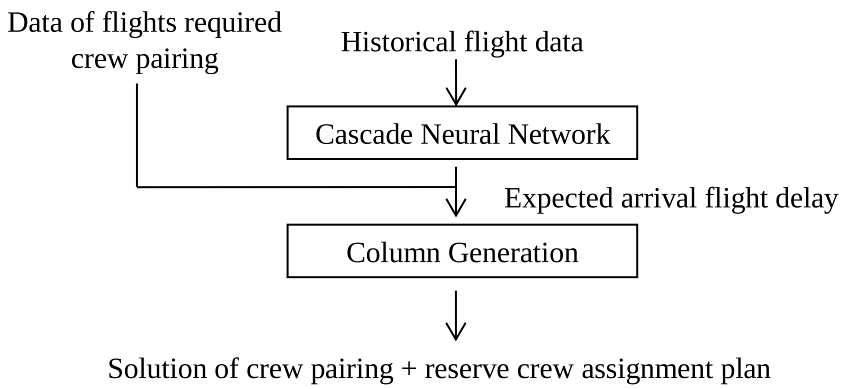

Fig. 1. Outline of the proposed algorithm

2. Flight Delay Forecasting Method – Cascade Neural Network

In the first part of the algorithm, the CNN model is used to forecast the expected fight delay for the assignment of buffer time and reserve crews.

2.1 Data Source

We obtained over one year of flight data (from April 2015 to March 2016) from one of the major flight data service providers. The flight data concerned one of the major airlines in Hong Kong and all the flight data in the related airports that it covered (with a total of 112 airports involved). The collected data included flight number, date of flight, scheduled arrival time, actual arrival time, scheduled departure time, actual departure time, flight time, departure airport, arrival airport, and aircraft type. We also obtain the weather data from "weather.org".(40)

2.2 Data Pre-processing

In the data collected, any flight departures earlier than the scheduled departure time are considered as on-time departures. A value of 0 min is used in this case in order to avoid negative values in the calculations, which may cause errors. In addition, any flight with a departure delay or arrival delay longer than 180 min is not considered, and actually involved only 0.3% of all fights. This is because we focused only on the regular daily operations. Moreover, these extreme cases can be regarded as serious disruption, which normally cannot be handled by regular robust scheduling approaches. Accordingly, we treat these as outliners. Similarly, any flight arrival delay within 5 min will be considered as on-time, which includes about 30% of flights, because such short delays do not affect the schedule very much in general.

2.3 Neural Networks

In this paper, we apply the Neural Network (NN) approach to predict flight arrival delays to support the crew pairing optimization. NN is a promising approach to capture the nonlinear relationship between various factors, as flight arrival delays are usually influenced by multiple factors.

2.3.1 Factors used for Flight Arrival Delay Forecasting

Some basic information such as flight number, departure airport, arrival airport, day of week, month, day of month, scheduled departure time, and scheduled arrival time, are used for forecasting the flight arrival delay. However, as stated in the literature, a flight arrival delay is affected by numerous factors, such as seasonal factors, airspace congestion, airport congestion, and weather. Accordingly, we analyzed the collected data and created the following indicators as the input variables of the NN.

A. Peak Hours Indicator

It is used to indicate how busy an airport is in each hour of the day without counting any other external factors, e.g. airspace congestion. In reality, it is known that airports are busier in the afternoon and in the evening, while in the morning and after mid-night are less so. In addition, Friday to Sunday is busier, while Monday to Thursday is less busy. Accordingly, the number of scheduled flight arrivals and departures at an airport each hour is considered. The average number of flight arrival and departure (avg^f) in an hour in each individual airport is calculated. In fact, instead of applying a continuous function for indication, a 5 points scale is applied to convert all the possibilities into 5 situations, a value of 5 representing severe congestion, and a value of 1 represents the least. The reason for this is to categorize the data into several situations so that it can avoid the data being too diverse, which may reduce the forecasting performance. The point scale is defined by the number of flights in the hour as shown in **Table I**.

Table I. Defining values for Peak Hours Indicator

Point Scale	Description
5	over 60% of avg^f
4	within 30% and 60% above avg^f
3	within 30% deviated from avg^f
2	within 30% and 60% below avg^f
1	below 60% of avg^f

B. Peak Season Indicator

It is used to indicate whether the day is close to or in the holiday period or not. As seen in the literature, it is known that flight delays are more frequent during the days around holidays, such as Christmas, Easter, summer holidays, etc. This can be regarded as a monthly/seasonal factor. Accordingly, a 3 points scale indicator is used with value of 1 representing a normal day, value of 2 representing 2 days before/after a holiday, and value 3 represents a holiday in the airport city considered.

C. Peak Typhoon Season Indicator

It is used to indicate the chance of getting a typhoon/hurricane hit in the month. It is known that flight delays are more frequent and severe when there is a typhoon or bad weather. As a typhoon is hard to predict exactly on which day it may occur, a 3 point scale indicator is used, with a value of 1 representing a low chance, value of 2 representing a medium chance, and value of 3 representing a high chance in the month. This can be estimated according to historical weather data.

D. Flight time Indicator

The relationship between the flight departure delay and flight arrival delay is not studied in the literature for flight arrival delay forecasting. We found that many flight arrival delays are caused by flight departure delays. However, some flight departure delay times can be absorbed during the flight times. In practice, this phenomenon can be explained by an increased cruising speed in order to reduce the flight arrival delay induced. Fig. 2 shows the delay time being absorbed during the flight time over the year for all the flights in the airline. The x-axis represents the flight time increasing from the left to the right from the shortest 53 mins to longest of over 16 hours. The values in the y-axis are calculated by the actual flight arrival delay time minus the actual flight departure delay time. The positive values represent the actual arrival delays, which are not caused by the actual flight departure delay. Such arrival delays can be caused by airspace congestion, arrival airport congestion, bad weather in the arrival airport, etc. The negative values represent the amount of delay that has been absorbed during the flight time. Fig. 2 shows that the amount of delay time can be absorbed more if the flight time is longer.

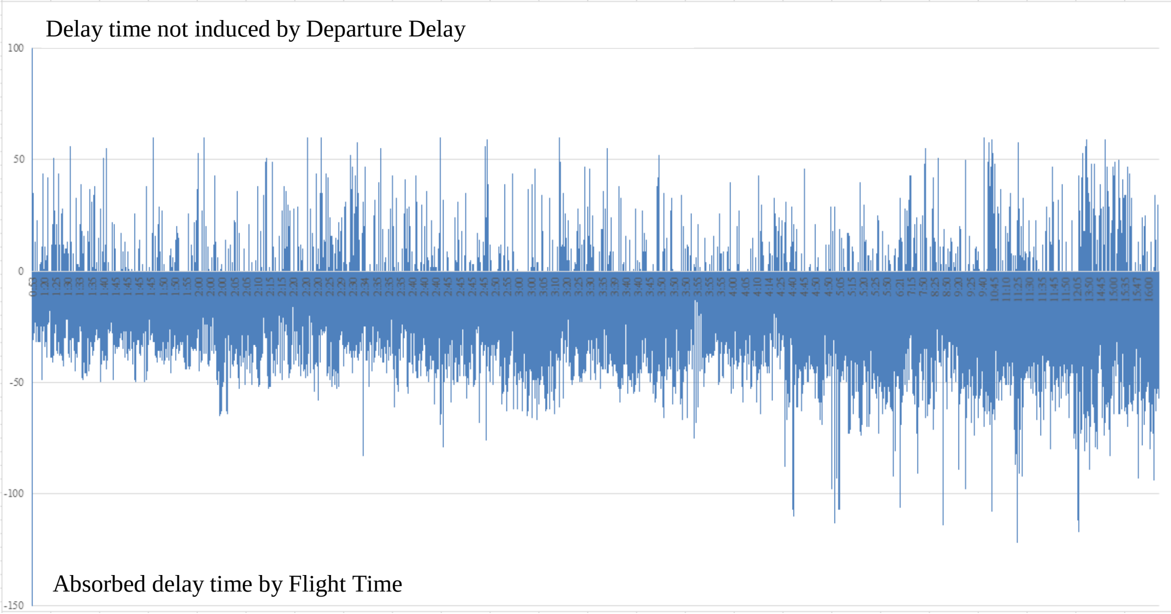

Fig. 2. Relationship between flight arrival delay, flight departure delay, and flight time

2.4 Neural Networks Structure

A. Multi-Layer Feed-Forward Neural Network

The Multi-layer Feed-forward neural network model is a popular structure now being used. It consists of an input layer, hidden layer and output layer. Multi-layer Neural Networks are widely used to model nonlinear relationship in the development of nonlinear prediction models.(41) Accordingly, non-linear sigmoid functions are used as the activation functions. The framework is shown in Fig. 3. In the model, the output variable is the expected flight arrival delay. The input variables are flight number, departure airport, arrival airport, day of week, month, day of month, scheduled departure time, scheduled arrival time, peak hour indicator, peak season indicator, peak typhoon season indicator, and flight time indicator.

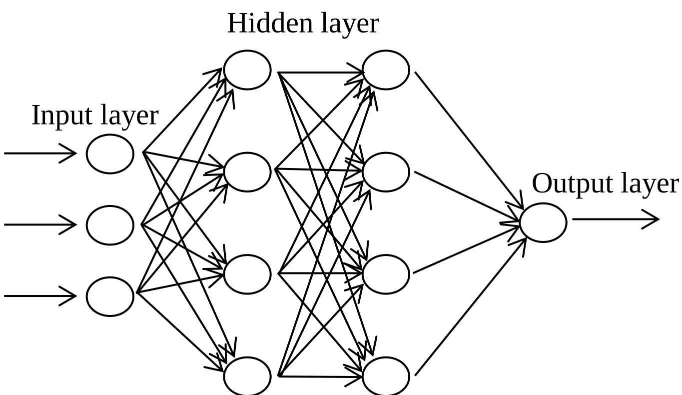

Fig. 3. Framework of Multi-Layer Feed-forward Neural Network

B. CNN

In fact, our purpose is to predict the flight arrival delay. However, referring to Fig. 2, we have found that flight arrival delays are more related to flight departure delays and flight times. Accordingly, we applied the cascade neural network modelling approach to predict the flight departure delay first and then use it as the input to predict the flight arrival delay, as shown in Fig. 4.[42] Set of Inputs are shown as in **Table II**.

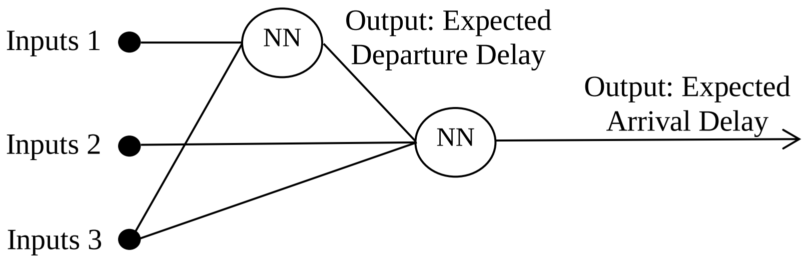

Fig. 4. Framework of Cascade Neural Network

Table II. Factors in Inputs Sets

Inputs Set	Factors
1	peak hour indicator, peak season indicator, peak typhoon season indicator
2	arrival airport, scheduled arrival time, flight time indicator
3	flight No., departure airport, day of week, month, day of month, scheduled departure time

2.5 Neural Network Model Selection and Assessment

In the literature, forecasting methods such as linear regression (LR) and ARIMA are commonly used for flight delay prediction[19], and we apply them for benchmarking. For NN and CNN, the supervised learning approach is used to train the neural network. For training, 70% of the data are used as training data and the remaining 30% used for model validation, including both the data at the input variables and output variables. Table III shows the RMSE obtained by using different forecasting methods. The results show that the performance of NN and CNN is better than LR, and ARMIA. In addition, by using the CNN modelling approach, the prediction accuracy can be further improved. Accordingly, CNN is used for forecasting in this paper.

Table III. Results obtained by different forecasting methods

Type of Forecasting Methods	RMSE
LR	40.8
ARMIA	39.2
NN	28.1
CNN	20.8

3. Description and Formulation of Crew Pairing

In CPP, a typical pairing is represented by a legal sequence of duties, with rest periods in between, performed by the same crew member. It starts and ends at the crew member's home and normally lasts for 2 to 5 days. Each duty contains one or more flights defined as a single non-stop flight between the origin and destination. A rest period is the time period in which the crew member is free of duties, i.e. overnight rest. Given a set of flights to be operated by the same aircraft type, CPP aims to determine a minimum-cost set of feasible pairings so that a qualified crew is assigned every flight.

Cost Components in Crew Pairing

In CPP, each pairing is associated with a cost, which can be a very complex function. Based on an approximate pairing cost introduced by Saddoune *et al.*,[35] some basic cost components are the waiting cost for flight connections and rest periods, fixed pairing cost, cost for pairing minimum duty guaranteed (PMDG), and deadhead cost. Here, we also consider propagated delay cost and reserve crew cost.

A. Basic Cost Components

Similar to the waiting cost function introduced by Mercier et al.,[21] we have developed a flight dependent cost function $g_f(\cdot)$ for each flight f as illustrated in Fig. 5, where $\delta_{ff'}$ is the duration of connection time between flight f and its following flight f'. A rest period cost function $k_d(\cdot)$ is developed for each duty d as illustrated in Fig. 5, where $\delta_{dd'}$ is the duration of the rest period between duty d and duty d'. To favour pairing robustness by absorbing the flight delay as much as possible, for $g_f(\cdot)$, the ideal connection time (with zero cost) between the flights is sum of the minimum connection time and the expected primary delay of the prior flight f in order to avoid disruptions. Waiting cost increases more significantly if the connection time is longer than the ideal time. On the other hand, the waiting cost also increases, but relatively more sharply, if the waiting time is shorter than the ideal time. In the case, if the waiting time exceeds 12 or 14 hours (depends on the duty period), it is considered as a rest period which occurs after finishing a duty. A rest period cost is incurred by $k_d(\cdot)$, which consists of a fixed rest cost and an additional penalty for each minute above an ideal rest period. This cost is also known as out-porting allowance in common airline practice. For crew resting at home base, no direct cost is incurred, but it is noted that additional employees may be needed when too many or too long rests are provided and incur extra cost. The cost for PMDG is to penalize the generation of a duty with a very short duty period. Deadhead cost is only assigned to a pairing in which a reposition of a crew is needed. These costs can only simulate the approximate operational cost of a pairing.

B. Propagated Delay Cost

To improve the robustness of the plan, we also use propagated delay cost and reserve crew cost. A flight's primary delay is regarded as self-delay. It may induce propagated delays to those later flight(s) with the same crews involved. The propagated delay can be very disruptive to the original plan and inflict severe penalty costs (e.g. extra fuel and other compensation etc.) upon the airline. Therefore, the propagated delay cost is used to penalize a connection of flights which may easily lead to propagated delay. Since the flight delay can propagate, one by one along the chain of flights in a pairing, the calculation can be very complex and is explained in the next section.

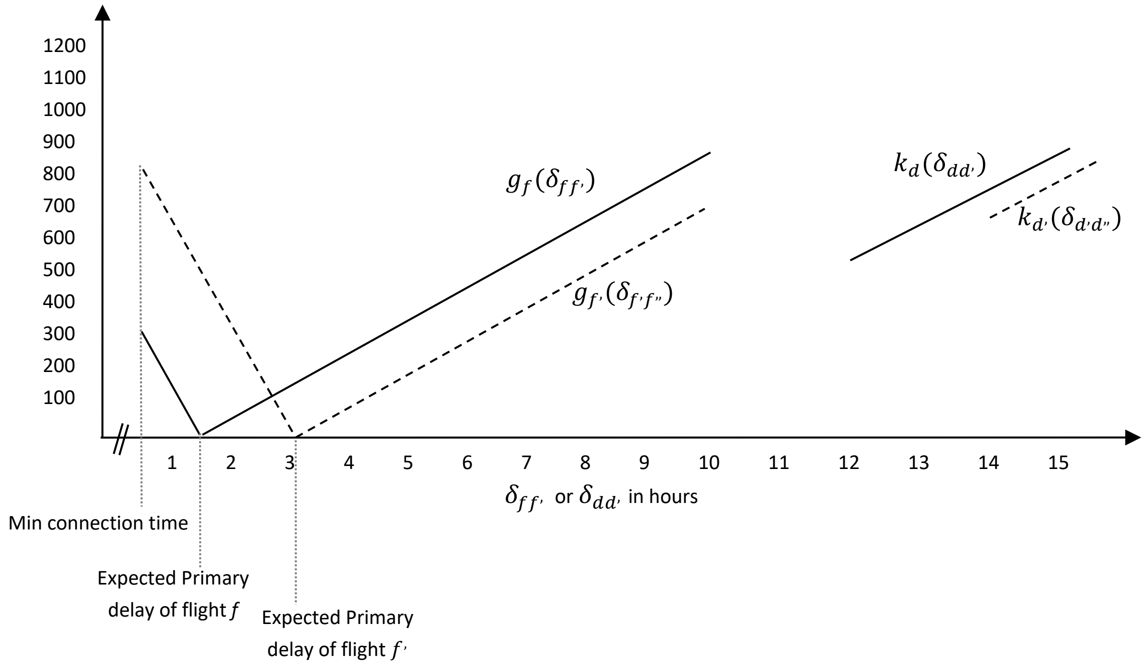

Fig. 5. Waiting Cost Functions

C. Reserve Crew Assignment and Cost

During the robust crew pairing, in the case in which an expected propagated delay is a over certain number of minutes, a reserve crew will be assigned and the reserve crew cost is given.

4. Column Generation with Modified Multi-label Correcting Algorithm

In this paper, we propose Column Generation with a Modified Multi-label Correcting Algorithm to solve the problem.

A. Master problem

The master problem of the CPP is to find a set of pairings, with least cost such that all the flights are covered, which can be formulated as a set covering model (1) – (3).

$$\min \sum_{p \in P} c_p \, x_p \tag{1}$$

Subject to

$$\sum_{f \in F} a_{fp} \, x_p \ \geq 1, \qquad \forall p \in P \tag{2}$$

$$x_p \in \{0, 1\}, \qquad \forall \, p \in P \tag{3}$$

where P is the set of all feasible pairings and F is the set of all flights to be covered. c_p is cost of pairing $p \in P$; a binary variable a_{fp} = 1 if flight $f \in F$ is covered by pairing $p \in P$, and = 0 otherwise. Hence, a binary decision variable x_p = 1, if pairing $p \in P$ is selected by the solution, and = 0, otherwise. The objective function is to minimize the total cost of the selected pairings, while constraint (2) ensures that each flight is covered by at least one selected pairing.

The master problem is converted into a restricted master problem (RMP) and solved iteratively by considering all constraints but only a subset of its variables, which is updated in each iteration. The RMP starts with a set of initial feasible solutions in which one pairing covers only one flight. Hence, the number of pairings in the initial set of solutions is equal to the number of flights to be covered. The deadheads can be utilized in order to ensure all the pairings are feasible even if its corresponding flight did not start or end at the base. The RMP is solved by a linear programming solver and a set of dual prices of the current RMP are obtained. Then, the dual prices are updated in the pricing sub-problem which corresponds to a shortest-path problem with resource constraints (SPPRCs) and is solved by the modified multi-label correcting algorithm. After solving the sub-problem, a column (a pairing) with the most negative reduced cost that can improve the objective function value of the RMP will be identified. The column is inputted to the RMP and then the next iteration starts. If no column with a negative reduced cost is obtained, the column generation process terminates and the computed primal optimal solution of the current RMP is also optimal for the master problem. If a fractional solution is found at the stopping condition, we solve the integer programming problem using the columns in the final RMP and then the integer feasible solutions for the RMP can be obtained.

B. Sub-problem

The objective of the pricing sub-problem is to find a column represented by a path ρ from the source to the sink node over a constructed duty network (see Fig. 6) with the minimum reduced cost that also satisfies all the restrictions related to the pairing formation, e.g. the maximum pairing duration, etc.

Pairing feasibility is mostly restricted by the regulations related to duties. Therefore, before constructing the network, consider a set of flights F. We generate all the feasible duties by connecting one or more flights $f \in F$ according to the related airlines regulations, so that all regulations related to duty feasibility do not need to be modelled explicitly in the shortest path network. Here, a duty set D is formed and each duty $d \in D$ consists of a sequence of flights, so that a flight-duty set is defined for each $d \in D$: $D_d^I = \{f_1, f_2, \dots, f_S\}$, where S is the number of flights in duty d. In this stage, all the infeasible connections of flights have been eliminated, and for each feasible duty, the duty period is obtained and thus its corresponding minimum rest period is known.

To construct a duty network, let $G = (\mathcal{N}, \mathcal{A})$ be the completed duty network where N is the node set, and A is the arc set. There is only a single source node (o) and a single sink node (e) representing the start and end of a pairing, and each generated duty $d \in D$ corresponds to a unique duty node $i \in \mathcal{N}^D$ for enumerating all possibilities, so that $\mathcal{N} = \{\mathcal{N}^D \cup o \cup e\}$, and D_d^I corresponds to D_i^I. The network also involves five subsets of arcs for connecting the nodes: (i) *Starting of pairing arcs* ($\mathcal{A}^s$) is used for connecting the source node with all the duties with the first flight departure from the base; (ii) the *deadhead starting arc* ($\mathcal{A}^{ds}$) is used to connect the source node with those duties which did not start at base, implying that all duties can be a feasible start of a pairing; similarly (iii) *ending of pairing arcs* ($\mathcal{A}^e$) connect the duty nodes with the last flight arrival at the base to the sink node; while (iv) *deadhead ending arcs* ($\mathcal{A}^{de}$) is used to connect the duties which did not end at base to the sink node, implying that all duties can be a feasible end of a pairing, and (v) *rest arcs* ($\mathcal{A}^r$) connect all feasible connections between two consecutive duties, where $\mathcal{A}^s \cup \mathcal{A}^e \cup \mathcal{A}^{ds} \cup \mathcal{A}^{de} \cup \mathcal{A}^r = \mathcal{A}$.

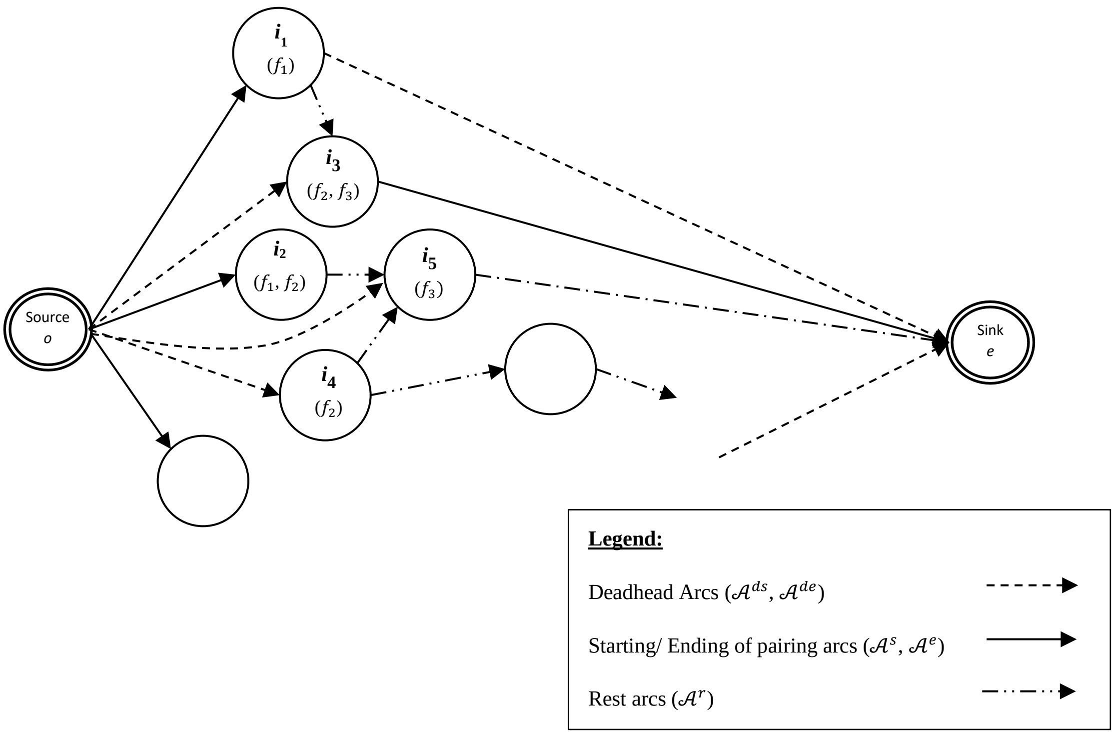

Fig. 6. A Duty Network

In the network, the resource variables are defined on all nodes in *G*. At each node, the quantity of these resources is restricted within a range called resource window. When constructing a path, the resources must be varied within the given window. This problem involves a resource constraint, i.e. *a maximum duty period in a pairing*. For instance, the maximum duty period in a pairing is 60 hours, and the resource variable r_i^1 denotes the number of hours consumed at the current node $i \in N$ (duty *i*). At each node of the duty network, the resource window is set as [0, 60] while the source node is set as [0, 0]. Therefore, when a path is constructing, this value starts at 0 and increases by the duty hours consumed at each node, meaning that a duty is added to the path. The resource windows forbid the assignment of 61 hours or more duty hours to the variable in the path,(8) so that the path with all feasible resource variables is regarded as a resource-feasible path while all the infeasible paths are discarded.

A path possesses a resource variable for each resource constraint and also a reduced cost that leads the problem to SPPRCs.(43) Hence, we explain the computation of the reduced cost, and elaborate on the modifications of the multi-label correcting algorithm in searching for the shortest path $\bar{\rho}$ with the negative reduced cost in the SPPRCs.

Let a resource-feasible shortest path $\rho = \{o, i_1, i_2, \ldots, e\}$ from *o* to *e* in *G* representing a feasible pairing *p*, the cost of a path is sum of the costs of its arcs. Each arc $(i^-, i) \in \mathcal{A}$, where i^- is the prior node of node *i*, is associated with a fixed arc cost $t^f_{i^-,i}$ which depends on the nodes i^- and i, and two variable arc costs, including the propagated delay cost $(t^p_{i^-,i})$ and the reserve crew cost $(t^r_{i^-,i})$ which depend not only the nodes i^- and *i*, but also all the preceding nodes of i^- in the path. Equation (4) explains the fixed cost, which is comprised of (i) deadhead cost $c^H_{i^-,i}$, (ii) connection time cost $c^W_{i^-,i}$, (iii) rest period cost $c^R_{i^-,i}$, and (iv) PMDG cost $c^D_{i^-,i}$. $c^H_{i^-,i}$ is set equal to a fixed value γ as in Equation (5). $c^W_{i^-,i}$ is for the connection time as in Equation (6), in which $g_{f^-}(\cdot)$ is the proposed flight dependent waiting cost function for each flight $f^- \in D_i^I$, and $\delta_{f^-,f}$ is the connection time corresponding to flight f^- and its following flight f in node *i*, which is calculated by the scheduled departure time of flight f minus the scheduled arrival time of flight f^-. $c_{i^-,i}^R$ is for the rest period as in Equation (7), in which $k_{i^-}(\cdot)$ is the rest period cost function corresponding to node i^-, and $\delta_{i^-,i}$ is the rest period which is calculated by the duty start time of *i* minus the duty end time of i^-. $c_{i^-,i}^D$ is used to ensure a minimum payment is given to the duty if it is shorter than a minimum time V_{min}. In other words, it is used to force the algorithm to form a longer duty period. This value is not issued if it is longer than V_{min} as in Equation (8), in which v_i is the total credit flying time in duty *i*, and *v* is the salary paid for each unit of flying time.

The fixed cost can be obtained once the network is constructed, while the variable costs have to be computed when solving the SPPRCs.

$$t_{i^-,i}^f = c_{i^-,i}^H + c_{i^-,i}^W + c_{i^-,i}^R + c_{i^-,i}^D, \quad \forall (i^-, i) \in \mathcal{A} \tag{4}$$

, where

$$c_{i^-,i}^H = \gamma, \quad \forall (i^-, i) \in \mathcal{A}^{ds}, \mathcal{A}^{de} \tag{5}$$

$$c_{i^-,i}^W = \sum\nolimits_{f^- \in D_i^I, f^- \neq f_1} g_{f^-}(\delta_{f^-,f}), \quad \forall (i^-, i) \in (\mathcal{A} - \mathcal{A}^{de} - \mathcal{A}^e) \tag{6}$$

$$c_{i^-,i}^R = k_{i^-}(\delta_{i^-,i})\, k, \ \forall (i^-, i) \in \mathcal{A}^r \tag{7}$$

$$c_{i^-,i}^D = v \cdot max\,\{0, V_{min} - v_i\}, \quad \forall (i^-, i) \in (\mathcal{A} - \mathcal{A}^{de} - \mathcal{A}^e) \tag{8}$$

The pairing cost c_p is equal to sum of the arc cost in path ρ, as shown in Equation (9), in which K is a constant to denote the basic fixed cost for the crew.

$$c_p = \mathrm{K} + \sum_{i \epsilon (\rho - o)} (t_{i^-,i}^f + t_{i^-,i}^p + t_{i^-,i}^r) \tag{9}$$

, where i^- is the node prior to *i* in path ρ. In fact, the goal of the sub-problem is to find the most negative reduced cost variables if existing. Therefore, the cost of the path needs to be modified to the reduced cost variable by subtracting the dual prices from the pairing cost. Let π_f, $\forall f \in F$ be the dual price associated with the Constraints (2) in the master problem. The reduced cost $\bar{c}_p$ of the pairing *p* is then given by Equation (10) and the objective function of the sub-problem can be rewritten as Equation (11).

$$\bar{c}_p = (c_p - \sum_{f \in F} \pi_f \cdot a_{fp}) \tag{10}$$

$$\bar{c}_\rho = \min\{ \mathrm{K} + \sum_{i \epsilon (\rho - o)} (t_{i^-,i}^f + t_{i^-,i}^p + t_{i^-,i}^r - \sum_{f \in D_i^I} \pi_f) \} \tag{11}$$

The multi-label correcting algorithm is used to identify the most negative $\bar{c}_p$ through the network. Let L be a set of nodes to be handled in the algorithm, and a set of attributes (referred to as labels) $\{ d_i^{TC}, d_i^1 \}$ are used for tracking the accumulated total cost and validating the resource constraint at each nodes $i \in N$ along the path. The values of these attributes are forward propagated through the network by adding the corresponding values of the new arc to the previously computed partial path by using the Equations (12) and (13) respectively, where $\rho(i^-)$ is the prior node to node *i* in path ρ.

$$d_i^{TC} = d_{\rho(i^-)}^{TC} + t_{\rho(i^-),i}^{f} + t_{\rho(i^-),i}^{p} + t_{\rho(i^-),i}^{r} - \sum_{f \in D_i^I} \pi_f \tag{12}$$

$$d_i^1 = d_{\rho(i^-)}^1 + r_i^1 \tag{13}$$

First of all, we set all the attributes $\{d_i^{TC}, d_i^1\}$, $\forall i \in N - \{o\}$ in the network as $+\infty$, while setting d_o^{TC} and d_0^1 as 0. Starting with the source node o, $L = \{o\}$, remove one node from L, i.e. o in this case, and for each arc $(\boldsymbol{o}, i) \in \mathcal{A}$, compute $\{\widetilde{d_i^{TC}}, \widetilde{d_i^1}\}$, where the tilde is used to denote a temporary calculation of the attributes at node i.

Variable arc costs $t_{i^-,i}^{p}$ and $t_{i^-,i}^{r}$ are computed when node i is added to connect to node i^- to form a partial path ρ. However, these costs may vary for different paths in which the preceding nodes are different. This is because propagation of delay to a flight may not only depend on the degree of its preceding flights' delays, but also the connection time and the rest period between these flights. Denote $\widetilde{d_i^p}$ as the temporary calculation of the propagated delay at node i. It is equal to the propagated delay of the last flight f_S in node i denoted as PD_{if_S}. PD_{if_S} is determined by the propagated delay of its prior node $d_{i^-}^{p}$, and of the entire flights in node i. There are two equations for determining PD_{if} , where Equation (14) is used for the first flight in node i and Equation (15) is for the remaining flights in node i. In Equation (14), the slack time for the connection $(i^-, i) \in \mathcal{A}^r$ is denoted as $B_{i^-,i}$ and it is the difference between the scheduled arrival time of the last flight f_S in node i^- and the scheduled departure time of the first flight f_1 in node i minus the minimum rest period for duty i^-. For the connections $(i^-, i) \in \mathcal{A}^s, \mathcal{A}^{ds}$, $B_{i^-,i} = 0$ and $d_{i^-}^{p} = 0$.

$$PD_{if_1} = \max\{0, (B_{i^-,i} - d_{i^-}^{p})\}, \quad \forall (i^-, i) \in \mathcal{A} - \mathcal{A}^{de} - \mathcal{A}^{e} \tag{14}$$

In Equation (15), an expected primary delay time denoted as ED_f (estimated in Section 2) for each flight $f \in D_i^I$ is given. The slack time for each connection of flights $(f^-, f) \in D_i^I$ is denoted as $S_{f^-,f}$, where f^- is the prior flight to flight f in node i, which is the difference between the scheduled arrival time of flight f^- and the scheduled departure time of flight f minus the minimum connection time. For example, the propagated delay of f_2, PD_{if_2}, will be equal to $\max\{0, (S_{f_1,f_2} - ED_{f_1} - PD_{if_1})\}$. If $PD_{if_2} > 0$, there is a propagated delay to f_2. This value will also be used for calculating the propagated delay for the next connection (f_2, f_3) and so on.

$$PD_{if} = \max\{0, (S_{(f^-),f} - ED_{(f^-)} - PD_{i(f^-)})\}, \forall (i^-, i) \in \mathcal{A} - \mathcal{A}^{de} - \mathcal{A}^{e}, \forall f \in D_i^I, \quad f \neq f_1 \tag{15}$$

In our model, if PD_{if} is above a desired acceptance level (RL), a reserve crew should be assigned to flight f, incurring a reserve crew cost c_{if}^{L} . Then, PD_{if} becomes zero, otherwise c_{if}^{L} is equal to zero. The propagated delay cost and the reserve crew cost for each connection of $(i^-, i) \in \mathcal{A} - \mathcal{A}^{de} - \mathcal{A}^{e}$ is given by Equations (16) and (17) respectively, where τ is a unit cost for each minute of delay. For the connections of $(i^-, i) \in \mathcal{A}^{de}, \mathcal{A}^{e}$, $t_{i^-,i}^{p}$ and $t_{i^-,i}^{r}$ are equal to zero as no flight is in the sink node.

$$\widetilde{t_{i^-,i}^{p}} = \widetilde{d_i^p}(\tau), \quad \forall (i^-, i) \in \mathcal{A} - \mathcal{A}^{de} - \mathcal{A}^{e} \tag{16}$$

$$\widetilde{t^{r}_{i^-,i}} = \sum_{f \in D^I_i} c^L_{if}, \quad \forall (i^-, i) \in \mathcal{A} - \mathcal{A}^{de} - \mathcal{A}^{e} \tag{17}$$

Subsequently, $\widetilde{d^{TC}_i}$ can be obtained by Equation (18). If the value of $\widetilde{d^{TC}_i}$ is less than the existing d^{TC}_i, and the resources attribute $\widetilde{d^1_i}$ is within the corresponding resource window, d^{TC}_i will be updated as $\widetilde{d^{TC}_i}$, similarity, d^1_i and $d^p_{i^-}$ are also updated as $\widetilde{d^1_i}$ and $\widetilde{d^p_{i^-}}$ respectively, and the prior node of i, $\rho(i^-)$, is set as $\boldsymbol{o}$. Then, node i is put into L, so L = $\{i\}$. For each node $i \in L$, if the connection $(i, i^+) \notin \mathcal{A}$, where i^+ is any node $i \in N$, $i^+ \neq i$, or the resources attribute $\widetilde{d^1_{i^+}}$ is invalid, node i will be simply removed from L but without adding any node i^+ into L The processes are repeated by removing a node from L until L becomes $\{\emptyset\}$. After that, the shortest path $\bar{\rho}$ can be obtained by $\rho = \{\boldsymbol{o}, \ldots, \rho(\rho(e^-)^-), \rho(e^-), \boldsymbol{e}\}$.

$$\widetilde{d^{TC}_i} = d^{TC}_{i^-} + t^f_{i^-,i} + \widetilde{t^p_{i^-,i}} + \widetilde{t^r_{i^-,i}} - \sum_{f \in D^I_i} \pi_f \tag{18}$$

Since $t^p_{\rho(i^-),i}$ and $t^r_{\rho(i^-),i}$ may change dynamically when solving the problem, they have to be computed each time from the source node to the node i when any preceding nodes of $\rho(i^-)$ have been changed, and this process induces a very heavy computational time. Therefore, it is expedient to avoid the change of the preceding nodes of $\rho(i^-)$ in the solution. In fact, it can be tackled by handling the nodes in L in acceding order of the node (duty) end time. To do that, after generated all the feasible duties, we perform an ascending sort of the duty end time which is the scheduled arrival time of the last flight of the duty, and then assign a node number in the same order to each duty. When solving the problem, the node is removed from L in ascending order, so that backward determination of the nodes can be avoided.

After determining the shortest path $\bar{\rho}$, the reduced cost can be obtained by (10). If $\bar{c}_p$ is negative, the path $\bar{\rho}$ is treated as a pairing p and is added to the solution pool of the master problem and goes through the iterative algorithm, where p is the p^{th} pairing generated for the master problem. If it is equal or larger than zero, the iterative process stops, and the variables determined in the master problem are the optimal set of pairings to cover the flights.

5. Numerical Experiment

In this section, we describe two experiments demonstrating (1) the significance of the proposed flight delay prediction method (i.e., CNN) in improving flight schedule stability, and (2) the significance of using the dynamic reserve crew to further increase the flight schedule stability. The proposed approach and other comparison approaches are coded in Java, and implemented on IBM ILOG CPLEX 12.5/ Concert Technology in solving the linear programs of the RMP on a 2.4 GHz PC with 4 GB RAM.

5.1 Experiment Settings

A. Creation of Instances

In the experiments, we selected one week of flight data in March 2016 of one of the major airlines in Hong Kong as the flight schedule problem to determine the robust crew pairing by using the proposed algorithm. Accordingly, the one year of flight data obtained is used to forecast the expected flight departure delay as input to forecast the expected flight arrival delay during that week. According to the airline practice, the flights are divided into long haul and short haul by regions for crew assignment, which is also common practice in the whole airline industry. As a result, the data can be divided into 5 instances, comprising 82 flights to 447 flights. Instance 1 mainly deals with long haul flights, while the rest of the instances are short haul flights. It is assumed that all the crew bases are the same.

B. Simulations

To test the performance of the crew pairing solution obtained in the experiments, the actual flight arrival delay data is used to calculate the actual cost of the solution. Accordingly, the number of flights being affected, the actual propagated delay cost (PDC), and the compensation cost (CC), can be calculated. The compensation cost (CC) depends on the degree of the propagated delay.

5.2 Numerical Experiment 1: Comparison of different forecasting methods to the flight schedule stability

The objective of experiment 1 is to test the performance of the crew pairing solution obtained using different forecasting methods to forecast the flight arrival delay for the assignment of buffer time. Accordingly, in this experiment, no reserve crew is assigned. In addition, 3 different forecasting approaches are used: (i) the proposed CNN, (ii) ARIMA, and (iii) F30, which is given a 30 min fixed expected flight arrival delay for each flight.

The results are summarized in Table IV. The Basic Pairing Cost (BPC) is the basic total operating cost required regardless of expected propagated delay costs and the costs used to force the solution to reach the ideal connection time in Equation (4). In other words, it includes the total basic fixed cost, the total deadhead cost, and total crew rest cost. The expected propagated delay cost (PDC) is the expected cost for the propagated delay during the planning phase, and the Time is the computational time required.

In Table IV, one can see that the performances in using different forecasting methods are not so significant in Instance 1 with 82 flights, mainly dealing with long haul flights. This phenomenon can be explained by the study by Barnhart et al., [38] who explained that the connectable flight legs and duties are relatively smaller in long haul networks. This implies that the choices for forming new duty combinations are smaller, and as a result, the improvement by using different forecasting methods is not significant. However, for short haul flights in Instances 2-5, the improvement becomes significant.

Throughout the 5 instances, the number of pairings and BPC obtained by using the proposed CNN approach is not the lowest. In addition, there is no single method that will generate the lowest BPC for every instance. By comparing to the lowest BPC in each instance, the BPC obtained by using CNN is 3% higher than the other approaches in Instance 2 to the highest of 11% in Instance 5. In other words, this implies that if there is no flight arrival delay, the operating cost by using CNN is higher and should not be recommended. However, in the condition of a flight delay occurring, the results show that the number of flights affected during disruption is much less by using the CNN approach and is the lowest for each instance. Moreover, the related disruption cost induced is the lowest as well. The percentage of disruption cost being minimized is remarkable with the highest up to 1284% lower in instance 4, comparing with approach F30.

In addition, one can see that in all the forecasting methods used, the expected PDC still deviates from the simulated PDC. In some cases, such as in Instance 2, the expected PDC is 28800 obtained by using CNN, which is even higher than the simulation case of only 19700. However, in other cases, such as Instances 3, 4, and 5, the expected PDC is lower than the simulated ones. However, for the other forecasting methods, the expected propagated delays are all significantly underestimated. These results demonstrate that the performance of using

CNN for the assignment of buffer time is the best among all the forecasting methods. The proposed CNN approach can increase the flight schedule stability for airlines.

Table IV. Results of Experiment 1

Instance (#Flights)	Approach	Planning					Simulation Results						
		No. of Pairings	Basic Pairing Cost (BPC)	% diff. in same Instance	Expected PDC	Time (s)	#Flights affected	PDC	CC	Total	% diff. in same Instance	Total Cost (BPC + PDC + CC)	% diff. in same Instance
1	**CNN**	**22**	**174400**	**0%**	9500	3.3	**3**	9500	30000	**39500**	**0%**	**213900**	0%
(82)	**ARIMA**	**22**	**174400**	**0%**	0	3.1	**3**	9750	30000	39750	**1%**	214150	0%
	F30	**22**	**174400**	**0%**	0	3.3	**3**	9750	30000	39750	**1%**	214150	0%
2	**CNN**	**18**	85200	3%	28800	5.6	**19**	19700	15000	**34700**	**0%**	**119900**	0%
(140)	**ARIMA**	**18**	**82800**	**0%**	17200	5.3	26	28000	15000	43000	**24%**	125800	5%
	F30	26	125400	51%	60750	5.3	25	36750	60000	96750	**179%**	222150	85%
3	**CNN**	39	249600	6%	12050	7.2	**9**	14950	15000	**29950**	**0%**	**279550**	0%
(219)	**ARIMA**	**33**	**236400**	**0%**	4150	7.4	14	31500	75000	106500	**256%**	342900	23%
	F30	35	237800	1%	9750	7.1	14	32750	75000	107750	**260%**	345550	24%
4	**CNN**	44	153200	10%	36100	53.2	**35**	68450	150000	**218450**	**0%**	**371650**	0%
(363)	**ARIMA**	**42**	**139800**	**0%**	17500	59.3	59	356550	1155000	1511550	**592%**	1651350	344%
	F30	**42**	144000	3%	26250	59.4	105	519350	2505000	3024350	**1284%**	3168350	753%
5	**CNN**	95	384800	11%	76450	287.1	**47**	146500	420000	**566500**	**0%**	**951300**	0%
(447)	**ARIMA**	**87**	**345600**	**0%**	88650	92.2	85	403300	1365000	1768300	**212%**	2113900	122%
	F30	102	479400	39%	73500	99.2	104	570800	2700000	3270800	**477%**	3750200	294%

5.3 Numerical Experiment 2: Comparison of different reserve crew strategies to the performance of flight stability

The objective of this experiment is to test the significance of the proposed dynamic reserve crew strategies on the performance of flight stability. In order to do so, we apply CNN as the forecasting method for the assignment of buffering time as it demonstrated that it outperforms the traditional regression based approaches in Numerical Experiment 1. We compare 6 different assignment strategies, (i) DRC-0, (ii) DRC-15, (iii) DRC-30, (iv) DRC-60, (v) T-20, and (vi) T-10. The first four strategies refer to dynamic reserve crew assignment (DRC), in which a reserve crew will be assigned if the expected propagated delay is expected to be longer than the sit time for 0, 15, 30, and 60 min. respectively in DRC-0, DRC-15, DRC-30, and DRC-60. For the last two strategies, a fixed reserve crew is assigned on each day regardless of the chances of having propagated delay, which is commonly used in literature. T-20 assigns 20 percent of crew level, while T-10 10 percent.

Table V summarizes the results obtained by using different strategies. First of all, we try to understand if there is any general pattern. However, by analyzing the BPC obtained, there is no pattern showing which strategies usually lead to a lower BPC. However, for the reserve crew cost, strategy DRC-60 is usually the lowest in all the instances. This can be expected because the chance of assigning reserve crew should not be very frequent. As a result, the number of reserve crews being used is less. On the other hand, the number of reserve crews using strategy T-20 is the highest.

One can see that in all the instances, strategy T-20 is a relatively better strategy as it leads to the lowest number of flights being affected and the lowest total disruption cost (Total DC), followed by DRC-0. This is expected because reserve crews are assigned very frequently. However, in terms of the total cost, strategy T-20 may not be a good approach because the high reserve crew cost cannot compensate for the disruption cost induced. In the case where the fixed reserve crew level is reduced from 20% down to 10%, as in strategy T-10, one can see that the total DC is also still relatively low, however, the reserve crew cost is still relatively higher than those using the dynamic assignment strategy, such as DRC-0, DRC-15, DRC-30, and DRC-60. As a conclusion, a dynamic reserve crew strategy is better than a fixed approach.

Moreover, it can be seen that the total disruption cost induced in Instances 1 – 4 is relatively lower than that in Instance 5. This implies that the flight arrival delay disruption is more serious. By comparing the dynamic strategies (DRC-0, DRC-15, DRC-30, and DRC-60), DRC-30 performs relatively better in Instances 1-4, while DRC-0 is better in Instance 5. This is because in situations having serious flight arrival delay disruption, immediately assigning reserve crews can lead to higher robustness. In addition, it may help in generating a lower crew pairing cost, so that the total cost can be lower.

As a conclusion, the results demonstrate that rather than applying a daily fixed reserve crew level strategy, the dynamic reserve crew assignment approach has more cost saving, but without affecting flight schedule stability. The results of strategy DRC-30 also demonstrate that in the situation where serious disruption is less likely to happen, airlines can assign a reserve crew when the expected flight arrival delay is longer than the sit time by 30 mins. On the contrary, in the case of serious disruption, it is suggested that airlines should assign a reserve crew even if the time difference is 10 mins according to the results of strategy DRC-10. These results provide guidance for airlines to determine the required reserve crew level in order to avoid disruption. In addition, in all the instances by using different reserve crew strategies, the overall flight schedule stability can be further enhanced when comparing the total cost as shown in Tables IV and Table V.

Table V. Results of Experiment 2

Instance (#flights)	Approach	Crew Pairing Planning: Basic Pairing Cost (BPC)	Crew Pairing Planning: Expected PDC	Reserve Crew Assignment: RC Cost	#RC	%	Daily Level (%): 1	2	3	4	5	6	7	Simulation Results: #Flights affected	PDC	CC	Total DC	Total Cost	%
1	**DRC-0**	**174400**	**0**	6000	3	200%	0	0	8	0	7	0	7	**0**	**0**	**0**	**0**	180400	1.0%
(82)	**DRC-15**	**174400**	**0**	4000	2	100%	0	0	8	0	7	0	0	1	250	0	250	**178650**	**0.0%**
	DRC-30	**174400**	**0**	4000	2	100%	0	0	8	0	7	0	0	1	250	0	250	**178650**	**0.0%**
	DRC-60	**174400**	**0**	**2000**	**1**	**0%**	0	0	8	0	7	0	0	2	3000	0	3000	179400	0.4%
	T20	**174400**	**0**	32000	16	1500%				20				**0**	**0**	**0**	**0**	206400	15.5%
	T10	**174400**	**0**	16000	8	700%				10				**0**	**0**	**0**	**0**	190400	6.6%
2	**DRC-0**	204200	**0**	40000	28	2700%	16	25	10	15	25	35	15	**0**	**0**	**0**	**0**	244200	149.9%
(140)	**DRC-15**	179600	6050	34000	17	1600%	0	10	10	15	20	20	10	8	4200	0	4200	217800	122.9%
	DRC-30	86200	19350	6000	3	200%	0	0	0	0	5	5	5	0	5500	0	5500	**97700**	**0.0%**
	DRC-60	**85000**	16200	**2000**	**1**	**0%**	0	0	0	0	0	0	5	16	14100	0	14100	101100	3.5%
	T20	85200	28800	56000	28	2700%				20				**0**	**0**	**0**	**0**	141200	44.5%
	T10	85200	28800	28000	14	1300%				10				5	3900	0	3900	117100	19.9%
3	**DRC-0**	242200	**0**	26000	13	333%	3	12	10	6	6	0	3	1	250	0	250	268450	4.8%
(219)	**DRC-15**	249600	**0**	24000	12	300%	3	12	10	6	6	0	0	2	500	0	500	274100	7.0%
	DRC-30	**235800**	5500	12000	6	100%	0	6	3	3	6	0	0	9	8250	0	8250	**256050**	**0.0%**
	DRC-60	239400	7850	**6000**	**3**	**0%**	0	6	0	0	3	0	0	11	12300	0	12300	257700	0.6%
	T20	249600	12050	86000	43	1333%				20				**0**	**0**	**0**	**0**	335600	31.1%
	T10	249600	12050	42000	21	600%				10				**0**	**0**	**0**	**0**	291600	13.9%
4	**DRC-0**	156800	**0**	48000	24	167%	6	11	7	5	4	5	5	**0**	**0**	**0**	**0**	204800	5.7%
(363)	**DRC-15**	150600	2450	42000	21	133%	6	9	5	3	4	3	7	13	4500	0	4500	197100	1.7%
	DRC-30	146600	25000	20000	10	11%	4	7	5	3	2	7	5	29	27150	0	27150	**193750**	**0.0%**
	DRC-60	**141200**	25350	**18000**	**9**	**0%**	4	1	3	3	0	3	0	36	45900	30000	75900	235100	21.3%
	T20	153200	36100	144000	72	700%				20				**0**	**0**	**0**	**0**	297200	53.4%
	T10	153200	36100	72000	36	300%				10				4	2800	0	2800	228000	17.7%

5	**DRC-0**	**186400**	**0**	52000	26	117%	4	12	4	4	4	4	4	10	23600	60000	83600	**322000**	**0.0%**
(447)	**DRC-15**	371800	3350	80000	40	233%	9	9	9	9	9	7	7	17	22100	60000	82100	533900	65.8%
	DRC-30	448000	51650	36000	18	50%	3	4	4	4	4	4	1	37	54900	75000	129900	613900	90.7%
	DRC-60	330200	54550	**24000**	**12**	**0%**	3	1	3	3	1	3	3	41	81100	165000	246100	600300	86.4%
	T20	384800	76450	178000	89	642%				20				**0**	**0**	**0**	**0**	562800	74.8%
	T10	384800	76450	88000	44	267%				10				3	7350	30000	37350	510150	58.4%

6. Conclusions

The crew pairing problem is crucial to airline operations because a high quality crew pairing solution can reduce the airline operating cost, as well as increasing flight schedule stability and reducing the cost when a disruption occurs. However, this problem is very complicated due to various regulations governed by union, airline, and aviation authorities. This paper proposes a robust crew pairing approach by forecasting flight arrival delays to support the assignment of buffer time in order to create robustness during the crew pairing phase. In addition, a reserve crew assignment strategy is proposed to assign reserve crew to further increase the robustness.

In doing so, we obtained one year of flight data from a major airline in Hong Kong and the flight data of the related airports covered. For forecasting, we applied some basic flight information, such as flight number, scheduled departure time, schedule arrival time, etc. and proposed some indicators, including Peak Hours indicator, Peak Season indicator, and Peak Typhoon/Hurricane indicator. In addition, analysis of flight arrival delays shows a certain amount of flight departure delay time can be absorbed by the shorter flight times. Accordingly, a new flight time indicator is proposed using the Cascade Neural Network modelling approach. By comparing our proposed CNN forecasting approach with different traditional methods, the results demonstrated the forecasting accuracy is significantly improved. This demonstrates that forecasting the expected flight departure delay to support the forecasting of flight arrival delay is crucial. It also demonstrates that traditional methods that only take obvious historical data into account are unable to make accurate predictions. It is simply because occurrence of flight delay arises from many factors so that simple descriptive statistics are too simple to describe the situation.

The experimental results also demonstrated that fixed and high reserve crew levels can successfully maintain flight schedule stability, but lead to high crew costs. Comparatively, a dynamic reserve crew assignment strategy is better because it can maintain flight stability but requires lower costs. It is suggested that strategy DRC-30 is suitable for situations where serious disruption is less likely to happen. For the cases of serious disruption, airlines are recommended to use DRC-10. More importantly, this also means a robust prediction of the delay lays

In this paper, the proposed algorithm is only designed for a hub-and-spoke airline network with both long haul and short haul flights. Reserve crew assignment can then be centralized in the hub. In recent years, budget airlines are becoming more prevalent, and the point-to-point network is the main framework being adopted. The assignment of reserve crews will then be decentralized and it will be even more complicated. Accordingly, it is suggested that more effort can be devoted to increasing the flight stability for budget airlines. Moreover, this CNN forecasting approach can also be used in other domains, such as vessel scheduling, which is also an important issue to terminal operations as the adoption of massive vessels is becoming more prevalent nowadays.

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